

Motion Artifact Reduction from Non-contact ECG Recording Systems

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Abstract

With the growing demand for real-time, long-term, and remote electrocardiogram (ECG) monitoring, non-contact capacitive sensors have emerged as a compelling solution due to their safety, comfort, and suitability for continuous use. However, a significant challenge remains; motion artifacts (MAs) caused by body movements and physiological vibrations. Such artifacts can significantly compromise diagnostic accuracy and may even lead to misinterpretations of cardiovascular conditions.

To address this, this PhD research begins by demonstrating the feasibility of capacitive ECG acquisition from the head area to broaden its application scope, then transitions to a torso-worn chest strap system for practical implementation and MA reduction. It also includes a structured review of MAs in capacitive ECG systems, analyzing their mechanisms and mitigation strategies, with focused attention on electrode-tissue impedance (ETI)-based reference signal techniques.

To further this development, the study tackles this challenge by developing novel techniques to reduce MAs and improve the quality of capacitive ECG signals. The Adaptive Noise Cancellation (ANC) technique is selected for MA mitigation, using a motion-correlated Reference Input Signal (RIS) and an Adaptive Filter (AF) to estimate and subtract MAs. A full-stack capacitive single-lead system is designed, spanning hardware, analog front-end design, and advanced signal processing.

In this system, ECG and a highly correlated ETI-based RIS are simultaneously acquired through an efficient voltage injection network, offering improved performance compared to previous studies. In the first phase, the RIS is fed to a Recursive Least Squares adaptive filter to suppress MAs. Signal enhancement is evaluated using root mean square (RMS) reduction, standard deviation (STD) reduction, and signal-to-noise ratio (SNR) per peak. The system demonstrates strong performance, achieving RMS, STD, and per-peak SNR improvements of 17.9 dB (650.2%), 4.24 dB (36.8%), and 2.8 dB (15%), respectively.

In the subsequent phase, a Variable Step-Size Least Mean Squares with Correlation Power Boosting (VSS-LMS-CPB) adaptive filter is proposed. Benchmarking against seven established AFs confirms its superior performance in dynamically adapting step size, maintaining stability, preserving ECG morphology, and robustly handling both intra- and inter-experiment MA variability, fluctuating RIS–MA correlations, and abrupt high-amplitude artifacts, all without instability or over-adaptation.

Although ETI-based RIS methods have not been widely assessed across diverse participants and conditions, the system is validated through both controlled and realistic motion experiments involving three participants. A total of nine motion scenarios, including stationary and dynamic conditions, are tested to assess generalizability and robustness. Performance is evaluated using correlation coefficients and RMS improvement, both showing marked enhancements.

Collectively, the results confirm the effectiveness of the RIS-based framework and VSS-LMS-CPB algorithm in significantly reducing MAs while preserving ECG integrity. The system effectively suppresses MAs, achieving an RMS improvement of up to 11.12 dB and reducing ECG-RIS correlation from 0.866 to 0.107.

By preserving full ECG morphology, including P, QRS, and T waves under motion conditions, this work advances the feasibility of wearable, non-contact ECG monitoring for telemedicine and continuous health tracking. The research contributes to biomedical signal processing by introducing practical, high-performance solutions for artifact mitigation in challenging non-contact recording environments.

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List of Abbreviations

Abbreviation	Definition
ADC	analog-to-digital converter
AFE	analog front-end
AF	adaptive filter
AM	amplitude modulation
ANC	adaptive noise cancellation
AVNRT	atrioventricular nodal reentrant tachycardia
BSS	blind source separation
CA	charge amplifier
cECG	capacitive ECG
CM	common-mode
CMI-SC	Common-Mode Interference Suppression Block
CMRR	common-mode rejection ratio
CVD	cardiovascular disease
DR	dynamic range
DRL	driven-right-leg
DSP	digital signal processing
ECG	electrocardiogram
EEG	electroencephalogram
EMI	electromagnetic interference
ENLMS	Error-Normalized Least Mean Square
ETI	electrode-tissue impedance
GSVS-LMS	Gradient-based Variable Step-Size Least Mean Square
HPF	high-pass filter
INA	instrumentation amplifier
KAF	Kernel adaptive filter
KCL	Kirchhoff's current law
LMS	Least Mean Square
LM	left mastoid
LPF	low-pass filter
LTI	linear time-invariant
MA	motion artifact
MD	Movesense Medical
MSE	mean squared error
NLMS	Normalized Least Mean Square
PACC	Peak Accuracy
PLI	power-line interference
PPPV	Positive Predictive Peak Value
PSNS	Peak Sensitivity
RIS	Reference Input Signal
RLS	Recursive Least Squares
RMS	root mean square
SNR	signal-to-noise ratio
STD	standard deviation
TECD	triboelectric charge density
TENG	triboelectric nanogenerator
VA	voltage follower amplifier
VR	virtual reality
VSS-LMS-CPB	Variable Step-Size Least Mean Squares with Correlation Power Boosting
VSS-LMS	Variable Step-Size LMS

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), and that ChatGPT was used solely for proofreading, grammar correction, and improving the clarity and readability of the written content. No AI-generated content or analysis contributed to the originality or scientific findings of the research. It also contains no material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Co-Authored works and Declaration of Collaboration

STUDENT AND SUPERVISOR APPROVALS

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Kuo	provided guidance and support to improve the quality of the research

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Lowe	Provided guidance and support to improve the quality of the research
GholamHosseini	provided guidance and support to improve the quality of the research
Kuo	provided guidance and support to improve the quality of the research

Patent Application Disclosure

It should be noted that a provisional Australian patent application arising from the research presented in Chapter 4 has recently been filed. The details of the application are as follows:

- **Application Number:** 2025902748
- **Title:** An Improved Device and Process for Differential Capacitively Coupled Capture of Biopotential Signals
- **Filing Date:** 1 July 2025
- **Applicant:** AUT Ventures Limited of AUT, 14th Floor, Wo Building, 56 Wakefield Street Auckland 1010 New Zealand
- **Inventors:** Andrew Lowe, Matin Khalili

Chapter Number:	5
Manuscript Title:	Motion Artifact Reduction in a Wearable Capacitive ECG System Using an Electrode-Tissue Impedance-Based Reference and a Novel Adaptive Filter
Publication Status:	Unpublished/Ready for submission for Publication
Reference if published:	
AUTHOR SURNAME: (order as per manuscript)	CONTRIBUTION (May copy from the guidelines above)
Khalili	Responsible for writing, ideas, and the content of the research
Lowe	Provided guidance and support to improve the quality of the research
GholamHosseini	provided guidance and support to improve the quality of the research
Kuo	provided guidance and support to improve the quality of the research

Chapter 1 Introduction

1.1 Overview

Cardiovascular diseases (CVDs) include a broad spectrum of disorders affecting the heart and blood vessels, such as coronary artery disease, cerebrovascular disease, and rheumatic heart disease. They remain the leading cause of mortality worldwide, accounting for more than 17.9 million deaths annually which is approximately 32% of all global deaths [1]. In New Zealand, CVDs have a significant impact, with around 175,000 individuals living with heart disease and nearly one-third of all deaths attributed to it. Alarming, one New Zealander dies from heart disease every 90 minutes [2].

Among various forms of CVD, cardiac arrhythmias contribute to nearly 80% of cases [3]. Arrhythmias are irregular heartbeats that may cause symptoms such as palpitations, dizziness, fainting, and shortness of breath. While some arrhythmias are benign, others, such as atrial fibrillation, premature ventricular contractions, and frequent supraventricular ectopic beats, can escalate to critical conditions, including stroke, cardiac arrest, or heart failure [4].

To effectively detect, monitor, and manage these cardiovascular conditions, clinicians rely on biosignals, which play a vital role in modern medical diagnostics [5]. Among them, the electrocardiogram (ECG) is one of the most widely used tools for identifying abnormal heart rhythms, investigating the cause of chest pain, and classifying cardiovascular diseases in clinical settings [6–8]. It is a non-invasive, cost-effective method that captures the heart's electrical activity through electrodes placed at specific locations on the body surface [3, 7–9]. This electrical activity, generated by myocardial contraction, is typically analyzed in the time domain. A standard ECG signal consists of repeating waveforms corresponding to individual heartbeats, including the P wave, QRS complex, and T wave, as illustrated in Figure 1-1. Deviations in these waveform features often indicate underlying cardiac abnormalities. Specifically, the ECG signal spans a frequency range of approximately 0.67 to 120 Hz [7], with lower-frequency components (5–9 Hz) corresponding primarily to the P and T waves, and higher-frequency components associated with the sharp and rapid QRS complex [7].

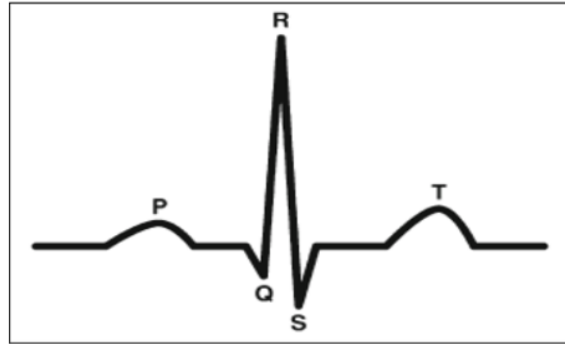


Figure 1-1. ECG signal [7].

Building on the diagnostic utility of ECG signals outlined above, early detection and continuous monitoring are essential for both preventing disease and improving outcomes once symptoms appear. It is estimated that up to 90 % of cardiovascular diseases can be avoided through early detection and timely intervention [10]. In emergency scenarios, rapid treatment during the “golden hour”, the first 60 minutes after symptom onset, can markedly reduce mortality and preserve quality of life in emergencies such as cardiac arrest [6, 11]. Two complementary strategies support this goal:

1. **Real-time ECG surveillance for emergency response:** Continuous telemetry enables immediate recognition of acute events, allowing clinicians or automated systems to trigger life-saving action within the golden hour.
2. **Long-term ECG tracking for chronic management:** Persistent monitoring captures day-to-day rhythm changes, helping physicians tailor therapy and adjust medications for patients with established CVD.

Despite these advantages, several barriers limit long-term in-hospital monitoring. Specifically, the prevalence of CVD is rising in ageing populations of high-income nations and poses an even greater burden in low- and middle-income countries [12]. Hospital capacity is finite, and prolonged admissions are costly. Moreover, in many rural regions, geographical isolation further hampers access to specialized cardiac care, prompting interest in virtual and home-based monitoring solutions [13]. Collectively, these pressures are driving a shift from hospital-centered to patient-centered healthcare, where physiological data are captured unobtrusively in everyday settings [12, 14].

Beyond cardiac diseases, continuous ECG monitoring holds potential for stress assessment. Heart-rate-derived metrics contribute to multimodal stress assessment, complementing self-report scales, hormonal biomarkers (e.g., cortisol), behavioral cues, and electrodermal activity [15]. Stress triggers neuro-endocrine responses that

modulate respiration, muscle tone, and cardiac rhythm [16]. Like disease surveillance, effective stress monitoring requires long-term, unobtrusive signal acquisition outside clinical environments.

Given these clinical, logistical, and societal factors, there is an increasing need for ECG monitoring systems that are comfortable, reliable, and suitable for deployment beyond traditional hospital settings. This need has driven the development of various electrode technologies designed to overcome the limitations of conventional ECG acquisition.

The following subsections describe the types of electrodes commonly used in ECG monitoring, their benefits, and the inherent challenges associated with each type, setting the stage for exploring more advanced non-contact solutions.

1.2 Types of ECG Electrodes

1.2.1 Gel Electrodes (Wet Electrodes)

Among the various ECG acquisition methods, wet electrodes remain the most widely used in clinical and research settings due to their proven accuracy, simplicity, and low cost. These electrodes require direct galvanic contact with the skin, established through the application of an electrolytic gel. The gel reduces skin-electrode impedance, facilitating the transduction of ionic currents into electrical signals, and enabling high-fidelity ECG recording [12, 17–22].

Despite their widespread use, wet electrodes present several limitations that make them unsuitable for long-term or out-of-hospital monitoring. They are typically single-use and disposable, necessitating regular replacement for continuous measurements. Additionally, their application requires professional skin preparation, often involving shaving and cleaning the site, which adds complexity and discomfort. Moreover, the gel contains potentially irritating or allergenic substances, and it tends to dry out over time, limiting the recording duration. The electrodes can also be dislodged by sweat or water exposure, reducing their reliability in ambulatory settings [18, 19, 21, 23–27]. Consequently, researchers actively investigate alternatives eliminating the dependency on gels and enabling non-invasive, routine monitoring without disrupting daily life [23].

1.2.2 Dry Electrodes

Dry electrodes, like wet electrodes, function through direct galvanic contact between the skin and electrode surface. However, instead of using an electrolytic gel, dry electrodes employ conductive materials such as

metal or conductive fabric. They rely primarily on natural skin moisture (e.g., sweat) to facilitate signal conduction.

Although they avoid the mess and irritation associated with gels, dry electrodes often exhibit higher skin-electrode impedance, particularly at the start of monitoring. This impedance typically decreases after a few minutes as sweat accumulates at the contact site, making their performance comparable to wet electrodes.

Metal-based dry electrodes are robust and easy to manufacture, but generally unsuitable for prolonged recordings due to their lack of inherent adhesion. This makes stable placement difficult and increases susceptibility to different types of interferences. Although adhesives can be added to secure dry electrodes for continuous monitoring, doing so often compromises their comfort, negating one of their primary advantages [23, 28].

1.2.3 Non-Contact Capacitive Electrodes

To overcome the limitations of traditional ECG measurement methods, non-contact capacitive electrodes have emerged as a promising alternative for biopotential sensing. Unlike wet and dry electrodes that require direct conductive contact with the skin, capacitive electrodes measure surface potentials across an insulating layer, allowing biopotential recordings even when separated from the skin by hair, clothing, air, or other dielectric materials [23]. This is achieved by coupling the body's ionic currents to the sensor via capacitive displacement, which is then converted into measurable voltage signals by the acquisition circuitry.

Capacitive sensors offer several advantages for long-term and user-friendly ECG monitoring, including comfort, reusability, biocompatibility, and the elimination of skin preparation. They have been successfully implemented in a wide range of everyday environments, such as beds, chairs, bathtubs, wheelchairs, automobiles, and wearable garments, enabling passive health tracking without disrupting users' routines [19, 23, 29–31]. Their unobtrusive nature makes them particularly attractive for preventive health monitoring, especially in individuals not yet diagnosed with CVD [31].

In clinical edge cases, capacitive electrodes provide important benefits where traditional placement is not feasible. For example, in patients with severe burns, conventional chest-based ECG monitoring may be impractical. In such cases, capacitive electrodes offer a feasible alternative, as they do not require adhesive or gel materials and can be positioned at sites such as the head or neck to enable continuous monitoring.

Despite their versatility, achieving diagnostic-grade signal quality with capacitive systems remains challenging due to environmental interference, particularly motion artifacts (MAs), which are more prominent than in

contact-based systems [26-27]. Analog circuits can partially reduce MAs but typically leave residual interference requiring additional digital processing [34].

Given these complexities and the persistent challenges associated with capacitive electrodes, particularly related to effectively managing MAs, a thorough exploration of these issues is required. A better understanding of both the potential and limitations of capacitive ECG technology will help clarify its role in clinical practice and everyday health monitoring. This exploration provides the basis for the detailed rationale and significance outlined in the next section.

1.3 Rationale and Significance of the Study

Although capacitive electrodes offer many advantages, some technical challenges still limit their use in clinical settings. Among these, MAs present the most significant challenge, severely affecting the stability and quality of recorded ECG signals. MAs broadly refer to signal distortions arising from voluntary or involuntary body movements, such as respiration, posture shifts, muscle contractions, and cardiac-induced motion [32, 35–38]. These artifacts significantly reduce the signal-to-noise ratio (SNR), impairing the accurate interpretation of ECG waveforms and potentially compromising clinical decision-making. For instance, MAs may mask or falsely mimic critical waveform features like the R-peak or ST-segment, leading to incorrect heart rate measurements or the erroneous detection of arrhythmic events [37, 38].

The spectral content of MAs commonly lies below 10 Hz [37, 39, 40], though in certain situations it can extend up to 20 Hz [41–43]. This frequency range notably overlaps with essential ECG signal components, including respiratory activity (0.1–2 Hz), body movements (0–10 Hz), and ballistocardiographic signals (up to 20 Hz) [41]. Consequently, simple frequency-based filtering techniques, such as high-pass or band-pass filters, often fail to adequately remove these artifacts without simultaneously suppressing critical physiological details, particularly the diagnostically important low-frequency P and T waves. This limitation greatly diminishes diagnostic accuracy and reliability.

Moreover, despite the growing number of studies focused on capacitive ECG, the exact mechanisms underlying MAs remain poorly understood, making effective artifact removal difficult [33]. Current mitigation methods struggle with the unpredictable and complex nature of these artifacts, underscoring a critical gap in knowledge and technology. Thus, there is an urgent need for more sophisticated and robust MA reduction approaches that can preserve clinically relevant ECG details, even during periods of extensive physical activity or significant motion.

Addressing these challenges is vital for the translation of capacitive ECG technology from controlled, experimental conditions to dependable real-world clinical applications. The significance of this PhD research, therefore, lies in developing, validating, and optimizing novel MA mitigation techniques that enable stable, accurate, and reliable ECG monitoring using capacitive electrodes. Such advances will not only enhance the clinical utility and acceptance of capacitive ECG systems but also significantly expand their applicability in outpatient, ambulatory, and remote patient monitoring scenarios.

1.4 Research Aim and Objectives

The overall aim of this PhD research is to develop a robust capacitive ECG measurement system that mitigates the impact of MAs, enabling accurate and reliable ECG acquisition for real-world healthcare applications. To achieve this aim, the research is structured around the following four interconnected objectives:

Objective 1: Demonstrating the Feasibility of Capacitive ECG Acquisition from Alternative Body Sites to Broaden Its Application Scope and Motivate Further Research

This objective investigates the feasibility and effectiveness of using capacitive electrodes to record ECG signals specifically from the head and neck regions, by designing and evaluating a capacitive system. Our primary goal is to evaluate the quality of signals obtained from these unconventional locations and identify practical clinical scenarios where such placements are advantageous. Demonstrating the feasibility of ECG monitoring from these regions broadens the application scope of capacitive electrodes and underscores the need for continued research in this field.

Objective 2: Comprehensive Understanding and Analysis of Motion Artifacts in Capacitive ECG Systems

A clear gap currently exists regarding the comprehensive and systematic understanding of MAs in capacitive ECG monitoring systems. To address this, this objective aims to:

- Provide a detailed overview of MAs by bringing together their definitions, origins, characteristics, and impacts on ECG signals, drawn from existing literature.
- Systematically review contemporary techniques for mitigating MAs, with particular emphasis on digital signal processing (DSP) methods.
- Analyze the strengths and weaknesses of existing mitigation strategies through a comparative study, clearly outlining their methodological differences, challenges encountered, and overall effectiveness.

- Discuss essential non-motion-related interferences such as common-mode (CM) interference, front-end electronic challenges, as understanding these interferences is crucial for clearly distinguishing and accurately addressing MAs.

Objective 3: Development of an Optimized Method for Extracting an Electrode-Tissue Impedance-Based Reference Input Signal Highly Correlated with Characterized Motion Artifacts

Building upon the comprehensive understanding of MAs, this objective aims to address key practical limitations previously overlooked. Specifically, the goal is to:

- Optimize electrode design parameters to achieve ECG signal quality comparable to conventional wet electrodes under stationary conditions.
- Precisely model and quantify MAs inherent in single-lead capacitive ECG configurations, comprising two sensing electrodes and a reference electrode, to strategically derive and optimize an electrode-tissue impedance (ETI)-based Reference Input Signal (RIS) closely correlated with actual MAs.
- Develop and validate a comfortable, wearable, single-lead capacitive ECG measurement system integrated into a chest strap.
- Demonstrate the effectiveness and reliability of the proposed system through comprehensive evaluation using multiple performance metrics.

Objective 4: Designing a High-Performance Adaptive Filtering Algorithm with Consistent Intra- and Inter-Experiment Performance, and Validating the Overall System Across Diverse MA Scenarios Involving Multiple Participants

To effectively mitigate MAs and improve diagnostic reliability, this final objective involves:

- Evaluating the reliability and robustness of the extracted ETI-based RIS through controlled experiments, each simulating realistic daily use conditions of ECG monitoring systems.
- Investigating the limitations and shortcomings of existing adaptive filters (AFs) and developing an innovative adaptive filtering algorithm designed specifically to overcome their drawbacks.
- Validating the proposed adaptive filter rigorously across both sets of experiments, using multiple subjects to assess its robustness and reliability under realistic motion-induced conditions.
- Comparing the developed filtering technique systematically against a range of existing adaptive filters to comprehensively demonstrate its superiority in terms of artifact suppression and preservation of diagnostic ECG information.

1.5 Research Methods

To achieve the research objectives outlined in this study, a combination of literature analysis, hardware development, system modeling, algorithm design, and experimental validation is employed. The methodological framework is summarized as follows:

- **For Objective 1**, the research involved the design and implementation of a capacitive ECG acquisition system, including custom electrode configurations. This stage also includes experimental testing and signal quality assessment.
- **For Objective 2**, an extensive literature review and critical analysis are conducted to examine the nature and characteristics of MAs in capacitive ECG systems.
- **For Objective 3**, the study focuses on the hardware optimization and practical implementation of a wearable capacitive ECG system capable of simultaneous ECG and RIS acquisition. This phase incorporates system modeling, reference signal extraction techniques, and multi-scenario testing to ensure robustness and correlation with real-world MAs.
- **For Objective 4**, the research employs a signal processing and algorithm development approach. The overall system performance, including the proposed ETI-based RIS and the adaptive filtering algorithm, is comprehensively assessed across multiple experimental conditions and benchmarked against existing linear and nonlinear filters using quantitative metrics and participant data.

The research methodology followed an iterative design-test-refine cycle, combining theoretical modeling with empirical validation to ensure technical rigor and practical relevance.

1.6 Thesis Organization

This PhD thesis is structured into six interconnected chapters, each progressively built upon the previous content, as illustrated in Figure 1-2.

Chapter 1 introduces the research by establishing the rationale and significance of the study. It clearly states the overall research aim, which is divided into four main objectives. Each objective raises specific research questions addressed sequentially in subsequent chapters. Additionally, the chapter briefly summarizes the research contributions, methodology, and the overall thesis structure.

Chapters 2–5 have been prepared as individual manuscripts for submission to high-quality peer-reviewed journals. The manuscripts corresponding to Chapters 2 and 3 have already been published, while those for Chapters 4 and 5 have been submitted. Additionally, a provisional Australian patent application was filed based

on the work presented in Chapter 4. To preserve the integrity of the original manuscripts, each chapter retains its original format and may contain some recurring content. Abbreviations are defined separately within each chapter to maintain consistency. Each chapter is preceded by a prelude to contextualize its contribution within the overall structure of the thesis.

Chapter 2, addressing Objective 1, investigates ECG signal acquisition from unconventional body locations such as the head and neck, and reviews their potential applications as documented in existing literature. This chapter details the design of a customized capacitive ECG measurement system and systematically evaluates different anatomical sites in the head and neck regions to identify the optimal electrode placement. Demonstrating the feasibility of ECG monitoring from these unconventional areas broadens the application scope of capacitive electrodes, underscoring the necessity for further research, especially in relation to MA, which remains a critical challenge in capacitive ECG systems. This challenge motivates further investigation in Chapter 3.

Chapter 3 addresses Objective 2 by providing a comprehensive understanding of MAs within capacitive ECG measurement systems. It begins with an introduction to the fundamental principles of capacitive ECG technology and subsequently identifies key limitations in capacitive electrode circuitry, along with potential solutions to enhance signal quality. Following this foundation, the chapter presents a detailed overview of MAs, discussing their definitions, origins, characteristics, and their impact on ECG signal integrity. State-of-the-art techniques for mitigating MAs are then critically reviewed across three main domains: analog circuit designs, electrode materials and fabrication techniques, and DSP methods. Although these three domains require parallel development, particular emphasis is placed on DSP techniques due to their effectiveness in addressing MAs. The chapter concludes by highlighting persistent gaps in current research, notably the need for a more strongly correlated RIS based on ETI or alternative references. These identified gaps are addressed subsequently in Chapter 4.

Chapter 4, corresponding to Objective 3, focuses specifically on characterizing MAs within a single-lead capacitive ECG measurement system and developing an optimized method for extracting an ETI-based RIS highly correlated with these characterized MAs. The chapter describes methodologies characterizing MAs, capacitive electrode design, analog front-end circuitry, and DSP techniques for MA mitigation. The experimental setup and data collection procedures are thoroughly detailed, followed by a presentation and discussion of experimental findings and results. The chapter concludes by acknowledging study limitations,

including the small sample size, the limited number of motion scenarios tested, and the need for further optimization of the adaptive-filter architecture to reduce residual artifacts and improve generalizability. These limitations are subsequently addressed in Chapter 5.

Chapter 5 is dedicated to Objective 4 by evaluating the proposed ETI-based RIS across two comprehensive sets of experiments simulating realistic, everyday chest-strap usage conditions involving multiple participants. Additionally, the limitations of existing adaptive filtering methods are carefully analyzed, resulting in the proposal of a novel adaptive filtering algorithm. The chapter assesses system performance across multiple conditions and participants, and presents comparative evaluations with existing adaptive filtering techniques. It further provides a detailed description of related work, system design, experimental setups, signal characterization, evaluation metrics, and results.

Finally, Chapter 6 presents a comprehensive discussion of the research findings, summarizes conclusions drawn from the overall study, and proposes future research directions. This concluding chapter synthesizes the outcomes of all preceding chapters, emphasizing the contributions made toward developing robust and reliable capacitive ECG systems suitable for clinical and real-world applications.

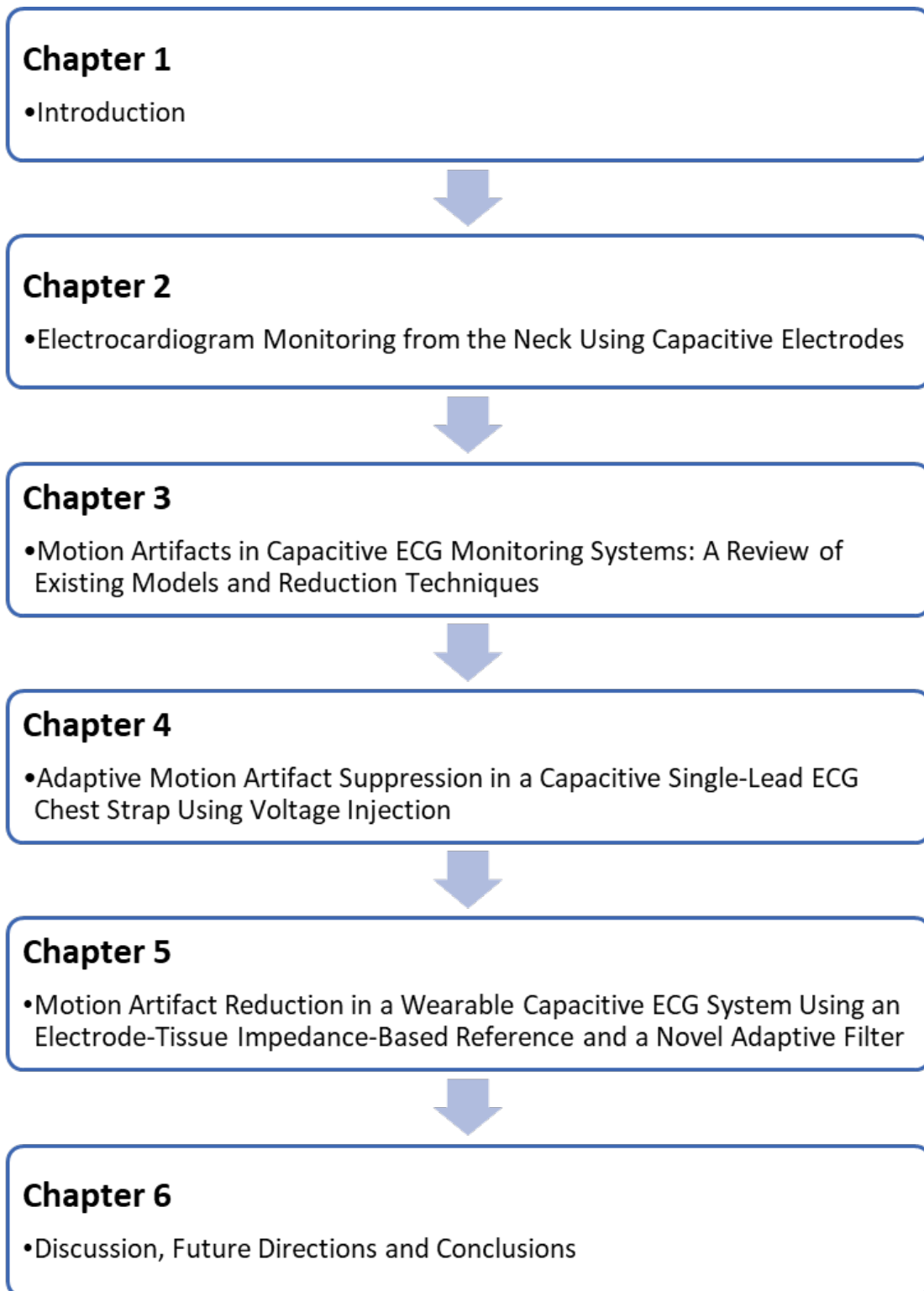


Figure 1-2 Thesis structure.

Chapter 2 Electrocardiogram Monitoring from the Neck Using Capacitive Electrodes

2.1 Prelude

The content of this chapter is a copy of the article titled “Electrocardiogram Monitoring from the Neck Using Capacitive Electrodes”, published in the peer-reviewed ASME Journal of Engineering and Science in Medical Diagnostics and Therapy (JESMDT) [44].

Capacitive ECG (cECG) measurement systems are widely recognized for their ability to enable comfortable, long-term, and real-time cardiac monitoring, particularly in wearable applications and furniture-integrated systems. These features make cECG highly suitable for out-of-hospital settings, where non-invasive, practical, and unobtrusive solutions are essential. These advantages also give rise to the potential for previously unexplored applications, prompting this research to investigate alternative electrode placements for ECG monitoring.

Through the course of this study, it became evident that the head and neck regions, though unconventional, offer promising alternative sites for ECG monitoring in addition to traditional chest-based placements. These areas are particularly relevant in scenarios where chest electrodes are impractical, such as in patients with torso injuries, or in applications involving virtual reality headsets, military helmets, or cascade hard hats. However, this thesis specifically addresses these alternative placements only within this chapter, with subsequent chapters returning the focus primarily to conventional chest-based capacitive ECG.

By demonstrating the feasibility of ECG monitoring from the head and neck regions, this chapter aims to broaden the scope of cECG applications and highlight the importance of continued research in this field. A deeper understanding of the limitations and technical challenges associated with cECG is essential. Effectively addressing these challenges is critical to enhancing system reliability, improving signal quality, and ultimately developing versatile solutions suitable for a wide range of real-world applications, including ambulatory monitoring, wearable devices, and remote patient management. The following chapter presents the design, development, and evaluation of a capacitive ECG system specifically optimized for neck and head placements. It systematically examines signal quality, discusses practical advantages, and identifies potential clinical use cases, thereby laying the groundwork for the next stages of this research.

2.2 Abstract

The monitoring of electrocardiogram (ECG) signals is crucial for both cardiac health and mental state assessment. Traditional ECG methods rely on chest electrodes; however, they pose challenges for individuals with chest injuries or burns and can cause discomfort over extended use. Capacitive electrodes offer a non-contact method, which is particularly beneficial for wearable applications, providing a comfortable and feasible alternative for long-term use. Findings suggest that neck-based monitoring can achieve effective ECG signal acquisition, reducing motion artifacts in certain configurations and potentially expanding the application of ECG for heart and mind monitoring. Additionally, using the neck area for diagnosing specific conditions could collect more information. This study explores the feasibility and advantages of using capacitive electrodes for ECG monitoring from the head and neck area.

2.3 Introduction

Electrocardiogram (ECG) monitoring is an essential tool in diagnosing and managing cardiac health, enabling the detection of arrhythmias, ischemia, and other heart-related issues [14]. Traditional ECG monitoring typically relies on wet electrodes placed on the chest, which allow for a direct electrical connection through conductive gel [21]. While effective, this approach has limitations, especially in cases where patients have, making contact-based electrodes uncomfortable or impractical. Additionally, conventional setups may not be ideal for continued monitoring due to the need for frequent reapplication of conductive gel, which can dry out, leading to inconsistent reading.

As the demand for remote and continuous cardiac monitoring grows, so does the need for alternative electrode technologies and placements that simplify monitoring and enhance patient comfort. Capacitive electrodes, which work without direct skin contact, address many limitations of traditional electrodes, particularly in wearable device applications. Locations, such as the head and neck areas, increasing their practical applications. For instance, in cases of serious injuries, like severe burns to the torso, accurate placement on the chest may be challenging or even impossible. Gard et al. [45] reported that at their regional burn center, which serves about 500 patients annually, chest burns accounted for 21% of admissions in both 2020 and 2021. In such cases, the head or neck areas offer viable alternatives for ECG monitoring.

Furthermore, early detection of cardiac events could be possible by continuously monitoring changes in cardiac activity patterns, providing a potential warning system before a heart attack occurs. For nonhospital settings,

a wearable device that combines clinical accuracy with a discreet design, especially one worn around the head or neck and connected to the cloud via smartphone, is ideal [46]. Such a device could also be integrated into furniture, like bed accessories, for nighttime monitoring [47].

Recent advancements in wearable technology have enabled continuous monitoring of biopotentials across various activities. In sports like cycling and motor racing, as well as in military applications, helmets with embedded sensors can conveniently monitor vital biosignals [48].

Beyond cardiac health, ECG monitoring from these areas holds potential for stress assessment. For stress assessment, several methods exist. Common approaches include self-reported questionnaires, biomarker analysis (such as adrenaline and cortisol levels), behavioral patterns, and physiological metrics like heart rate and skin conductivity [15]. Stress, an inherent aspect of daily life, can induce a hyperarousal state, resulting in subconscious neuroendocrine responses that alter respiration, muscle tone, and heart rate [16]. Like health monitoring, stress assessment benefits from long-term biosignal tracking outside of clinical environments. In this context, the head and neck areas show promise for stress monitoring.

Recent studies have highlighted the importance of measuring ECG from nontraditional locations, such as the neck and head, for improving cardiac monitoring accessibility and reliability. The Necklace-ECG device has demonstrated high sensitivity and specificity in detecting atrial fibrillation using a single-lead wearable ECG sensor positioned between the palm and chest, providing an alternative to traditional chest-based ECG measurements [49]. Another study explored neck-based ECG monitoring, emphasizing its advantages in detecting arrhythmias and palpitations, particularly in response to stress, exercise, and medication. The posterior neck region benefits from increased neural activity and enhanced electrode conformability, making it suitable for high-quality ECG signal acquisition [50]. Additionally, ear-based ECG monitoring has been investigated for seamless integration into hearable devices, showing strong agreement with traditional lead I ECG measurements and demonstrating feasibility for real-world applications, such as cardiac monitoring during driving tasks [51]. These studies collectively highlight how measuring ECG from the neck and head can enhance wearable cardiac monitoring by enabling continuous, comfortable, and effective ECG acquisition in various real-life scenarios.

While capacitive electrodes and nontraditional ECG placements have been independently studied, their integration remains underexplored. Existing research on capacitive electrodes has primarily focused on chest-based applications, while neck-based ECG studies have predominantly used wet or dry electrodes, which

require firm skin contact. The combination of capacitive electrodes with head and neck ECG monitoring could bridge this gap, offering a noninvasive, comfortable, and effective alternative for both cardiac and stress monitoring, which is rarely found in the literature.

This study aims to explore the feasibility and effectiveness of capacitive electrodes for ECG acquisition from the head and neck, assessing their signal quality and practical applications in an initial stage.

2.4 Capacitive Electrodes as a Novel Approach

Long-term ECG monitoring plays a crucial role in diagnosing and managing chronic cardiovascular diseases, as well as in assessing mental health states through heart rate variability [11, 52]. Capacitive electrodes represent a non-contact alternative to traditional ECG electrodes, measuring electric fields rather than relying on direct electrical conduction [53]. By detecting the displacement currents generated by heart activity, capacitive electrodes allow for indirect ECG signal acquisition. The non-contact nature of capacitive electrodes makes them highly suitable for integration into wearable devices, which can be embedded into clothing, accessories, or even furniture [19].

The advantages of wearable technology are particularly significant in patient-centered healthcare, as it reduces the need for frequent hospital visits and enhances healthcare management [12]. The ability to use capacitive electrodes in nontraditional locations, such as the neck, further enhances their practicality, as the neck can provide stable signal acquisition points while avoiding the challenges associated with chest-based monitoring for ambulatory ECG measurements.

2.5 The Potential of the Head and Neck Area for ECG Monitoring

The head and neck areas are more easily accessible than the chest, especially in emergency or critical care situations where quick electrode placement is essential. This reduces setup time and improves patient comfort. Placement in these areas can also be more comfortable for long-term monitoring, particularly for patients who find chest-based electrodes unpleasant.

Traditional chest-based ECG setups are often affected by motion artifacts (MAs) due to chest movements, especially during physical activities.

Figure 2-1 demonstrates the influence of body movement on the recorded ECG signal using a capacitive chest-strap. The first part exhibits baseline wander, which can be filtered out using a high-pass filter to obtain a clean signal. In the second part, the QRS complex is completely masked by MAs, but it can potentially be restored

using state-of-the-art MA removal techniques. However, in the saturation region, the amplifier becomes saturated, resulting in a signal that is entirely lost and cannot be reconstructed. In contrast, neck-based monitoring can result in reduced MAs since neck movements tend to be less disruptive to electrode positioning. This makes neck-based monitoring particularly suitable for physically active individuals, as it offers a more stable baseline signal.

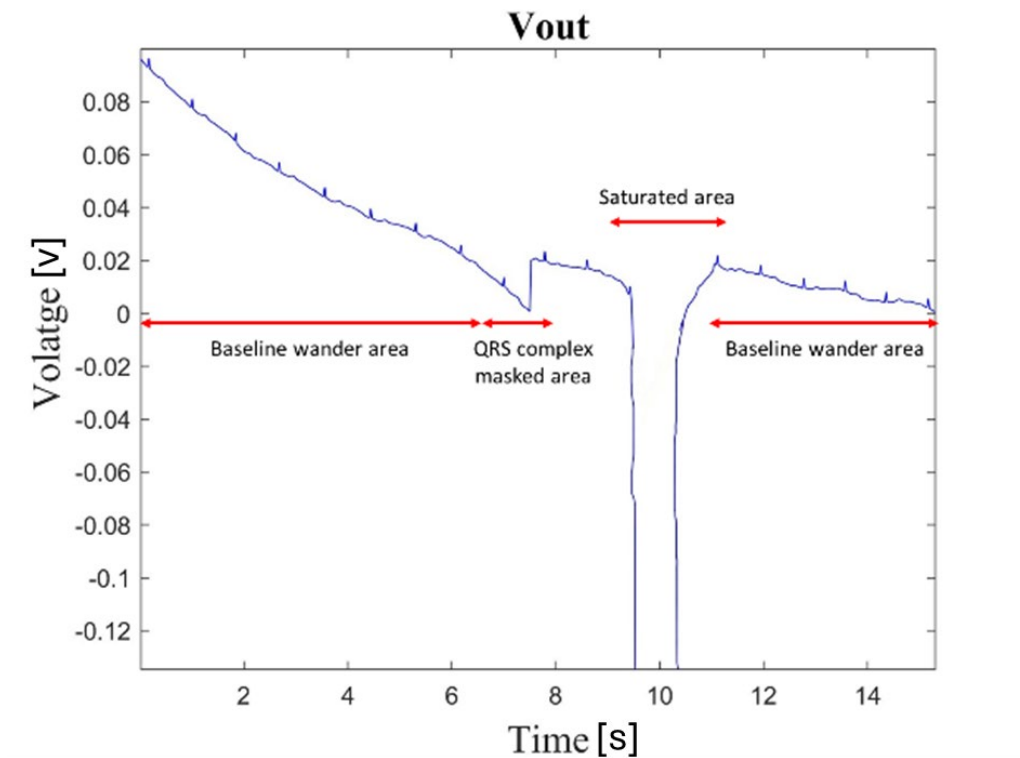


Figure 2-1. ECG signal captured from a capacitive measurement system using a chest strap during body movements

Moreover, for individuals recovering from surgeries, burns, or other medical conditions affecting the chest, ECG measurement presents several challenges, including chest palpation, lead adherence and removal, and signal conduction. Each of these factors requires a modified approach based on the burn severity and healing stage [45, 54]. In these cases, head or neck areas can serve as possible replacements for ECG measurement. Monitoring ECG signals from the neck could significantly aid in diagnosing atrioventricular nodal reentrant tachycardia (AVNRT). A study involving 370 patients identified that clinical variables, particularly the sensation of neck palpitations, are crucial indicators for AVNRT diagnosis. Notably, this symptom was the only significant predictor of AVNRT when positive ECG findings were absent [55].

The integration of ECG sensors into head- and neck-worn devices, such as necklaces, collars, patches, helmets, and headsets has expanded its potential applications. Researchers have explored various designs, including:

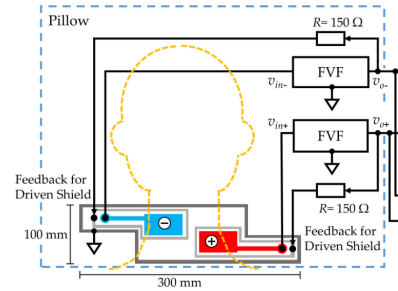
- A wearable ECG necklace for continuous cardiac monitoring, capable of detecting early cardiac abnormalities (Figure 2-2(a)) [46].
- A smart pillow that simultaneously monitors cough-associated electromyogram and ECG during sleep, assisting in the diagnosis of asthma and chronic obstructive pulmonary disease (Figure 2-2(b)) [47].
- A smart helmet designed for biopotential measurement (ECG and electroencephalogram (EEG)) in applications such as sports, motor racing, and military use (Figure 2-2 (c)) [48].
- A neckband with dry electrodes developed for stress and anxiety detection, which identifies R-peaks in ECG signals (Figure 2-2 (d)) [52].
- Virtual reality headsets that integrate ECG and EEG monitoring for real-time stress assessment, allowing experimental simulations that would be impractical or unsafe in real life (Figure 2-2 (e)) [16].

Additionally, several emerging wearable ECG technologies further highlight the feasibility of head- and neck-based monitoring:

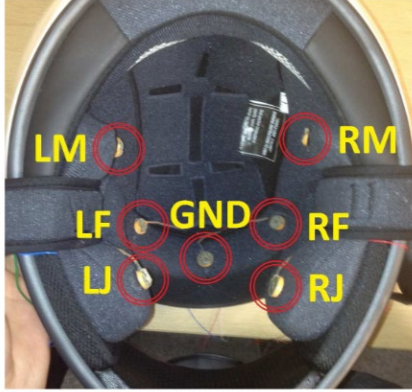
- Elango et al. developed a three-electrode wearable ECG sensor with dry hexagonal labyrinth electrodes, enabling continuous chest and neck monitoring. The design enhances skin contact and signal acquisition, making it effective for detecting arrhythmias and palpitations caused by stress, exercise, or medication. It is wireless, lightweight, and suitable for integration into wearable fabrics, demonstrating comparable performance to a 12-lead Welch Allyn ECG monitor (Figure 2-2 (f)) [50].
- Ear-based ECG monitoring leverages hearable devices to track cardiac rhythms with high correlation to standard Lead I ECG, showing minimal amplitude and timing deviations. Tested in long-duration driving simulations, it proves feasible for real-time cardiac monitoring in everyday activities (Figure 2-2 (g)) [51].
- The Movesense Medical (MD) sensor is a wearable, single-lead ECG device designed for remote cardiac monitoring and arrhythmia detection. It captures ECG and movement data, transmitting it via Bluetooth to a smartphone or PC for analysis. With a configurable sampling rate (125-512 Hz) and high sensitivity and specificity for atrial fibrillation, it meets ISO 13485 standards as a Class IIa medical device, making it ideal for both clinical and home use Figure 2-2 (h) [56].



(a)



(b)



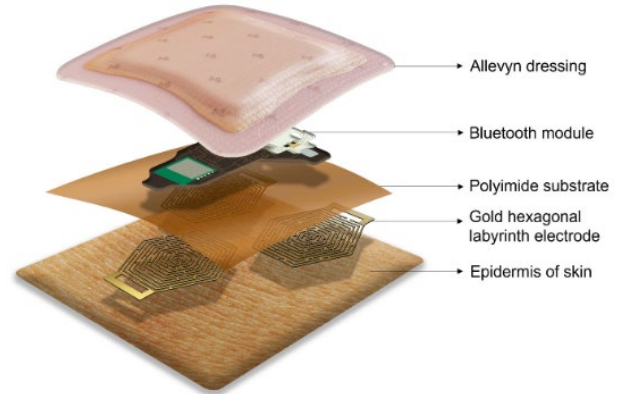
(c)



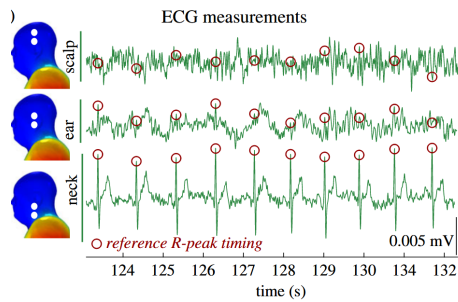
(d)



(e)



(f)



(g)



(h)

Figure 2-2: (a) necklace developed for continuous ECG monitoring [46]. (b) smart pillow designed to detect both cough-associated EMG and ECG [47] (c) smart helmet capable of measuring biopotentials such as EEG and ECG [48]. (d) neckband designed for ECG monitoring to assist in stress and anxiety management [52]. (e) using virtual reality (VR) headsets while measuring biopotentials [16]. (f) schematic of the wearable and wireless dry electrode ECG device attached onto the skin [50]. (g) recorded ECG traces from the scalp-, ear- and neck-ECG channels from a single subject [51]. (h) Movesense Medical (MD) sensor [56].

2.6 Methodology

The methodology of this article includes the design and configuration of the capacitive ECG system, the specific placement of electrodes on the head and neck, and the procedures followed to assess signal quality and feasibility. Finally, the results obtained from these trials will be analyzed and discussed.

2.6.1 Experimental Setup

In this study, a capacitive ECG monitoring system is developed. The setup utilizes two active capacitive electrodes, each forming a coupling capacitor (C_c) between the electrode and the body. The output of each electrode is connected to a main board containing an AD620 instrumentation amplifier, which is configured to enhance signal clarity and minimize noise, with a gain set at 10. A galvanic electrode is also used as the reference electrode, as shown in Figure 2-3.

Each active electrode circuit, shown in Figure 2-4, is designed using a voltage follower amplifier (VA) configuration. This noninverting amplifier setup is often preferred for front-end stages due to its relatively high input impedance, which reduces signal attenuation compared to a charge amplifier [34]. The circuit incorporated an LTC6240 operational amplifier in the VA configuration.

Each electrode has a diameter of 36 mm. To estimate C_c , we used a Zurich Instruments Impedance Analyzer. Since measuring the capacitance requires a conductive plate forming a capacitor with the electrode, we placed a copper sheet on the opposite side of the electrode. The measured coupling capacitance (C_c) ranged from 450 pF to 550 pF, depending on the applied pressure of the electrode against the copper sheet.

Additionally, a 10 G Ω bias resistor (R_B) is used to provide a bias current path, as bias current cannot flow through the human body. This prevents charge buildup at the front-end input [34]. To mitigate the effects of stray parasitic capacitance, we implemented a technique known as "guarding." This involves creating a guard layer around the input channel, maintained at the same potential as the input itself, along with a guard ring to effectively minimize parasitic and noise effects.

The complete setup, shown in Figure 2-5, consists of two active electrodes and a galvanic reference electrode, all connected to the main board. Data acquisition is performed using a National Instruments NI-9239 module, which is a 24-bit data acquisition system. The sampling frequency is set to 1.613 Hz (the minimum sampling frequency of the NI-9239).

No analog filters are applied; instead, digital filters are used. A fourth-order Butterworth low-pass filter with a 40 Hz cutoff and a high-pass filter at 0.67 Hz are implemented. These are specifically chosen for ambulatory ECG measurements to eliminate unwanted noise [57].

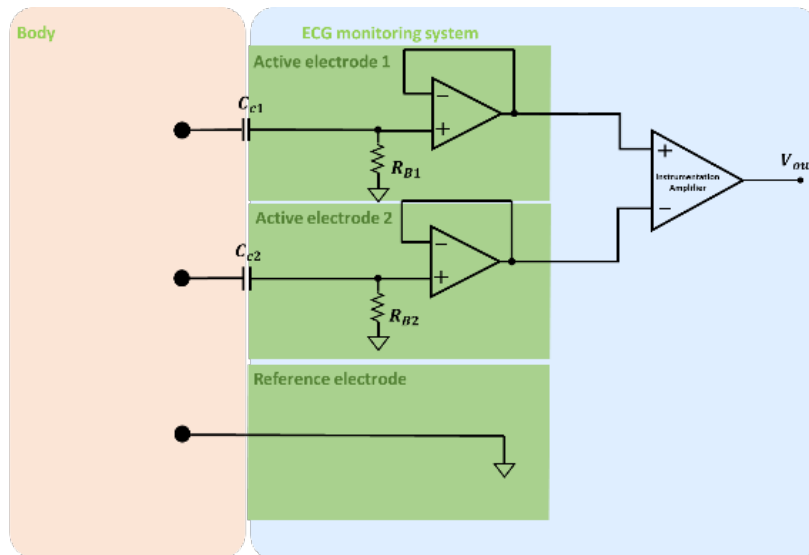


Figure 2-3: capacitive ECG measurement system



Figure 2-4: active capacitive electrode

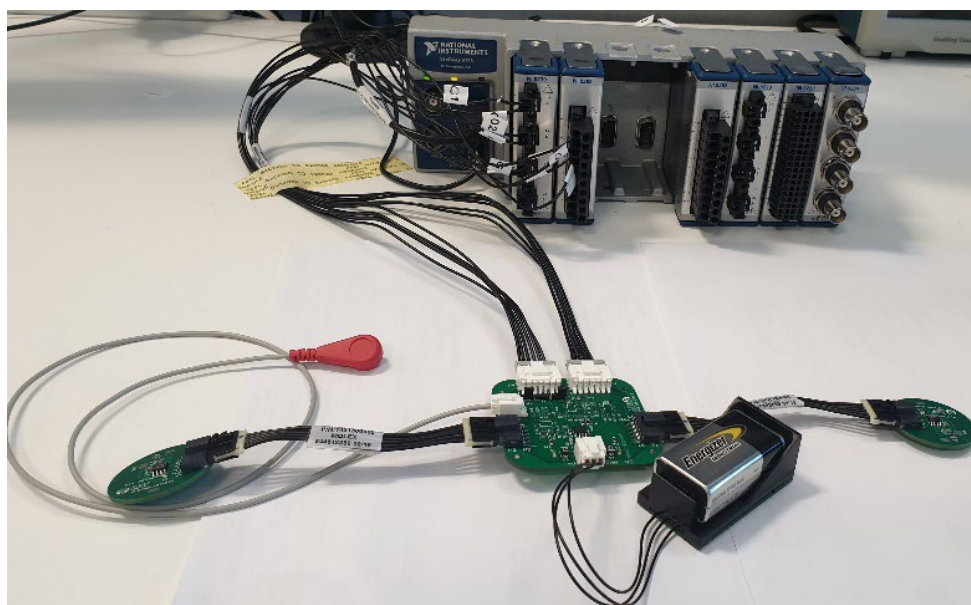


Figure 2-5: ECG measuring setup

2.6.2 Electrode Placement Trials

The study involved multiple trials using capacitive electrodes positioned around the head and neck area, focusing on signal quality, clarity, and noise levels. These trials aimed to identify the optimal electrode placements that provided the highest signal quality with minimal interference.

The following electrode placements are tested:

1. First experiment: Electrodes are placed on the left side of the neck, the right cheek, and the right neck as the reference.
2. Second experiment: Electrodes are positioned on the left side of the neck, near the right ear, with the right neck serving as the reference.
3. Third experiment: One electrode is held in the left hand, while the others are placed near the right ear and on the right neck as the reference.
4. Electrodes are positioned on the left side of the neck, the right side of the neck, and the right side of the neck as the reference.

For this study, only one subject is selected: a 35-year-old female with no known heart disease, including acute myocardial infarction, atrial fibrillation, or cardiac dysrhythmia.

2.6.3 Results

In the first experiment (results shown in Figure 2-6), the signal quality is decent, and R peaks are clearly visible in most of the recording. However, the blinking noise is prominent, making this placement unsuitable. The blinking artifacts can be mistaken for R peaks, compromising accuracy. As a result, this trial is excluded from the experiment.

To compare the results of remaining experiments, a quantitative metric is needed. Various methods have been employed in the literature to evaluate ECG signal quality, generally categorized into two main groups:

1. Subjective methods – These rely on expert assessment by cardiologists or other professionals.
2. Objective methods – These use mathematical equations to quantify signal quality.

Regarding objective methods, since root mean square (RMS) and standard deviation are typically used when MA or baseline wandering is significant, they are not ideal for this study. Here, ECG is recorded while the subject is sitting still, as the main goal is to assess the feasibility of measuring ECG from the head and neck area using capacitive electrodes. Therefore, signal-to-noise ratio (SNR) is chosen as the evaluation metric.

SNR is generally defined as:

$$SNR = 20 \cdot \log \frac{P_s}{P_n} \quad (2-1)$$

where P_s is the signal power and P_n is the noise power. However, in ECG analysis, signal power is proportional to heart rate, making this definition unreliable for R-peak detection, which is crucial for ambulatory monitoring.

to address this, a modified SNR definition, proposed by Xu et al. [37], is adopted:

$$SNR = 20 \cdot \log \frac{v_{pp}}{v_n} \quad (2-2)$$

where v_{pp} is the maximum value of each R peak, and v_n is the maximum noise value in two surrounding intervals. These intervals are defined as:

- $[t(i-1) + 300ms, t(i) - 75ms]$
- $[t(i) + 75ms, t(i) + 250ms]$

where $t(i-1)$ is the time of the previous R peak. These intervals ensure that the selected segment is free of QRS complexes, accommodating heart rates between 30 and 200 bpm.

We further refined the SNR calculation by replacing v_n with its RMS value over the two surrounding intervals:

$$SNR = 20 \cdot \log \frac{v_{pp}}{RMS(v_n)} \quad (2-3)$$

This SNR is calculated for each R peak, and an average SNR is computed for comparison.

It is important to note that SNR alone is not sufficient for evaluating ECG quality. In some cases, a lower SNR may occur due to the loss of P and T waves, even if R-peak detection remains unaffected. Therefore, SNR should always be used alongside visual assessment for a comprehensive evaluation.

For consistency, 10-s segments from each ECG experiment are selected for comparison.

Result of second experiment, illustrated in Figure 2-7, this electrode arrangement provides good signal quality for detecting R peaks, and the increased distance from the eyes effectively removed blinking noise. The SNR of each R peak is calculated, with a maximum of 19.3 dB, a minimum of 6.2 dB, and an average of 13.24 dB. Based on subjective evaluation, QRS waves are clearly detected. However, detecting P waves is challenging due to noise in that segment, while T waves are more identifiable.

In the third experiment, depicted in Figure 2-8, the signal quality improved compared to the previous placements. The SNR of each R peak is calculated, with a maximum of 18.6 dB, a minimum of 15.8 dB, and

an average of 16.99 dB, which is 3.75 dB higher than the previous experiment. The signal appears less noisy, allowing for easier wave detection. Based on subjective evaluation, QRS waves are clearly detected. Due to the reduced noise, detecting P waves is easier compared to the previous setup, and T waves are easily distinguishable.

Finally, in the fourth experiment, shown in Figure 2-9, the SNR of each R peak is calculated, with a maximum of 16.1 dB, a minimum of 12.6 dB, and an average of 14.25 dB, which is 2.74 dB lower than the third experiment. However, this does not necessarily indicate a lower quality signal. In this case, the T wave amplitude is higher than in the previous experiment due to electrode placement, leading to a lower SNR despite better wave detection. While P and T waves are more distinguishable in most cycles, the P wave is masked in the 12th cycle. This electrode placement also offers practical advantages for designing wearable ECG devices, such as collars and necklaces. Additionally, by relocating the electrodes from the arms to the neck, it remains possible to capture the Lead I vector from Einthoven's triangle, allowing the neck to reflect the same electrical activity as traditional limb leads [46], as demonstrated in Figure 2-10.

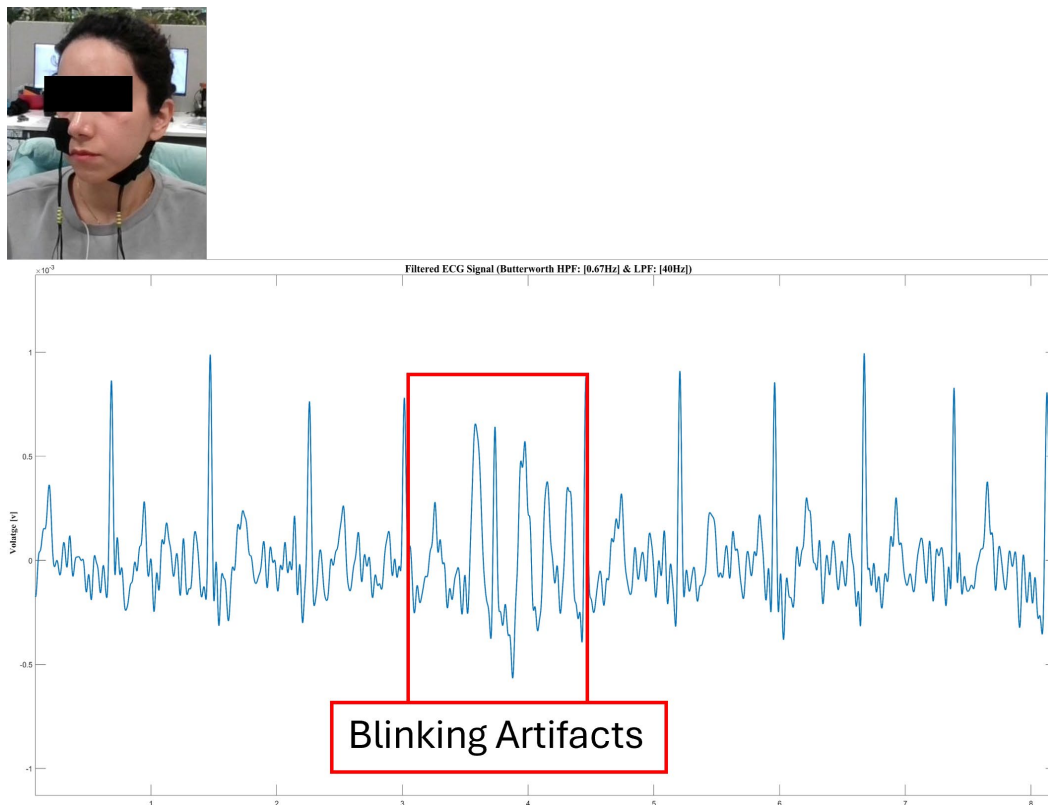


Figure 2-6: EXPERIMENT 1: Electrodes are positioned on the left side of the neck, the right cheek, and the right neck as the reference.

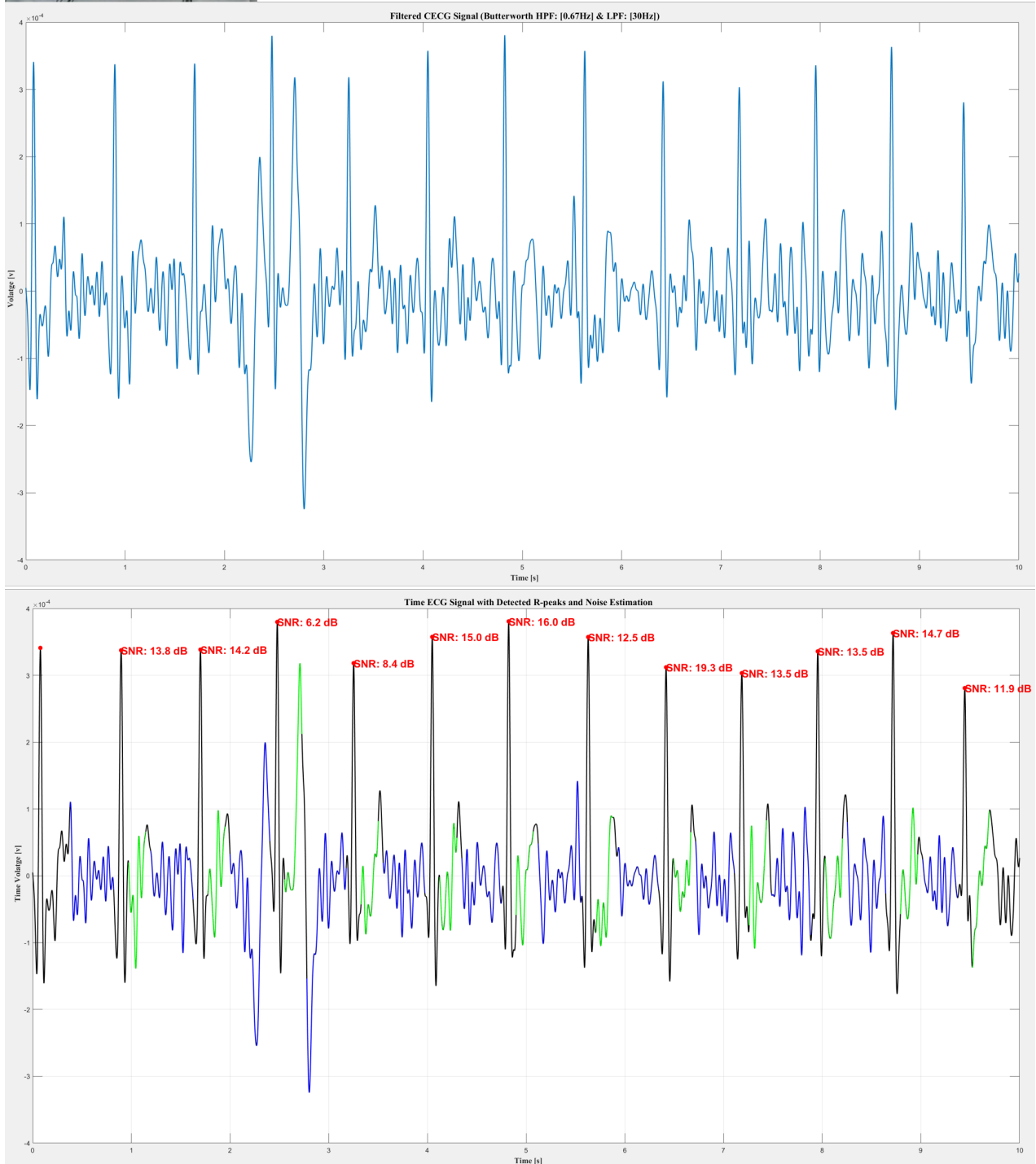


Figure 2-7: EXPERIMENT 2: Electrodes are positioned on the left side of the neck, near the right ear, with the right neck serving as the reference.

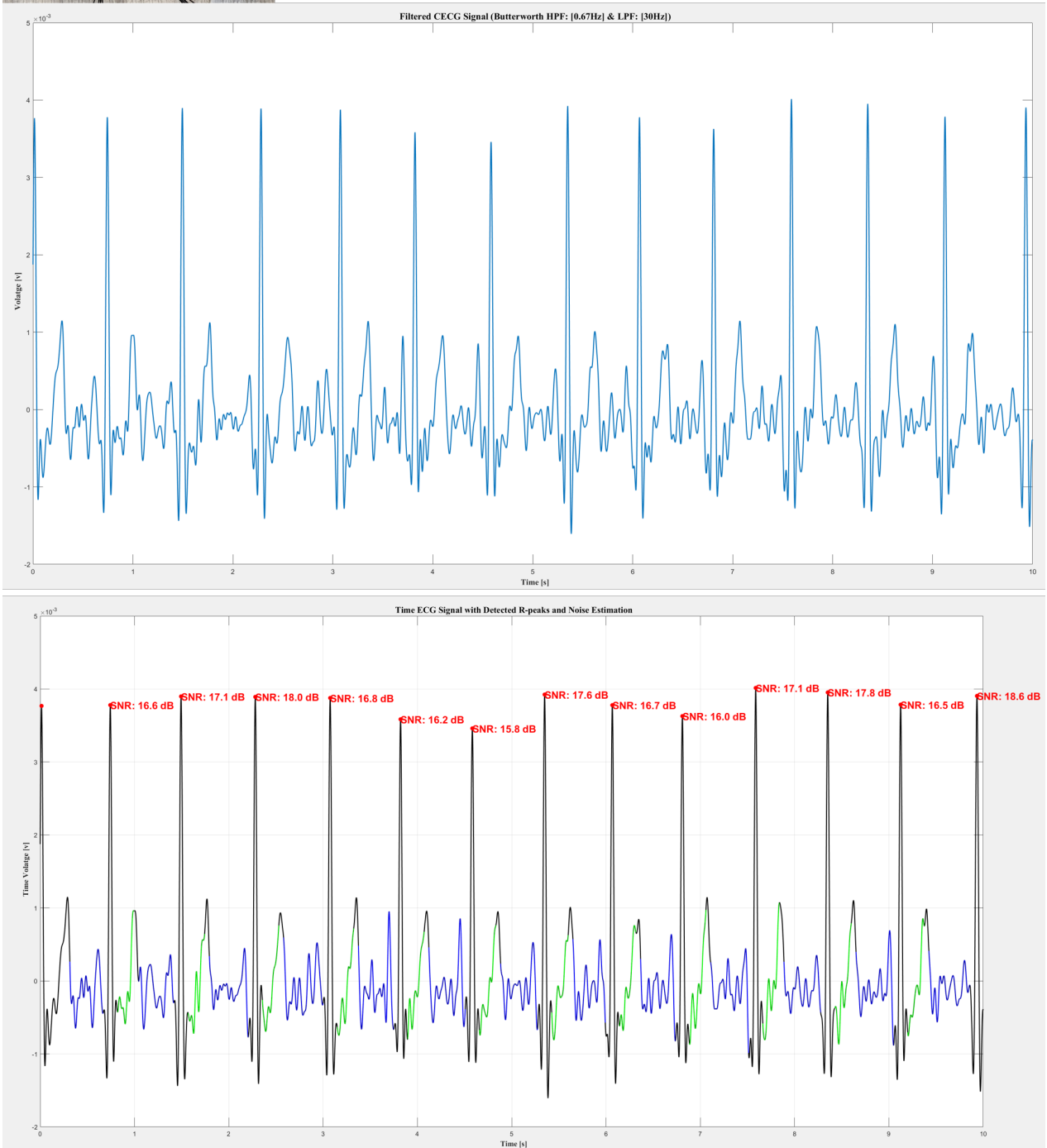


Figure 2-8: EXPERIMENT 3: One electrode is held in the left hand, while the others are placed near the right ear and on the right neck as the reference.

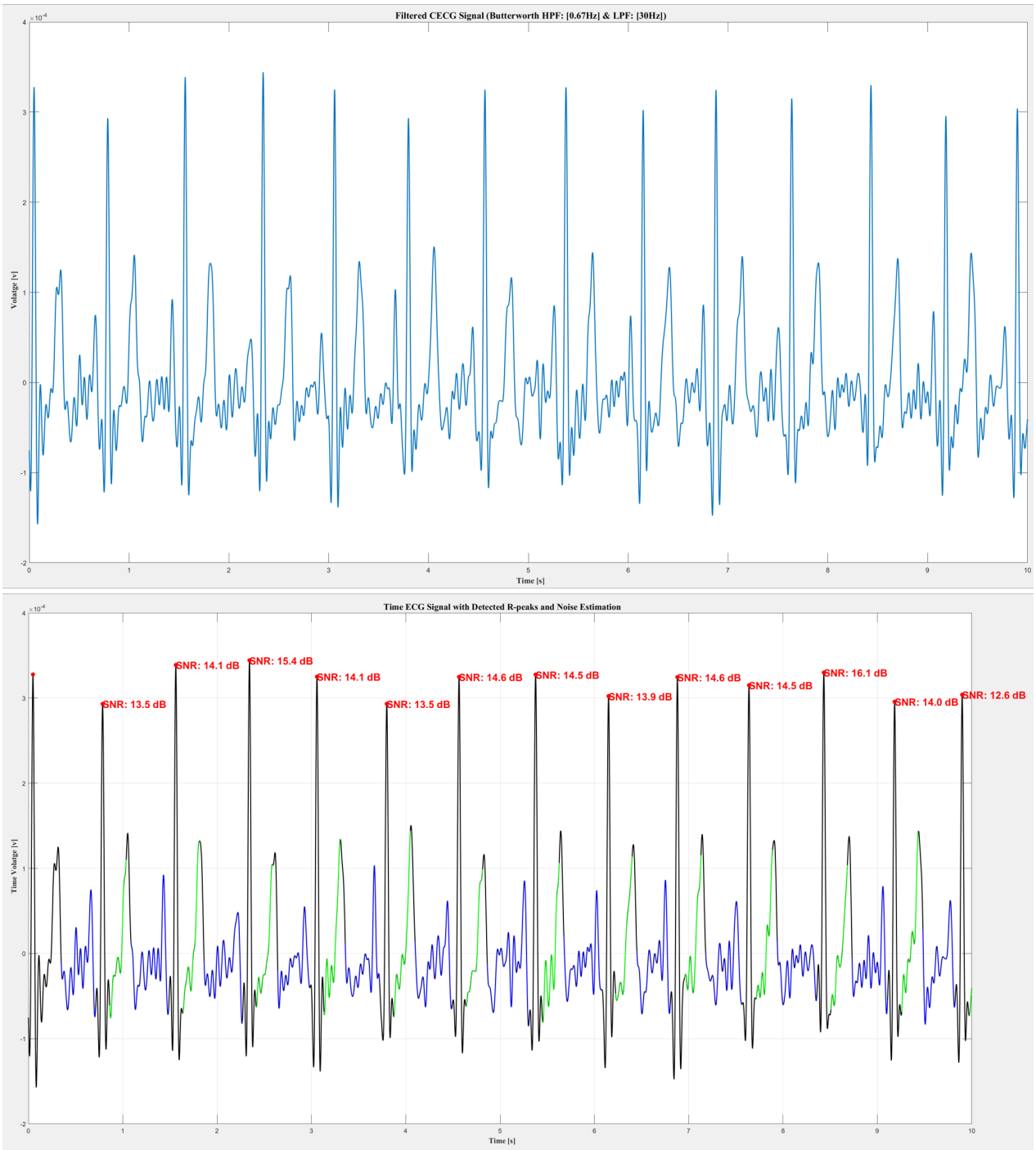


Figure 2-9: EXPERIMENT 4: Electrodes are positioned on the left side of the neck, the right side of the neck, and the right side of the neck as the reference.

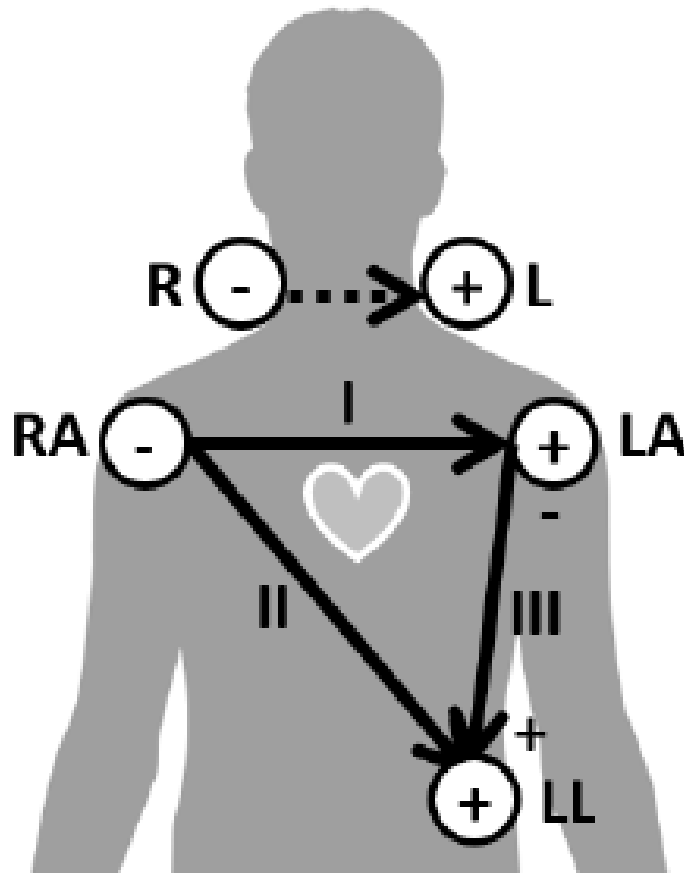


Figure 2-10 : Illustration of the Einthoven triangle with the electrode placement on the neck [46].

2.7 Discussion

The primary goal of this study is not to compare the results with previous research but rather to assess the feasibility of ECG measurement using capacitive electrodes in the head and neck area and determine the practically optimal electrode placement. Comparing our findings with other studies is inherently challenging, as each study has a different objective.

Most studies that have explored ECG measurement from the head and neck primarily focused on detecting R-peaks and evaluated performance using R-peak-specific metrics such as Peak Sensitivity (PSNS), Peak Accuracy (PACC), and Positive Predictive Peak Value (PPPV) values [46–48, 51, 52]. In contrast, our study goes beyond R-peak detection to assess the feasibility of identifying other ECG waves, such as P and T waves. For instance, Iskandar et al. [46] primarily focused on R-peak detection using wet electrodes. A visual comparison of their results with ours (Figure 2-11) suggests that our capacitive electrodes achieved better signal quality, despite the inherent challenges of capacitive sensing.

Similarly, Takano et al. [47] also utilized capacitive electrodes. While their study reported false detection of T-waves as R-peaks, our results (Figure 2-12) demonstrate clear identification of R-peaks and other ECG waves, indicating improved signal fidelity.

In the study by Von Rosenberg et al. [48], R-peak detection was deemed sufficient, and their results (Figure 2-13) compare ECG signals from the arm (upper signal) and face (lower signal). However, ECG signals measured from the neck using capacitive electrodes appear to be highly noisy, which may limit their reliability for clinical applications.

Mizuno et al. [52] presented ECG signals obtained using dry electrodes (Figure 2-14, lower plot), which were sufficient for R-peak detection but did not provide clear visibility of other waves.

Elango et al. [50] used dry hexagonal labyrinth electrodes, but their study focused on evaluating electrode shape variations rather than ECG signal quality. Their results, which showed no observable signal, are not directly comparable to ours, as their primary objective was electrode design optimization. Yarici et al. [51] explored the feasibility of ear-based ECG monitoring but also provided ECG measurements from the neck using gel electrodes. As they noted, additional gel was applied to reduce electrode-skin impedance. Their neck-based ECG results (Figure 2-15) can be compared to ours, highlighting the differences in signal quality between gel and capacitive electrodes.

Finally, the Movesense MD sensor [56] enables single-lead ECG detection from various body locations. However, as a commercial device, it is designed for sporadic ECG acquisition rather than continuous monitoring. This limitation makes it unsuitable for detecting transient cardiac dysfunctions such as arrhythmia [58]. Furthermore, detailed technical information about its sensor type and motion artifact removal methods is not publicly available, making direct comparisons with our study difficult.

2.8 Limitation and Future Directions

While this study demonstrates the feasibility of ECG measurement from the neck using capacitive electrodes, several limitations must be acknowledged. The signal amplitude is inherently lower than that recorded from the chest or arms due to the neck's greater distance from the heart and its smaller conductive surface area, which attenuates the heart's electrical signals.

Additionally, this study is conducted only in a seated, resting position, meaning MAs are not observed or analyzed. However, in real-world applications, head movements, jaw clenching, and swallowing are likely to introduce MAs that could degrade signal quality. Before optimizing the system, a thorough investigation of

MAs under different activities and postures is necessary to understand the extent of the challenge. Once MAs are well-characterized, hardware design and signal processing techniques can be refined to mitigate their effects.

Another limitation is the small sample size, as only a single subject is examined. Future studies should include a larger and more diverse group of participants to assess the variability in ECG signals across different users and improve the system's generalizability.

From a technical standpoint, further research should focus on hardware optimization, including electrode design and placement, to enhance signal acquisition and stability. Additionally, advancements in adaptive filtering techniques could improve noise suppression and artifact rejection. The integration of machine learning algorithms could also be explored to enhance robust ECG feature extraction and enable multi-modal health monitoring by combining ECG with other wearable sensors.

Addressing these challenges will be crucial for developing a reliable, motion-resilient, and widely applicable neck-based ECG monitoring system.

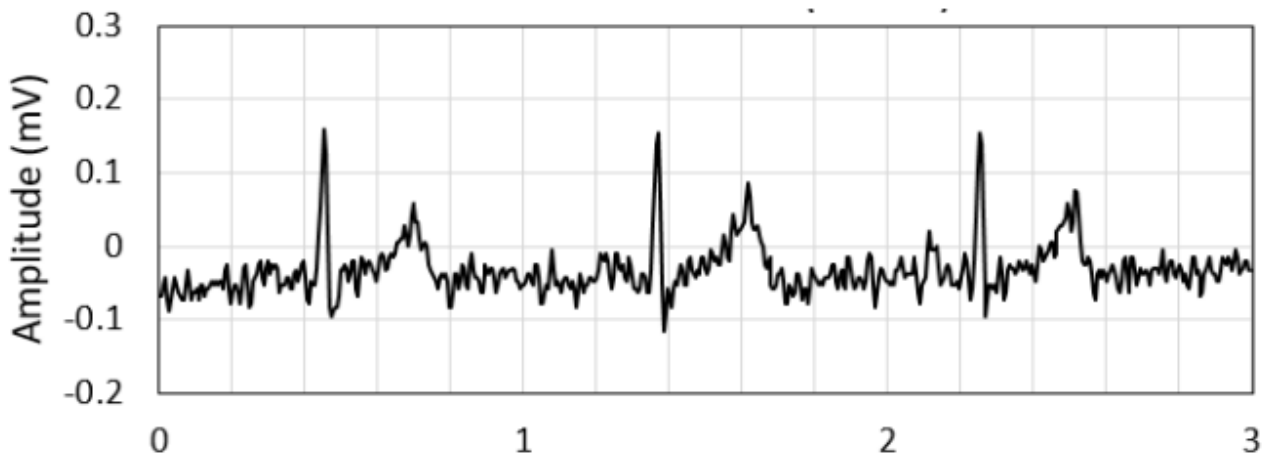


Figure 2-11: ECG signal from the backside of the neck [46].

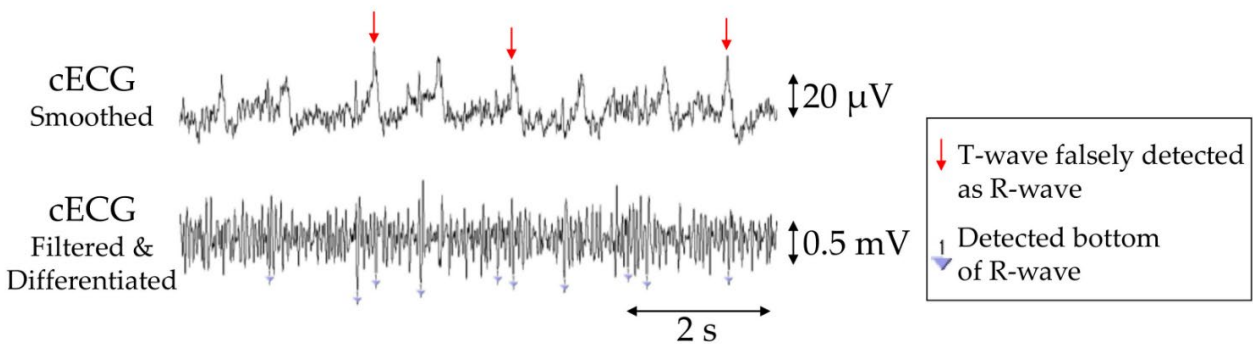


Figure 2-12: Recordings of cECG and filtered and differentiated cECG [47].

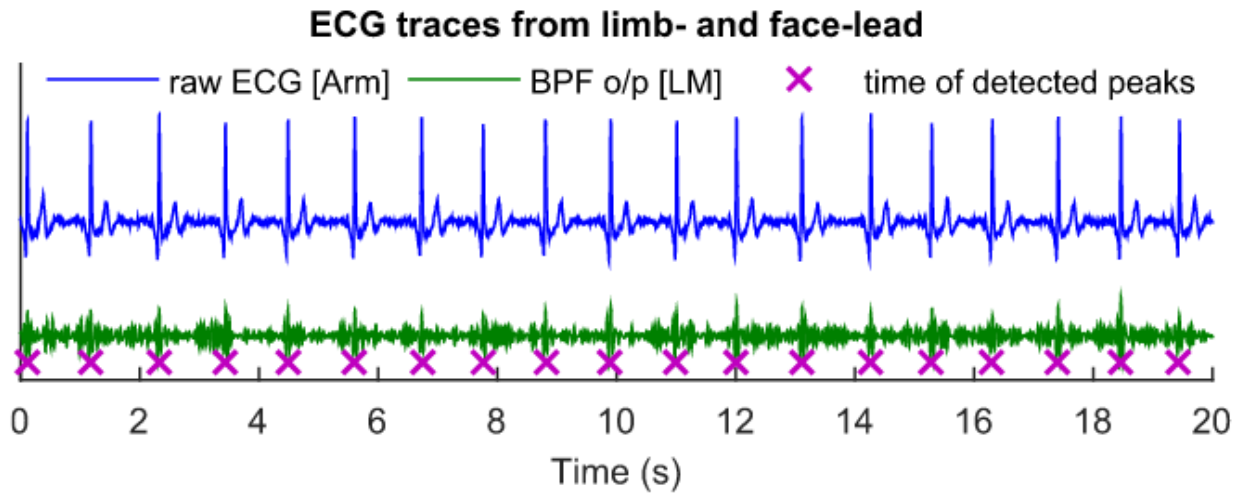


Figure 2-13: ECG recorded on Left Mastoid (LM) and its detected R-peaks compared to the reference from the arms [48].

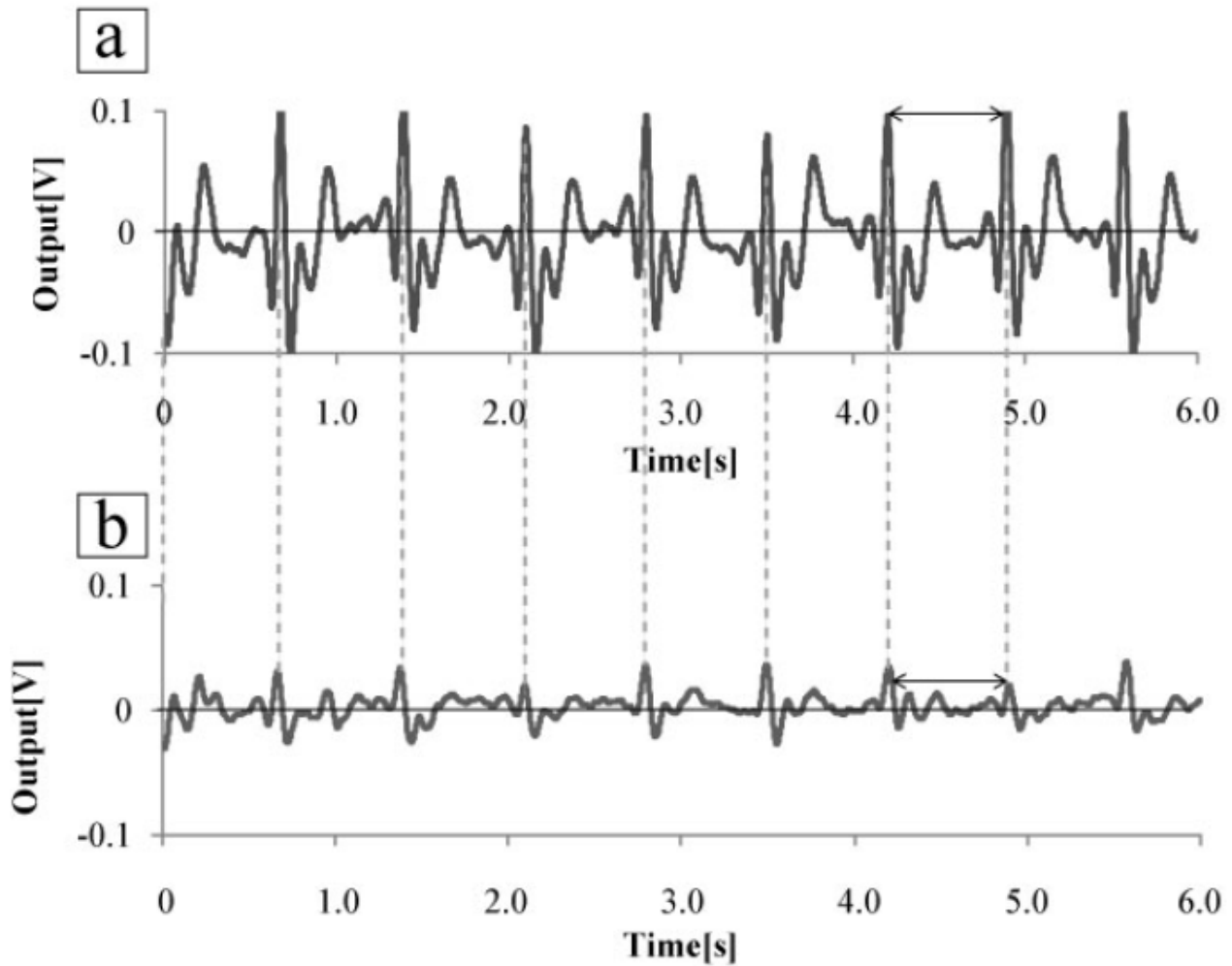


Figure 2-14: ECG measured by the neck band system ECG lead method and the conventional limb lead method during rest [52].

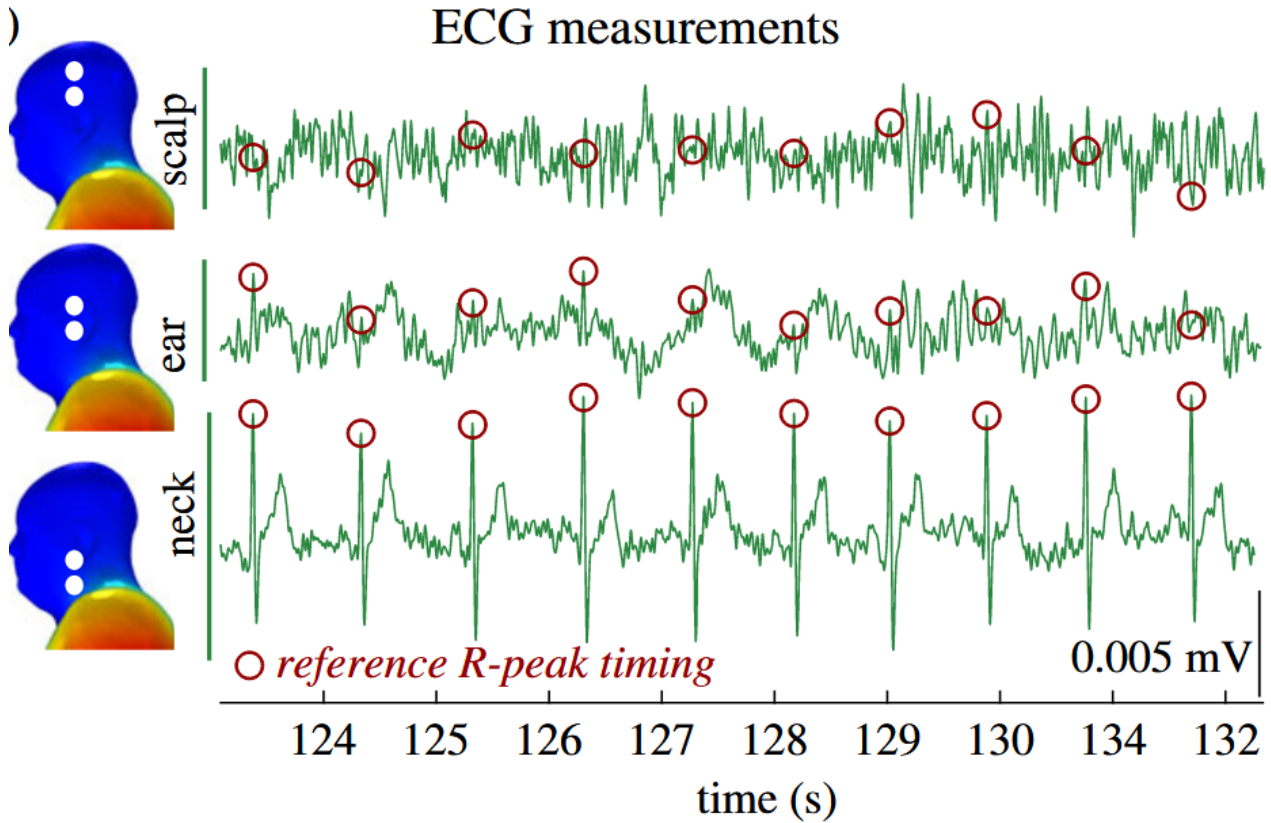


Figure 2-15: Recorded ECG traces from the scalp-, ear- and neck-ECG channels from a single subject [51].

2.9 Conclusion

This study demonstrates the feasibility of using capacitive electrodes for ECG monitoring from the neck, offering several advantages over traditional wet and dry electrodes. Unlike conventional electrodes, capacitive sensors do not require direct skin contact, making them well-suited for wearable and furniture-integrated ECG systems. They can operate effectively even when separated from the skin by a small gap due to hair, air, or fabric, increasing user comfort and long-term usability.

Through a systematic evaluation of different locations in the head and neck region, we identified the neck as the optimal site for capacitive ECG measurement. This location provided a SNR of 14.25 dB and enabled the detection of multiple ECG waveform components, not just R-peaks. Additionally, the convenience of electrode placement on the neck makes it particularly suitable for emergency and critical care applications, where rapid setup is essential.

Beyond cardiac health monitoring, neck-based capacitive ECG could also support mental health assessments, broadening its diagnostic applications. Moreover, this approach is especially beneficial for patients with chest injuries, postsurgical recovery, or burns, where traditional chest electrode placement may be impractical or

uncomfortable. Wearable implementations, such as neckbands or necklace-style ECG devices, could integrate capacitive sensing into everyday life, making continuous heart monitoring more accessible.

Despite these advantages, challenges remain. MAs are not assessed in this study, as measurements are conducted only in a seated, resting position. Future research should systematically evaluate MAs under different movements and postures, followed by hardware and signal processing optimizations to enhance robustness against artifacts. Additionally, larger-scale studies with diverse subjects are necessary to validate signal consistency across different users.

By addressing these challenges, capacitive ECG monitoring from the neck can become a viable, user-friendly alternative to conventional ECG systems, contributing to the development of next-generation wearable health technologies for both medical and everyday applications.

Chapter 3 Motion Artifacts in Capacitive ECG Monitoring Systems: a Review of Existing Models and Reduction Techniques

3.1 Prelude

The content of this chapter is a copy of the article titled “Motion artifacts in capacitive ECG monitoring systems: a review of existing models and reduction techniques”, published in the peer-reviewed journal *Medical & Biological Engineering & Computing* by Springer Nature [34].

In Chapter 2, the feasibility of using capacitive electrodes for ECG monitoring from unconventional body regions was demonstrated. This broadened the scope of capacitive ECG (cECG) applications and emphasized the importance of continued research in this area. However, capacitive electrodes inherently face specific limitations in their front-end circuitry, resulting in several noise and artifact challenges that degrade signal quality. Among these interferences, electromagnetic interference (EMI) and motion artifacts (MAs) are particularly problematic, with MAs significantly compromising ECG signal integrity during physical activities. Since Chapter 2 conducted measurements exclusively in a seated, resting position without significant movement, the critical issue of MAs was not addressed. This limitation motivates the investigation presented in this chapter.

This chapter therefore addresses Objective 2 outlined in Section 1.4, with the goal of providing a comprehensive and systematic understanding of MAs in capacitive ECG monitoring systems.

Ultimately, this structured review establishes the foundation for the subsequent design and development of advanced cECG systems with mitigated MAs.

3.2 Abstract

Current research focuses on improving electrocardiogram (ECG) monitoring systems to enable real-time and long-term usage, with a specific focus on facilitating remote monitoring of ECG data. This advancement is crucial for improving cardiovascular health by facilitating early detection and management of cardiovascular disease (CVD). To efficiently meet these demands, user-friendly and comfortable ECG sensors that surpass wet electrodes are essential. This has led to increased interest in ECG capacitive electrodes, which facilitate signal detection without requiring gel preparation or direct conductive contact with the body. This feature makes them suitable for wearables or integrated measurement devices. However, ongoing research is essential as the signals they measure often lack sufficient clinical accuracy due to susceptibility to interferences,

particularly motion artifacts (MAs). While our primary focus is on studying MAs, we also address other limitations crucial for designing a high signal-to-noise ratio (SNR) circuit and effectively mitigating MAs. The literature on the origins and models of MAs in capacitive electrodes is insufficient, which we aim to address alongside discussing mitigation methods. We bring attention to digital signal processing approaches, especially those using reference signals like electrode-tissue impedance (ETI), as highly promising. Finally, we discuss its challenges, proposed solutions, and offer insights into future research directions.

3.3 Introduction

Cardiovascular diseases (CVDs) are a group of disorders affecting the heart and blood vessels. They are a leading cause of death worldwide, claiming more than 17.9 million lives annually [1]. Cardiac arrhythmia significantly contributes to almost 80% of CVD cases [59]. While some arrhythmias are not life-threatening, others, such as atrial fibrillation, premature ventricular contractions, and excessive supraventricular ectopic beats, can result in severe conditions like stroke, cardiac arrest, or heart failure [4]. The early detection of arrhythmias can prevent around 90% of CVDs [10]. To achieve this goal, physicians extensively employ electrocardiogram (ECG) technology to identify abnormal heart rhythms, investigate the origins of chest pains, and categorize CVDs in clinical settings. Typically, an ECG signal comprises P waves, QRS complexes, and T waves [6–8], with any variations in these parameters indicating potential abnormalities in heart function. The frequency range of ECG signals generally spans from 0.67 to 120 Hz [7], although the literature often reports deviations from this range depending on the intended ECG application and the risk profile of the studied population [57, 60]. Additionally, real-time and long-term ECG monitoring has become important, serving two crucial purposes. Firstly, timely emergency care within the 'Golden Hour', the first hour following the onset of cardiac symptoms, can significantly reduce mortality and improve the quality of life for patients with specific heart conditions, such as cardiac arrest [6, 11]. Secondly, continuous disease monitoring facilitates ongoing health management by effectively treating patients with certain types of CVDs. These conditions require extended monitoring periods to enhance disease diagnosis and prescribe the most effective treatment for the patients. However, the excessive cost of medical treatment poses a significant challenge, prompting a shift from hospital-centered to patient-centered healthcare [14]. This shift has led to the development of intelligent solutions and telemedicine applications [12]. This offers two distinct advantages: reducing patients' reliance on hospitals and lowering expenses. Moreover, telemedicine can improve public health, particularly in ageing societies in developed countries and in low- and middle-income areas. Presently, many studies are

exploring the possibility of virtual care for people living in rural areas affected by CVDs [13]. After the COVID-19 pandemic, the importance of telemedicine has further grown. Notably, researchers such as Jiang et al. [61] have proposed wearable telehealth solutions for monitoring essential physiological parameters in COVID-19 patients, such as heart rate, blood oxygen saturation, and respiratory rate.

Telemedicine should provide patients with independent remote sensors, ensuring safety, comfort, precision, and real-time long-term monitoring capabilities without the need for specialized assistance. Traditional gel/wet ECG electrodes (Ag/AgCl), extensively used in clinical and research settings, are not useful in this field because these electrodes require direct skin contact through an electrolytic gel applied by technicians [12, 17–22]. They need multiple disposable electrodes, frequent need to be replaced, and there is significant potential for skin irritation. Consequently, they are not suitable for prolonged monitoring or use outside of a hospital setting [18, 19, 21, 23–27]. To address the limitations of conventional ECG measurement methods, capacitive electrodes were introduced as an innovative approach to measure skin surface potentials without necessitating direct conductive coupling to the skin, allowing measurement through materials such as hair, cloth, insulation layer, or air [62]. Their versatility has led to integration into numerous personal healthcare applications, including furniture, exercise aids, automotive devices, and wearable devices [19]. This innovation offers a cost-effective, long-term diagnostic solution for personal healthcare monitoring that avoids skin preparation and irritation [23, 29, 30]. Using these sensors can embed healthcare monitoring into patients' daily lives and improve the health condition of people who have not yet developed a disease [31]. Moreover, they play a key role in monitoring heart activity beyond clinical settings in ambulatory ECG measurement systems. In contrast to traditional ECG systems that utilize ten electrodes, ambulatory ECG systems are characterized by their compactness, portability, and reliance, typically, on only 2-3 electrodes [27]. However, the design of electrodes involves finding a balance between comfort and reliable monitoring [23] and ensuring comparable quality to traditional medical instruments remains paramount. Despite the availability of heart rate monitoring sensors for consumers as standalone devices and integrated into smart technology, the challenge persists in achieving diagnostic precision comparable to hospital-grade 12-lead systems [32, 33]. Some of these challenges is because of some limitations in capacitive ECG electrode front-end. Moreover, there are several types of interference that can potentially contaminate the ECG signal in capacitive electrodes, including electromagnetic interference (EMI) and motion artifacts (MAs). EMI, particularly power-line interference (PLI), consistently introduces significant common-mode (CM) noise. PLI, with a frequency of 50 Hz in Europe

and 60 Hz in the United States, is a major noise source in any ECG measurement system and is especially evident in capacitive ECG measurements. Generally, PLI is primarily caused by displacement currents coupling either into the measurement system or into the subject's body, and it appears in the final recordings due to unbalanced electrode impedance. However, it can be reduced to some extent by optimizing front-end electronics and system design [23, 35, 37]. On the other hand, the unidentified interference is commonly referred to as MA while its exact origin, cause, and definition remain unclear. MAs are commonly explained by the fluctuating high impedance between the body and the electrode because of body movements [23]. The variation of this impedance can modulate circuit leakage potentials and leads to MA. Another potential cause of MA is the triboelectric potential, which arises from the friction and separation between the electrode and the body. These interferences need to be mitigated to increase the SNR and ensure the reliability of the ECG signal for interpreting different types of cardiovascular diseases (CVDs) without misdiagnosis.

In many studies on capacitive ECG electrodes, MAs and their impact on the ECG signal are recognized as significant challenges, prompting numerous investigations to address these issues. Despite the proven adverse effects of MAs in ECG recording systems, their origins remain poorly understood and subject to varying interpretations across different research studies. However, these interpretations can vary due to differences in analog designs, electrode materials, and environmental conditions such as temperature and humidity, all of which uniquely influence system performance. A notable gap exists where these varied definitions and interpretations have not been consolidated into a single source for comparative analysis. To address this gap, we provide a detailed overview of MAs, encompassing their origins, effects on ECG signals, and contributing factors based on existing literature, to enhance the understanding of MAs.

We proceed by reviewing the latest techniques for mitigating MAs, focusing particularly on Digital Signal Processing (DSP) methods. Specifically, we emphasize reference-assisted techniques using electrode-tissue impedance (ETI) as a reference, as studies suggest that the variable high impedance between the body and electrodes during motion significantly contributes to MAs. While this method shows potential, there is a lack of thorough reviews in the existing literature, which we intend to address. To facilitate discussion, we present a comparative table summarizing previous works. However, comparing their efficiencies directly poses challenges due to variations in R&D statuses, design approaches, experimental methodologies, and selected performance metrics among others. Our primary objective is to explore methodologies used by each study, the

challenges encountered, approaches taken to address them, and the success of their techniques. Finally, based on these reviews, we outline future research directions for those continuing work in this area.

However, addressing MAs is not the sole focus of our review. A complete understanding of capacitive ECG systems is crucial for identifying their causes and distinguishing them from other interferences. Therefore, optimizing signal quality by mitigating non-motion-related interferences precedes directly addressing MAs. To start, we discuss the fundamentals of capacitive ECG systems, which include discussing the limitations of capacitive electrodes and the impact of CM interferences on signal quality. Following this, we investigate strategies for enhancing front-end electronics and techniques aimed at improving the CMRR throughout the entire system.

Therefore, this article is structured as follows: Section 3.4 introduces the basics of capacitive ECG measurement systems. Section 3.5 addresses drawbacks in capacitive electrode circuitry and discusses solutions to improve the signal quality. Section 3.6 discusses the defined concept of MA in the literature, its origins, and its impact on the ECG signal. Current techniques for reducing MAs are addressed in Section 3.7. This part is divided into three key domains: analog circuits, electrode materials and fabrication, and DSP techniques. These domains must be addressed in parallel to achieve optimal results. Notably, this article emphasizes the DSP domain as a principal technique for effectively mitigating MAs. Section 3.8 engages in a discussion of the presented techniques and outlines potential directions for future research. Finally, Section 3.9 concludes the paper.

3.4 Capacitive ECG Measurement Systems

In capacitive ECG sensors, an interface between skin and electrode transfers the ionic current in human body into biopotentials that can be measured by a signal acquisition circuit [23]. Before exploring the specifics of capacitive ECG measurement systems, it's crucial to address the electrode-body interface for capacitive electrodes.

3.4.1 Electrode-Body Interface for Capacitive Electrodes

Biopotential sensing utilizes electrodes to acquire signals from the body. Often, these electrodes are not in direct contact with body fluids; instead, they reside on the surface of the skin, known as surface electrodes [23, 63]. The characteristics of the electrode-body interface for surface electrodes depend on the skin's electrical properties and the type of electrode [63]. In general, the coupling between the skin and electrode can be described as a layered conductive and/or capacitive structure, with series combinations of parallel R and/or C

elements. The general layer stack and equivalent circuit model of capacitive electrodes coupled with the skin, based on various models found in the literature, result in structures depicted in Figure 3-1a and Figure 3-1b respectively.

The skin consists of three primary layers: the epidermis, dermis, and subcutaneous layer. The inner layers, dermis, and subcutaneous layer are highly conductive and are in direct contact with inner bodily fluids rich in ions, which is equivalent to the resistance R_d [63, 64]. In the epidermis layer, the Stratum Corneum, a high-resistance layer of the skin, is dominant, considered to have a resistance R_{sc} and capacitance C_{sc} in parallel [28, 64, 65]. The cloth layer is considered as a resistance R_{cl} in parallel with a capacitor C_{cl} , where R_{cl} is the resistance of the fabric surface and C_{cl} is the skin-electrode capacitance. This coupling impedance in the body-sensor interface is primarily influenced by the subject's clothing in this scenario [42, 64].

Since there is no electrode-electrolyte interface present, the circuit model of capacitive electrodes excludes impedances associated with this interface, as well as the electrode-electrolyte potential at equilibrium, referred to as the half-cell potential, V_{HC} , which is characteristic of wet electrodes. However, in numerous papers, the skin potential, V_{sc} , is considered for these electrodes [37, 41, 63]. The stratum corneum acts as a semipermeable membrane, effectively separating electrolytes, sweat, and body fluids of varying ionic concentrations. Consequently, this arrangement creates a potential difference across the stratum corneum, referred to as the skin potential [63]. It is worth noting, though, that in many papers, this potential is not accounted for in the context of capacitive electrodes.

Moreover, in some papers, the cloth layer is omitted, indicating that the capacitive electrode is directly connected to the skin, as shown in Figure 3-1c. In this scenario, C_c is considered to model the insulation layer between the electrode and the skin surface, and no resistor is taken into account [28, 63, 65].

In numerous articles where the electrode directly interfaces with the body, there's an assumption that C_c represents the dominant layer in capacitive electrodes, thereby disregarding the impedance of other layers. This assumption stems from the fact that the value of this capacitor is typically lower compared to the other layers. Conversely, if the impedance of this layer is higher than that of the others, it leads to the equivalent model illustrated in Figure 3-1d [19, 37, 41, 66].

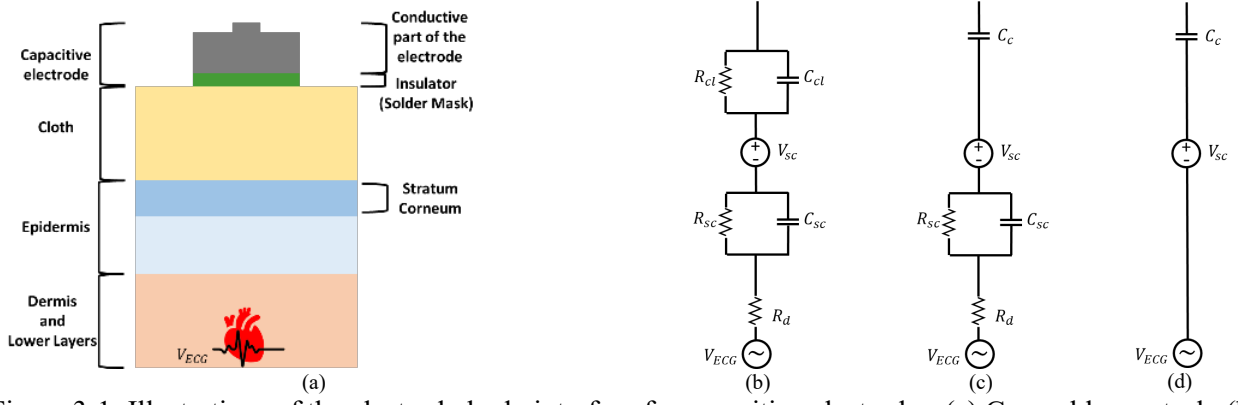


Figure 3-1: Illustrations of the electrode-body interface for capacitive electrodes. (a) General layer stack. (b) General equivalent circuit model. (c) Equivalent circuit model without cloth (Representation of direct contact between electrode and skin). (d) Simplified circuit model without considering cloth.

3.4.2 Equivalent Circuit of the Capacitive Measurement System

After introducing the electrode-body interface for capacitive electrodes, the equivalent circuit of the capacitive measurement system should be introduced. For simplicity, the capacitive electrode, along with the body surface, can be modelled by a coupling capacitor C_c , in series with the skin potential V_{sc} , as shown in Figure 3-1d. In practice, C_c can be as small as a few pF, depending on factors like electrode size, dielectric material, and material thickness. Typically, an active electrode is used as an ECG acquisition system, with the front-end circuit including a buffer, usually an OpAmp with an ultra-high input resistor R_i and a low input capacitor C_i , along with active shielding. This setup enables transmission over long cables and mitigates sensitivity to PLI and cable movement [23]. This can be achieved using a voltage follower/amplifier (VA) or a charge amplifier (CA), depicted in Figure 3-2 and Figure 3-3, respectively. Other circuits like Instrumentation Amplifiers (INAs), bootstrap circuits, or application-specific integrated circuits (ASICs) with high input impedance [67] are also mentioned in the literature, designed for high input impedance. The VA, a noninverting amplifier, is preferred for the front-end in most cases due to its relatively high input impedance, resulting in less signal attenuation compared to CA [23]. Conversely, CA is rarely employed for capacitive biopotential recording [68, 69] although some studies have reported successful ECG recordings using a CA [68]. Researchers like Peng et al. [53] have compared VA and CA designs in terms of their common-mode rejection ratio (CMRR), noise performance, and frequency response. Xiao et al. [70] extended this comparison to their responses to artifacts caused by motion or interference. Their experiments indicated that the CA performs better under conditions of poor coupling (small capacitance, of the order of a few pF) due to its linear gain response and quicker recovery from triboelectricity artifacts. On the other hand, the VA performs better under good coupling conditions (hundreds of pF) due to its improved CMRR, stable gain, low noise, and reduced susceptibility to

C_c variation artifacts. These two interferences are multiplicative in a VA, but remain independent in a CA. Consequently, a VA is preferred when triboelectricity artifacts are low and coupling capacitance is high whereas a CA is preferred when these artifacts are high, due to its faster recovery time [53, 67, 70]. However, overall, the VA is more widely adopted and accepted, and this paper exclusively focuses on investigating the VA.

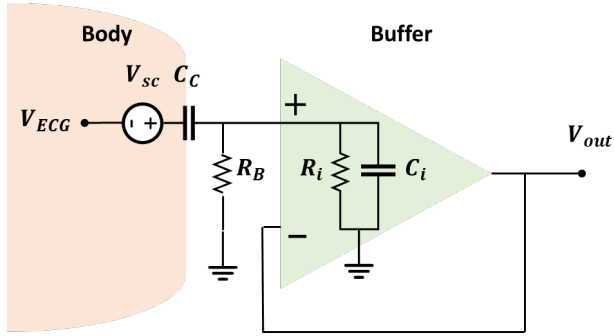


Figure 3-2: Voltage follower schematic.

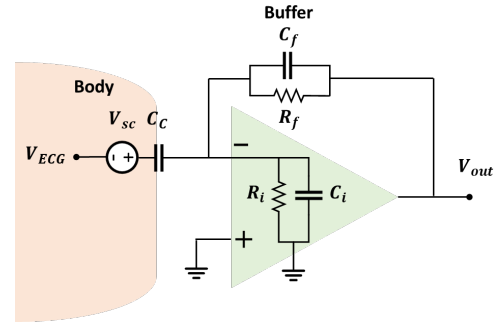


Figure 3-3: Charge amplifier schematic.

3.5 Limitations in Capacitive ECG Measurement Circuits

The electrical equivalent model shown in Figure 3-2 is depicted in Figure 3-4. It consists of the capacitor formed between the electrode's plate and the body (C_c), the skin potential source (V_{sc}), and the ECG signal represented as V_{ECG} . The front-end circuit includes the input resistor (R_i) and capacitor (C_i) of the OpAmp. Additionally, the bias resistor (R_B) is typically used with this configuration. In the subsequent discussion, we study the mentioned parameters and the difficulties encountered during the circuit design. However, it should be noted that due to the significant impact of V_{sc} on the circuit, it will be discussed later in Section 3.6.

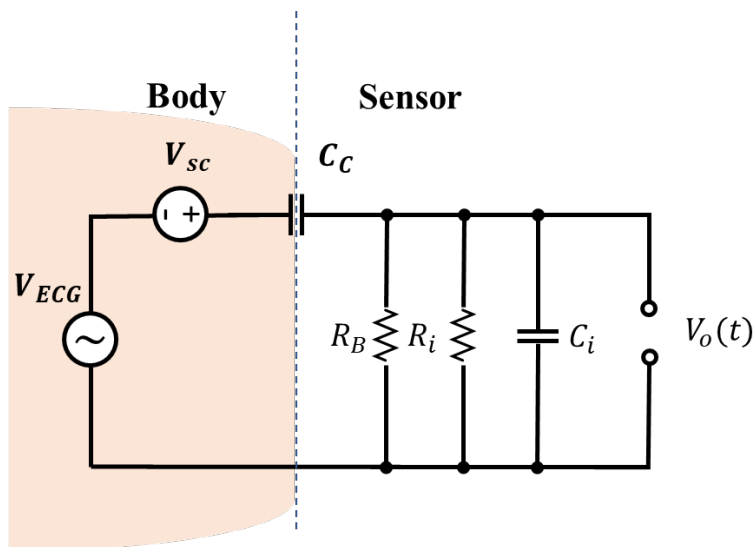


Figure 3-4: Equivalent circuit model of the capacitive measurement system

3.5.1 Bias Resistor

Ideally, op-amps would exhibit zero bias current. However, practically, bias current exists, and its magnitude varies depending on the type of op-amp. To address this issue, a bias current path can be used by connecting a resistor to the ground (refer to Figure 3-4). This path is essential since bias current cannot flow through the human body and the charge will accumulate at the input front end [23, 30]. While a bias resistor is needed to discharge the input of the amplifier from its input bias current, it can introduce other problems. In this type of measurement, achieving a large input resistance is desirable, often by selecting an op-amp with a large input resistance, typically within the Tera Ohm range [23]. However, placing the bias resistor in parallel with the op-amp's input resistance can significantly reduce the overall input resistance. To overcome this, using a high-value resistor is a solution, although this can introduce issues related to drift and thermal noise. Moreover, it is difficult to fabricate tera-Ohm off-chip resistors. Additionally, using a bias resistor can cause an offset in the circuit. Though the induced offset voltage can be relatively high, it can be removed by filtering the dc component or by using negative feedback [71, 72]. Another consideration is the potential for op-amp saturation. In such cases, the maximum value of the resistor should be lower than $\frac{V_{cc}}{i_{Bias}}$ for rail-to-rail input stages [73]. Some researchers have tried including reset switches to manage saturation [70, 74, 75]. Moreover, Moreno-García et al. [19] found that the op-amp they employed, LMP7721, had a sufficiently low leakage current. In this case, they did not use a bias resistor in their design. They employed a passive RC high-pass filter to eliminate the generated offset. There are alternative approaches to establishing the bias path without relying solely on high-value resistor, for instance, the reverse leakage current of a low leakage silicon diode [28, 67], or bootstrap circuits [76–78]. However, implementing these circuits can cause more complexity and pose new challenges.

3.5.2 Frequency Response of Front-End Circuit

A high-pass filter is formed in the front-end circuit due to the presence of C_c and the input impedance of the buffer. The input resistance of the circuit is determined by $R_i || R_B$. Since R_i (the input impedance of the op-amp) is significantly larger than R_B , the total input resistance can be approximated as R_B .

The frequency response of this filter is calculated using Equation (3-1). The magnitude of the filter can be obtained from Equation (3-2). By considering a very high bias resistor, this Equation can be simplified to (3-3).

The cut-off frequency of the filter can be obtained from Equation (3-4).

$$H(j\omega) = \frac{R_B C_c \omega j}{1 + R_B \omega j (C_c + C_i)} \quad (3-1)$$

$$|H(j\omega)| = \frac{R_B C_c \omega}{\sqrt{1 + (R_B \omega j (C_c + C_i))^2}} \quad (3-2)$$

$$|H(j\omega)| = \frac{C_c}{C_i + C_c} \quad (3-3)$$

$$f_c = \frac{1}{2\pi R_B (C_c + C_i)} \quad (3-4)$$

It is important that the cut-off frequency of the formed high-pass filter, f_c , be low enough to allow the lower ECG frequency components to pass through [30]. The question arises: how low should this cut-off frequency be? As previously mentioned regarding the ECG frequency range, the answer depends significantly on the intended application and the risk profile of the studied population. This underscores the importance of understanding the significant information gained or lost by selecting a specific frequency range. To address this concern, Young [57] published the proposed frequency requirements for the 80601-2-86 committee draft in 2019, which can be found in Table 3-1, providing general guidance on selecting the ECG frequency range. Consequently, deviations can be observed in papers discussing capacitive measurement systems. For instance, Sun and Yu [23] proposed an ECG range starting from 0.05 Hz to preserve complete signal information, particularly emphasizing ST measurements shown in Table 3-1. In contrast, Torfs et al. [66] have suggested a cut-off frequency of 0.67 Hz for ambulatory ECG measurements, while, Asl et al. [30] recommend a cut-off frequency of 0.1 Hz, citing alignment with commonly used band-pass filters in ECG analysis.

After determining the value of f_c , the remaining parameters in Equation (3-4) can be calculated. The value of C_c varies based on factors like sensor size, material, distance from the body, and insulator material. For instance, it may be as low as 0.1 pF when the signals are picked up through clothes and an air gap at a distance of >100 mm. However, when the sensor is tightly attached to a cotton layer, the value be around 30 pF.

Furthermore, the input capacitance of op-amps, C_i , has remained relatively constant over the past decades, typically ranging from 3-10pF [79]. As mentioned earlier, R_i is almost equal to R_B . Based on Table 3-1 for general usage and adopting $f_c = 0.67$, and $C_c = 30$ pF, using Equation (3-4) allows us to deduce R_B , yielding a minimum value of 7 G Ω .

Ideally, the front-end circuit should act as a buffer with a flat frequency response. However, due to the voltage divider formed by C_c and C_i in Equation (3-2), there may be some signal attenuation [19, 80]. The ECG signal

voltage typically ranges from 1 mV to 5 mV. Therefore, even slight attenuation in the front end can decrease SNR, leading to a lower quality signal. Therefore, selecting an amplifier with a very small input capacitor is essential to minimize this attenuation. If C_i is sufficiently low, and the electrode, firmly attached to the body with a large area, results in a high C_c there should be no problem. But in situations where the distance between the body and the electrode increases, leading to a decrease in C_c , difficulties may arise. To address this issue, techniques like power supply bootstrapping have been used over the years to reduce input capacitance [79, 81–83].

Table 3-1 Summary of proposed frequency requirements in the 80601-2-86 committee draft [57]

Intended use	Frequency response requirement
General use (rhythm interpretation)	0.67–40 Hz for all populations
ST measurement	Meets rectangular or triangle impulse response (0.05 Hz IIR or 0.67 Hz ZPD filter)
Diagnostic ECG (contour interpretation)	0.67–150 Hz for all populations and meets ST monitoring requirement

In capacitive ECG measurement, the electrodes are not fixed to the body, and even if they are tightly fastened, some movement remains. Additionally, the body's natural physiological vibrations can impact the coupling capacitance, even when no deliberate or unintended body movements occur [42]. These physiological vibrations include respiration and cardiac contraction, which can alter this coupling capacitance [43]. While many studies have overlooked this issue, Uguz et al. [42] studied the mechanical vibrations of the human body itself as a source of time-variant coupling capacitances. According to Equation (3-5), changes in the front-end capacitor value are due to the varying distance between the electrode and the subject's body. However, the dielectric constant (ϵ_r) and the effective area of the electrode surface (A) remains constant.

$$C_c(t) = \frac{\epsilon_r A}{d(t)} \quad (3-5)$$

In this case, we are not dealing with a linear time-invariant (LTI) system due to the varying component $C_c(t)$. Even if we approximate the system as LTI within short intervals with a constant C_c , equations (3-1) to (3-4) will remain time-variant due to this changing C_c . Consequently, both f_c and $|H(j\omega)|$ exhibit time-variant values.

For the specific values $R_B = 10\text{G}\Omega$, $C_i = 3\text{pF}$, along with seven different C_c values, Figure 3-5 illustrates the Bode diagram of the circuit. Notably, when $C_c = 1\text{pF}$, $|H(j\omega)|$ is -12dB, considerably lower than 0dB. As C_c increases, $|H(j\omega)|$ approaches 0dB. Simultaneously, the rise in C_c , leads to a decrease in f_c , aligning with the

desired outcome. Essentially, the system behaves like a dynamically changing high-pass filter for the ECG signal, $v_{ecg}(t)$ [41]. In simpler terms, the time-varying coupling impedance causes multiplicative distortion of the ECG signal, resulting in a distorted version of $v_{ecg}(t)$.

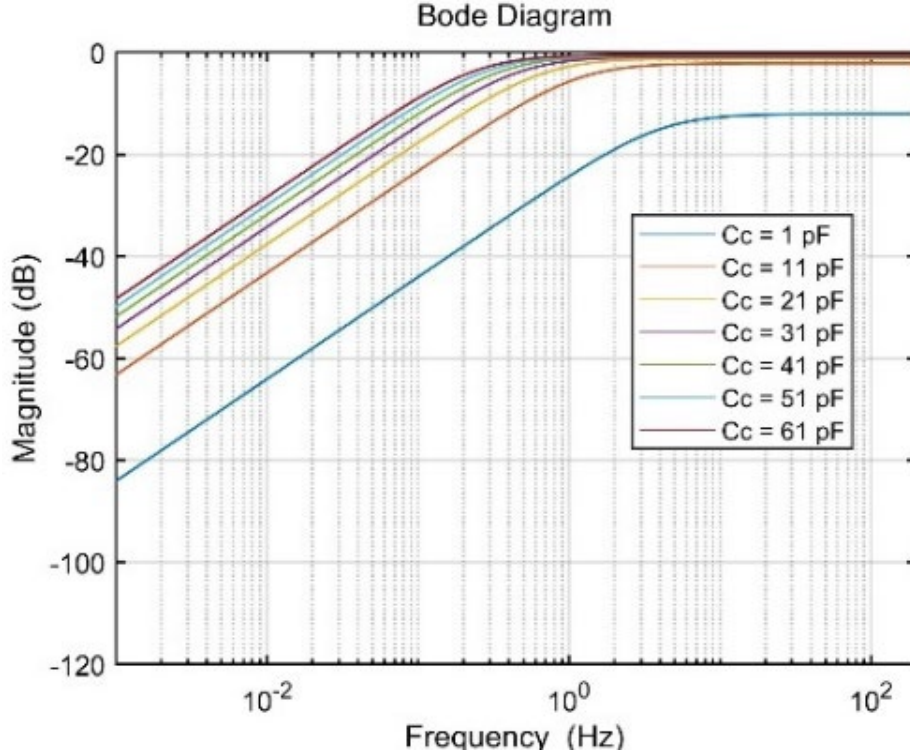


Figure 3-5: Front-end circuit Frequency response for different values of C_c .

3.5.3 Challenges of Reduced CMRR and Solutions

In this section, we introduce a comprehensive integrated electrical model for ECG capacitive recording systems, as depicted in Figure 3-6. Within this model, there are non-common-mode voltages denoted as V_{E1} and V_{E2} which are specific to each electrode and thus cannot be rejected using the differential measurement method and will be addressed later in the text. These individual voltages stem from various sources such as skin potential (V_{sc}), as discussed in Section 3.4.1, or other sources. The primary focus of this section is on CM noises, which are typically mitigated using the differential measurement technique in many applications.

In capacitive measurement systems, the body is electrically isolated, and this floating state makes it highly susceptible to external noises, thereby affecting the measurement system, particularly the CM noise [84]. The presence of CM noise sources, such as power lines, EMI, or wireless power transfer systems, can significantly disrupt the accurate detection of signals [17]. In an ECG system, considerable EMI can couple to the patient's body through the skin. Additionally, EMI may couple to the ECG system through coupling capacitors C_p and

C_B , as illustrated in Figure 3-6. Moreover, it can also be introduced to the system through the long ECG signal measuring cables and protection circuitry, typically located at the front of the ECG system. Furthermore, capacitance C_S is coupled between the AC ground and the ground of the ECG subsystem. The entire system's CMRR is dependent on the capacitance value of C_S [85]. The voltage source V_{cm} represents other CM voltages that are detectable throughout the body. The values of capacitors and V_{cm} are indicative and may vary depending on the measurement methodology, environmental conditions, and parameters of the measuring device.

In general, the differential measurement method is highly effective in reducing CM noise due to its high input impedance and CMRR [86]. However, in capacitive ECG measurement systems, this method does not perform well because of the large asymmetry in the two signal paths. This asymmetry is caused by the difference in impedances between the two electrodes (Z_{E1} and Z_{E2} in Figure 3-6). The capacitances between the body and the capacitive electrodes can differ due to body motion, leading to various amplitudes and phases of noise signals at the input of the differential amplifier. In this scenario, the external noise cannot be considered as the CM signal for the differential amplifier, as they are not the same in each path. Consequently, despite the high CMRR of an INA (around 120 dB), the amplifier's overall CMRR is decreased [77, 84, 87, 88]. Equation (2-1) shows the differential voltage resulting from the asymmetry in Z_E proportional to the CM potentials, $V_{CM} \cdot \Delta Z_E$ stands for the difference of two electrode-skin impedances and Z_{in} represents the mean value of input impedances of the OpAmps (Z_{in1} and Z_{in2}) [77, 87, 88].

$$V_{diff} \approx V_{CM} \frac{\Delta Z_E}{Z_{in}} \quad (3-6)$$

Referring to Equation (3-6), to enhance interference suppression, it is crucial to minimize the difference of impedance (ΔZ_E) or reduce the CM voltage (V_{CM}) as much as possible, or alternatively, increase the Z_{in} . In the literature, there are four known methods to improve the CMRR of the system. These methods are:

1. Active guarding
2. Isolation Capacitance
3. Driven-Right-Leg circuit (DRL)
4. Common-Mode Interference Suppression Blocks (CMI-SC).

By employing these techniques, the system's ability to reject CM interference can be significantly enhanced, resulting in better overall performance.

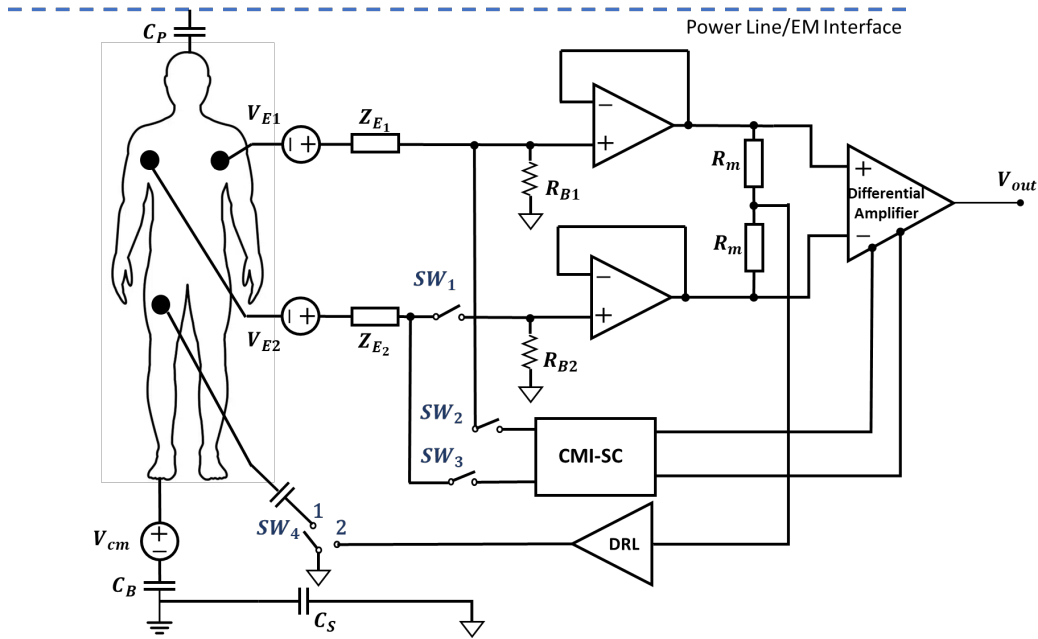


Figure 3-6: General integrated electrical model for ECG capacitive recording systems.

3.5.3.1 Active Guarding

To mitigate the adverse impact of increased stray parasitic capacitance, a commonly employed technique is known as "guarding". This method involves creating a guarding layer that encircles the input channel and maintains the same potential as the input itself. The primary purpose of this guarding network is to minimize any voltage difference between the input wire and the guarding layer. It can effectively eliminate any parasitic capacitance that may exist between them and safeguard high-impedance sensors from environmental EMI [89, 90].

3.5.3.2 Isolation Capacitance

Improving the isolation between the device ground and the patient ground leads to a decrease in C_S , which, in turn, helps to enhance the system CMRR. This improvement is particularly noticeable in portable instruments that operate on batteries, where the CMRR tends to be exceptionally high [85, 91].

3.5.3.3 Driven-Right-Leg (DRL) Circuit

In the DRL circuit, the reference electrode plays a crucial role by actively controlling the body's potential through a feedback mechanism. The primary objective is to maintain the body's potential close to a known bias point of the device, which is typically set to the desired CM level of the AFE. This feedback loop helps suppress the body's potential swing with respect to the AFE's ground, effectively reducing the CM input swing into the

AFE. The DRL electrode is responsible for sensing the CM voltage on the body. By doing so, it can provide essential feedback to the patient's body, leading to a reduction in the V_{CM} as indicated in Equation (3-6). Although the actual pathway of the current fed to the body is unknown, it is likely to be more controlled than the pathway taken by the measurement system itself. This process contributes to enhancing the overall performance and stability of the circuit, particularly by improving the CMRR.

3.5.3.4 Common-Mode Interference Suppression Blocks

In specific designs, the methods mentioned earlier are not employed. Instead, they rely solely on two sensing electrodes along with a CMI-SC Block in a feedback configuration to effectively reduce CM noises [92, 93]. However, in the absence of a third electrode, a two-electrode ECG AFE results in the grounding potential being virtually isolated from the CM potential on the body. This leads to a difference between the body's CM potential and the device's grounding, resulting in significant CM input. This significant CM input can saturate the differential amplifier, particularly when operating under low-voltage power supply conditions, rendering it unable to accurately reconstruct the ECG signal. Therefore, a critical aspect in preventing system saturation is to limit the CM input range. This is where the CMI-SC Block comes into play, as it detects the CM voltage from an internal node within the AFE and generates a proportional CM suppression signal. By implementing this mechanism, the circuit effectively reduces CM fluctuations at the AFE's input pads through a feedback loop.

By considering all the mentioned techniques, various systems and applications utilize different recording setups, such as single, two, or three electrodes, to measure ECG signals. The general setup is illustrated in Figure 3-6, which can be modified using switches $SW_1 - SW_4$, as detailed in Table 3-2.

The first model employs a single electrode for ECG signal collection and another as a ground reference, as demonstrated by Serteyn et al. [41]. Their setup includes an active guard to eliminate CM noises effectively.

In the second model, two electrodes measure the biosignal without a reference electrode, a technique known as standard bipolar capacitive measurement [94]. In this configuration, a differential amplifier or INA is utilized to provide gain and convert the differential signal to a single-ended signal. In this configuration, the absence of any techniques aimed at enhancing the overall CMRR may result in a suboptimal signal quality. However, Yong et al. [95] devised an ECG measurement setup in a bathtub employing only two electrodes and made efforts to minimize PLI through the use of narrow-notch filters. In contrast, many other designs

employing a two-electrode setup focus on integrating a CMI-SC circuit, representing the third model [92, 93, 96], to reduce CM noises and improve the SNR of the output signal.

However, many of these designs opt for a more conventional approach found in the literature, utilizing a three-electrode setup. This includes two active electrodes for sensing ECG and one passive electrode, forming the fourth model in Table 3-2. Alternatively, some designs employ a DRL active electrode as the reference, constituting the fifth model. This choice is made with the aim of enhancing the overall CMRR.

Table 3-2 Various configurations of measurement systems

No	Type	SW ₁	SW ₂	SW ₃	SW ₄
1	One active electrode + One ground electrode as reference	Open	Open	Open	Connected to “1”
2	Two active electrodes	Close	Open	Open	Open
3	Two active electrodes + CMI-SC	Close	Close	Close	Open
4	Two active electrodes + One ground electrode as reference	Close	Open	Open	Connected to “1”
5	Two active electrodes + One DRL electrode as reference	Close	Open	Open	Connected to “2”

3.6 The source of Motion artifacts (MAs) and their impact on the ECG signal

The primary concern of capacitive measurement systems is the presence of MAs. In numerous studies, any disturbance in the output signal caused by body movements is termed MA [32, 35–38]. Such body movements involve respiratory or cardiac activity, as well as voluntary body motions. On the other hand, other studies interpret MAs as transient (but not step) random baseline wander resulting from either patient or electrode movement. These studies establish a separate category for baseline wander noise caused by respiration and electromyography noise arising from muscular movements [26, 97]. Breathing-induced MAs lead to baseline wander appearing in the low-pass filtered signal, making R-peak detection challenging. However, the baseline wander resulting from body movement is significantly more substantial when compared to that caused by breathing alone [37]. Furthermore, MA extends the necessary dynamic range (DR) of input for recording devices, often requiring existing systems to employ low amplification gain in their signal amplification stages [38].

Figure 3-7 demonstrates the influence of body movement on the recorded ECG signal. The first part exhibits baseline wander, which can be filtered out using a high-pass filter (HPF) to obtain a clean signal. In the second part, the QRS complex is entirely obscured by MAs, but it can potentially be restored using state-of-the-art MA removal techniques. However, in the saturated area, the amplifier is overwhelmed, resulting in a signal

that is entirely lost and cannot be reconstructed. This issue can result in physicians facing challenges in diagnosing various CVDs accurately, and in critical situations, it may lead to the misdiagnosis of heart conditions. Recently, a phenomenon known as "toothbrush tachycardia" has gained significant attention, as depicted in Figure 3-8. The illustration explains a scenario where a patient with paroxysmal atrial fibrillation, who had initiated flecainide treatment three weeks prior, underwent a Holter ECG examination. The recording indicated two brief episodes of rapid heart activity, occurring before bedtime and in the morning. Upon further inquiry, it was discovered that these episodes coincided with the patient's toothbrushing routine. Currently, the only reliable method to confirm or refute this observation is through cross-referencing with the patient's diary, a detail that physicians may not always have readily available.

While MA is widely recognized as a significant drawback in many studies, certain researchers, such as Wang et al. [64] identify the main challenge in capacitive measurement systems as the high impedance created between the body and the electrode. To mitigate this issue, they focused on reducing this impedance by designing a negative impedance in series with the formed impedance. In another study, Zompanti et al. [98] considered CM signals generated by EMI as the only interferences, and they attempted to eliminate them by implementing DRL circuits and filtering techniques.

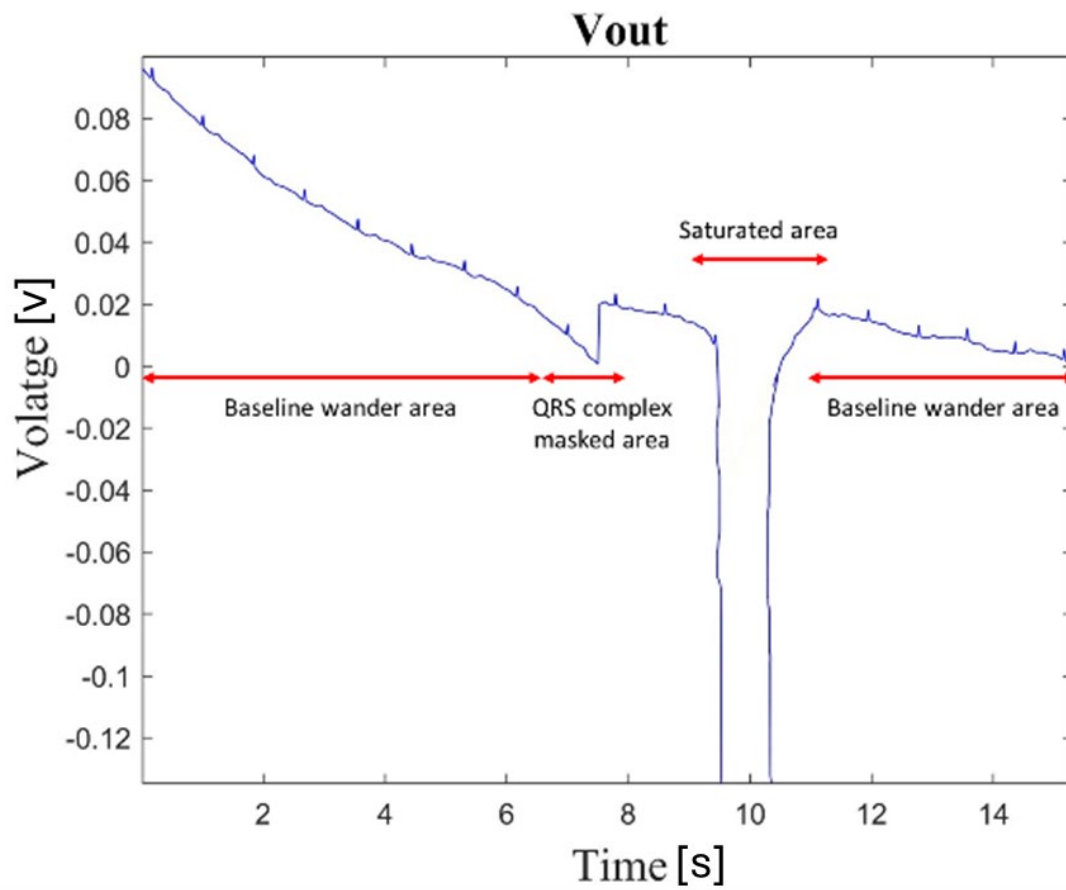


Figure 3-7: Example of a capacitive ECG signal with body movements.

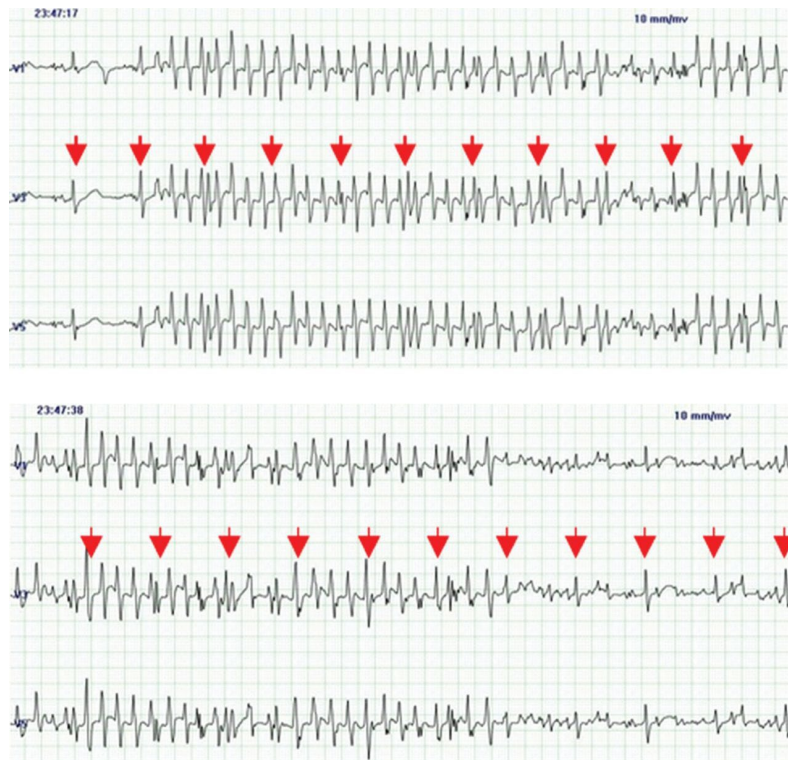


Figure 3-8: A case of toothbrush tachycardia [99]

In many studies investigating and modelling MAs in capacitive measurement systems, researchers have explored an electrical equivalent model for a single capacitive electrode, akin to the one shown in Figure 3-9 [12, 37, 41, 42, 94, 100].

In this model, the ECG signal is represented as $V_{ecg}(t)$. The input resistor and capacitor of the buffer are modelled as R_i and C_i . Furthermore, $C_C(t)$ symbolizes the variable capacitor created between the body and the capacitive electrode. The leakage potential between the body's virtual ground and the reference point of the measurement system is determined by the sum of V_{DC} and $V_{AC}(t)$. The voltage across the coupling capacitor can originate from various sources, leading to debates and disagreements about its origin. One contributing factor is triboelectricity [41], which results from the accumulation of static charges due to friction between the body and the electrode surface. The act of rubbing two materials together can produce significant voltages [12, 37, 41], although the exact underlying physics remains somewhat uncertain. A potential explanation involves an enlarged contact area due to rubbing, facilitating electron transfer between the materials. In addition to the effects of electrical double layers, other mechanisms contribute to contact voltage, such as the removal of charged particles or mass transfer between the two objects [101]. This phenomenon is also observable in classical ECG sensors, but it poses a greater challenge in capacitive sensors. This challenge stems from the prolonged negative impact resulting from the delayed discharge caused by the high impedance between the body and these sensors [12, 42, 102]. Consequently, this situation can lead to the generation of more substantial electric fields than those produced by the actual ECG signal [12].

A significant aspect originates from the skin potential, often referred to as electrodermal voltage [37, 41]. This voltage stands as a major contributor to MAs within the ECG signal; however, it has received limited attention, particularly in the capacitive measurement field. Comprehensive information concerning the nature and magnitude of this voltage remains elusive. Current research on wet electrodes reveals the presence of an inherent voltage source across the epidermis. This voltage has been observed to change due to skin deformation caused by lateral stretching, rotational stretching, or vertical forces [103, 104]. Notably, variations in impedance do not influence this voltage. The design of the electrode's structure significantly affects the degree of interference [105]. Despite its significance, there have been no studies to date that explore the fluctuations in skin potential in response to pressure or the motion of capacitive sensors. This knowledge gap emphasizes the necessity for additional research in this specific area.

DC bias currents from amplifiers can also contribute to this phenomenon [41]. An additional source of leakage potential comes in the form of PLI potential. Moreover, it can be related to earthing, also known as grounding, occurs when the human body comes into direct contact with the Earth, allowing for the free transfer of ions between the two. Recent research has highlighted a prevalent belief suggesting that the human body tends to maintain a positive charge, a phenomenon that cannot be effectively balanced due to the prevalent insulation from the Earth in modern lifestyles. In the past, routine activities such as walking barefoot and sleeping on the ground provided continual grounding, but today, the use of insulated footwear and the insulation of buildings from the ground have become commonplace [106]. Since these potentials contain a combination of both DC and AC voltages, they are represented as $V_{DC} + V_{AC}(t)$ in the model.

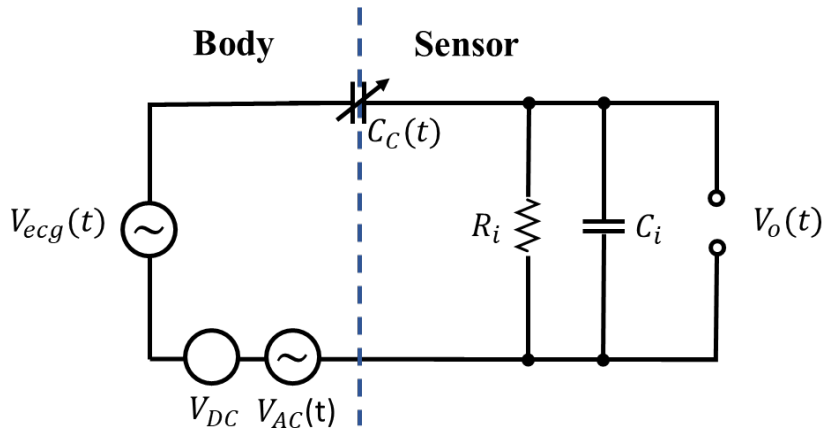


Figure 3-9: Electrical model of a single capacitive electrode.

In the illustrated model shown in Figure 3-9, the expected output is $V_{ecg}(t)$. However, the calculation of the current flow through a variable capacitor is expressed by Equation (3-7) and this Equation changes the characteristics of leakage potentials [37, 41, 42, 102].

$$I_c = \frac{d(C(t)V(t))}{dt} = C(t) \frac{dV(t)}{dt} + V(t) \frac{dC(t)}{dt} \quad (3-7)$$

The equivalent circuit of the capacitive sensor shown in Figure 3-9 can be mathematically described in the time domain by a differential Equation according to Kirchhoff's current law (KCL) as

$$\begin{aligned} \frac{d[(C_c(t) + C_i) \cdot v_{out}(t)]}{dt} + \frac{v_{out}(t)}{R_i} = \\ \frac{d[C_c(t) \cdot (v_{ecg}(t) + v_{dc} + v_{AC}(t))]}{dt} \end{aligned} \quad (3-8)$$

As a linear system, the output signal $v_{out}(t)$ is expected to comprise the superimposition of four components, which are the output due to $v_{ecg}(t)$, $v_{AC}(t)$, and v_{dc} as shown in (3-9).

$$v_{out}(t) = v_{out_{ecg}} + v_{out_{DC}} + v_{out_{AC}} \quad (3-9)$$

By using standard techniques for differential equations with time-varying coefficients we can solve (3-8) and obtain

$$v_{out_{ecg}} = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{ecg}(u)]}{du} e^{-\int_u^t f(s)ds} du \quad (3-10)$$

$$v_{out_{dc}} = v_{dc} \cdot A(t) \int_0^t \frac{dC_c(u)}{du} e^{-\int_u^t f(s)ds} du, \quad (3-11)$$

$$v_{out_{AC}} = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{AC}(u)]}{du} e^{-\int_u^t f(s)ds} du, \quad (3-12)$$

with:

$$A(t) = \frac{1}{C_c(t) + C_i}, \quad f(t) = \frac{1}{R_i[C_c(t) + C_i]} \quad (3-13)$$

Reveal that each component in v_{out} is a function of the coupling capacitance $C_c(t)$ and the corresponding source.

Equation (3-10) demonstrates the dynamic high-pass filter effect discussed in section 3.5. It illustrates how the time-varying coupling impedance distorts the ECG signal [12]. This distortion converts $v_{ecg}(t)$ into $v_{out_{ecg}}(t)$, producing multiplicative noise [37], which is of lesser significance if the cut-off frequency of the high-pass filter in Equation (3-4) is low enough.

The main challenge relates to equations (3-11) and (3-12), where V_{DC} and V_{AC} undergo amplitude modulation due to $C_c(t)$. The changing coupling impedance transforms leakage voltages into an AC signal with an unknown frequency, producing additive noise [37] to $v_{out_{ecg}}$ which is shown in Equation (3-9). Various studies have indicated that both intended and unintended body movements mostly occur within a frequency range below 10 Hz [37, 39, 40], although some have suggested a range from 0 to 20 Hz [41–43]. The chosen frequency range (0.1-20 Hz) covers breathing movements (0.1-2 Hz), body motion (0-10 Hz), and ballistocardiograph vibrations (0-20 Hz), aligning with the changing $C_c(t)$ [41]. As this range overlaps with the ECG signal, basic frequency-based filtering may not adequately eliminate AC-transformed voltages.

Additionally, the leakage voltages across $C_c(t)$ can reach several hundred millivolts or even a few volts, primarily depending on the static charge on the body surface or textile layers at the body-electrode junction.

In the worst-case scenario, this voltage could entirely mask the measured biopotential and potentially cause

system distortion. This transformation of mechanical vibrations into undesirable electrical signals is sometimes called microphonics [41], sharing similarities with signals resulting from membrane movements in microphones [28]. In summary, microphonics can modulate the amplitude of body surface potentials captured by capacitive electrodes, regardless of whether these potentials originate from bioelectric or triboelectric sources. This modulation reflects variations in the distance between electrode plates triggered by activities like breathing, heartbeats, and voluntary body motions [43]. In Equation (3-14), $a(t)$ represents what is known as the MA (additive noise), regardless of the source of leakage voltages ($V_{DC} + V_{AC}$). The signal $s(t)$ represents the distorted version of the ECG signal in Equation (3-15), contaminated with multiplicative noise. Consequently, $x(t)$ in Equation (3-16) describe the recorded signal by the system.

$$a(t) = v_{out_{dc}} + v_{out_{tri}} \quad (3-14)$$

$$s(t) = v_{out_{ecg}} \quad (3-15)$$

$$x(t) = s(t) + a(t) \quad (3-16)$$

While these equations have been validated in numerous papers using the defined model, some studies suggest that the alteration in impedance may not be the sole cause of MA [107, 108]. Nevertheless, it is generally agreed that both electrode motion and changes in electrode-skin impedance contribute to MA [109].

In another existing category, MA is divided into two sectors: MA caused by transversal and lateral electrode movements. Transversal movement brings about changes in coupling distance, which alters coupling capacitance and gives rise to the microphonic effect. On the other hand, lateral movement creates friction at the interface between the body and the electrode, resulting in triboelectricity [28, 32, 94, 101]. Nevertheless, this explanation might not cover all aspects. Transversal movement, alongside lateral movement (sliding and friction), can also generate triboelectricity. This is especially true when using rigid PCBs as electrodes that may not align perfectly with the body's surface. In such cases, significant changes in the gap between the PCB and the body occur during motion [110]. Furthermore, when two surfaces previously in contact separate from each other, there is charge accumulation and redistribution due to triboelectricity. This leads to a significant amount of noise being introduced and interfering with the desired signal. However, lateral motion produces even greater friction and triboelectricity. This phenomenon is like what happens in triboelectric nanogenerators (TENGs). In this model, the coupling between the electrode and skin consists of not only a capacitor ($C_c(t)$) but also includes a voltage source (V_{Tribo}), connected in a series, as illustrated in Figure 3-10 [32, 111]. TENGs

operate based on the triboelectric effect and displacement current principle, similar to capacitive electrodes. They have different operational modes with specific structures, among which the transversal contact-separation mode (Figure 3-11. a) and lateral mode (Figure 3-11. b) exhibit a triboelectric effect like that of capacitive electrodes.

A model explaining the triboelectric effect on capacitive electrodes can be derived from the V-Q-x relationship of TENGs, as shown in Equation (3-17). Sirtoli et al. [32] formulated this model for situations involving contact-separation, as expressed in Equation (3-20). The derivation of this Equation involves calculating $C_c(y)$ using Equation (3-18), where $y(t)$ signifies the time-variable distance between the electrode and the body surface. Additionally, the calculation of $V_{Tribo}(y)$ is carried out using Equation (3-19). σ_d represents the surface charge density, $y(t)$ refers to the displacement at a given time (t), ϵ_{die} is the dielectric permittivity of the capacitive electrode, and ϵ_0 stands for the vacuum permittivity.

$$V_{tot} = -\frac{1}{C_c(y)}Q + V_{Tribo}(y) \quad (3-17)$$

$$C_c(y) = \frac{A\epsilon_0}{\frac{d_{die}}{\epsilon_{die}} + y(t)} \quad (3-18)$$

$$V_{Tribo} = \frac{\sigma_d y(t)}{\epsilon_0} \quad (3-19)$$

$$V_{tot} = -\frac{Q}{A\epsilon_0} \left[\frac{d_{die}}{\epsilon_{die}} + y(t) \right] + \frac{\sigma_d y(t)}{\epsilon_0} \quad (3-20)$$

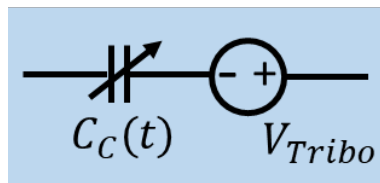


Figure 3-10: Electrical coupling of skin-electrode interface for a capacitive electrode.

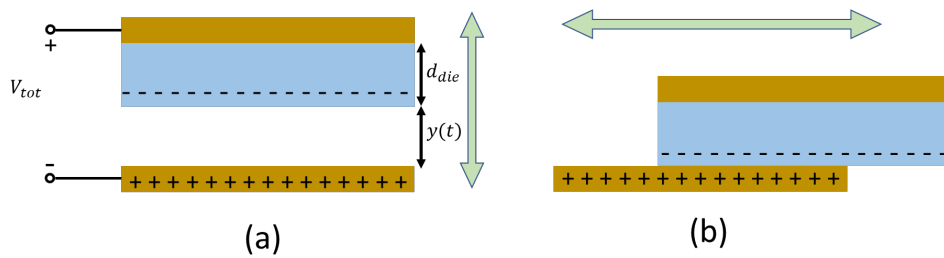


Figure 3-11: Fundamental modes of TENGs. (a) Transversal contact-separation mode. (b) Lateral mode.

3.7 The Latest Techniques for MAs Reduction

To minimize the disturbance from MA, it's crucial to address three key areas: Analog circuits (dealing with electrical components), Materials and Fabrication (selecting suitable electrode materials, and optimizing fabrication) and DSP approaches. These elements must collaborate to efficiently reduce noise and improve the overall quality of the ECG signal.

3.7.1 Analog Circuits

The circuit design techniques in Section 3.5 can help reduce MA by mitigating leakage potentials. Therefore, addressing this section is highly necessary. However, when measuring ECG with two active electrodes, a challenge arises as these electrodes can move independently, causing varying MAs. Different frequency changes of $C_c(t)$ and leakage voltages ($V_{dc} + V_{ac}$) for each electrode lead to different additive MA, ($a(t)$ in Equation (3-14)). Additionally, the triboelectric voltage from Equation (3-20). varies due to the varying distance between the electrode and the body ($y(t)$). Consequently, the CMRR factor cancels out extra CM voltages, except for the portion transformed into a differential signal due to the skin-electrode impedance mismatch. This transformed portion is then amplified by the differential mode gain of the differential amplifier, degrading the output signal [88]. Enhancing CMRR through the mentioned techniques in Section 3.5 does not offer a solution to this issue.

3.7.2 Materials and Fabrication

Research in another area examines the characteristics of capacitive electrodes, size, shape, and material, that affect system performance. Expanding the surface area is beneficial for increasing coupling capacitance. However, rigid materials have limitations in surface expansion, as shown in Figure 3-12. (a), due to difficulties in full adherence to the body. Even with added layers of cotton or cloth, gaps persist, impacting impedance and signal quality [23]. To overcome this, researchers are investigating flexible electrodes that can conform to the chest's curvature, as depicted in Figure 3-12. (b). This improves contact surface and, consequently, enhances coupling capacitance [23, 110]. Nevertheless, Lee et al. [112] suggested that when conventional flexible electrodes are used, air gaps can still exist due to the chest's uneven surface caused by ribs. To compensate for this, they propose the use of conductive foam, as depicted in Figure 3-12. (c), to eliminate additional air gaps. Moreover, Asl et al. [30] proposed that by increasing capacitance with flexible electrodes, we can use a lower bias resistor to achieve a low enough f_c in Equation (3-4), thereby minimizing voltage noise. Importantly, prior research [30] indicates that the electrode shape (circular, rectangular, etc.) has no

effect on voltage noise. Additionally, High-spatial resolution ECG recordings provide valuable insights for diagnosing a wide array of cardiac abnormalities, including infarction and arrhythmia [113]. To enhance spatial resolution in ECG, researchers have developed body surface potential maps by expanding the standard 12-lead ECG to encompass a greater number of recording points across the body surface [114]. It is widely recognized that reducing the spacing between electrodes leads to higher spatial resolution [113]. Additionally, it is important to consider the impact of electrode size on spatial resolution. Studies have shown that enlarging the area of the plate electrode reduces spatial resolution [115]. While our discussion primarily focuses on capacitive electrodes with fewer leads, it is essential to consider the trade-off between increasing the surface area to enhance capacitance for improving signal strength and preserving spatial resolution. This balance requires further exploration.

Numerous research studies have explored diverse dielectric materials and their influence on bioelectrode performance. A higher dielectric constant enhances capacitance, but the intended application must be carefully considered. Metal oxides, for example, provide a high dielectric constant suitable for capacitive biosensing; however, their reactivity with sweat may lead to more MAs [22]. Moreover, fabrics and polymers are typically characterized through chemical processes, making it essential to consider their reactivity with skin exudates [22]. Capacitive electrodes with insulated layers are designed to minimize skin reactions, ensure stable interfaces, and enhance overall patient comfort [23]. However, the selection of unsuitable materials can impede the achievement of these goals. For instance, using anodic aluminum oxide (Al_2O_3) as the dielectric can lead to interactions with sweat chloride ions, causing discomfort for patients [116]. Furthermore, as stated earlier, friction and the separation of dielectric surfaces can produce charges against the skin, ultimately leading to MA. In such scenarios, two fundamental principles are employed to assess the quantity of generated charge from a dielectric material on a surface, aiding in the selection of materials with reduced charge generation. The first principle is “charge affinity”, which classifies materials based on their inclination to exchange electrons through contact/friction. The second is triboelectric charge density (TECD), a measure of the interaction between two materials influenced by factors such as humidity, surface roughness, temperature, stress, and other mechanical properties [32, 111].

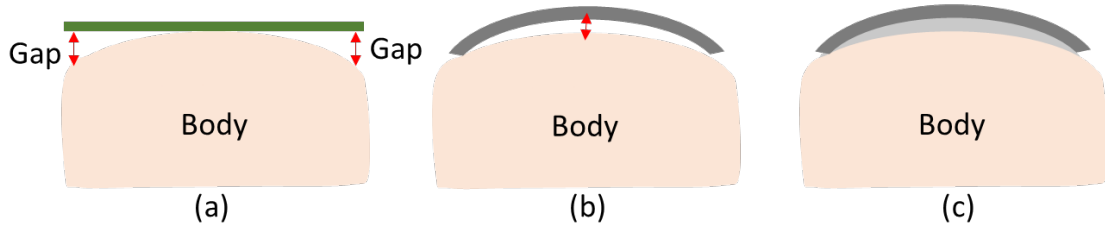


Figure 3-12: (a) Rigid electrode. (b) flexible electrode. (c) flexible electrode with conductive foam.

3.7.3 DSP Approaches

After addressing interference in the two previous sections, any remaining issues can be tackled within the DSP domain. DSP is an integral component of ECG monitoring systems. Figure 3-13 presents a general overview of the multi-channel artifact suppression techniques discussed in this review, inspired by previous articles [23, 32, 117]. Three matrices, $S(n)$, $A(n)$, and $X(n)$, comprise multiple column vectors of signals. Each rectangular block symbolizes a generalized transfer function, such as linear time-variant, nonlinear time-invariant functions, etc. The process involves combining two signals: $S(n)$ (uncontaminated ECG signal) and $A(n)$ (MAs), using a transfer function denoted as $H(\cdot)$. The outcome is the final recorded signal, $X(n)$, which contains both multiplicative and additive MAs. $X(n)$ represents Equation (3-16) discussed in Section 3.6. Triboelectric potential outlined in Equation (3-20) can also be integrated into this signal. This diagram can also incorporate future modifications to the MA model.

Various filtering methods can be conducted through the filtering subsystem, represented as operator $F(\cdot)$. Some studies employ high-pass or band-pass filters, represented by opening switches $SW_1 - SW_4$ in Figure 3-13, to eliminate MA. However, these approaches are rudimentary and can introduce further signal distortion due to the overlap of MA frequencies with the ECG signal, as well as similarities in shape to P and T waves [38, 118]. By utilizing switches $SW_1 - SW_4$, optional paths and blocks can be employed. The configuration and positioning of these elements differ across various systems. Instead of selecting a straightforward filtration process, a different approach was taken by Ottenbacher and Heuer [94]. They investigated restoring the ECG signal by solving the inverse system function, $H^{-1}(\cdot)$, and utilizing it as $F(\cdot)$. However, their reconstruction technique demands knowing all model parameters, a challenge that is frequently hard to meet.

Consequently, many studies have turned to computationally intensive algorithms for suppressing MAs. These approaches can be categorized into two groups: self-referencing techniques that do not require additional signals, and therefore, do not necessitate the use of $G(\cdot)$ and $U(\cdot)$ (indicated by the open switches SW_1 - SW_3),

and those that necessitate supplementary signals for signal analysis (SW_1 - SW_2 are closed, while SW_3 - SW_4 are optional).

3.7.3.1 First Category: Self-Referencing Techniques

The first category exclusively relies on DSP techniques to filter out MA. More traditional methods, such as filter banks [119], use time averaging and frequency analysis, assuming the statistical independence of MA and the signal, which has not been verified and can distort the original ECG signal to some extent [120].

On the other hand, the wavelet transform is widely used as a denoising method due to its time-frequency localization and multi-resolution characteristics [121–124]. This method can effectively describe the non-stationary characteristics of the signals, such as ECG. This method has three steps: decomposition, denoising, and reconstruction. First, the original signal is decomposed into an approximate coefficient and several levels of detail coefficients using low-pass and high-pass decomposition filters. Then, all the decomposed coefficients are processed with a denoise algorithm, and the inverse discrete wavelet is applied to reconstruct a noise-free signal [100]. However, the choice of wavelet is important for denoising performance, and comparative studies have shown different conclusions mainly due to differences in the noise characteristics used. The wavelet transform is also computationally intensive and depends on specific MA and ECG signal characteristics and parameters, which may limit its effectiveness. Additionally, since MA is time-varying, wavelet transforms may not be effective in separating the artifact from the ECG signal [97].

Blind source separation (BSS) techniques assume that the sources of ECG and MA are uncorrelated and require input ECG signals to be linearly independent from each other [125, 126]. Although these methods are popular and widely used, they require many recording channels and high computational power due to their high algorithm complexity for good performance. Additionally, BSS methods are blind to the wider sensing situation and assume that all ECG channel signals are affected by the same source of noise, which is implausible due to the spatial distribution of skin impedance under the electrode sensors [118, 127].

According to the literature, these methods are not effective enough, and MA remains largely in the system output [97]. They are also unsuitable for wearable applications that require a low number of parallel channels, small size, and quick setup, while the available processing power is limited by power consumption constraints [127].

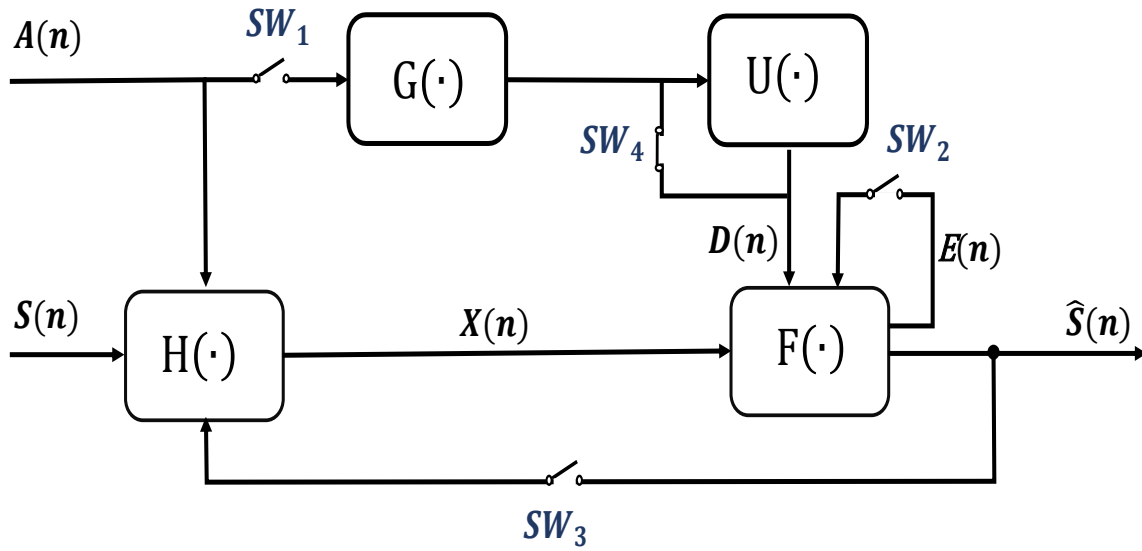


Figure 3-13: A general framework for artifact removal in DSP methods.

3.7.3.2 Second Category: Reference-Assisted Techniques

Figure 3-14 provides a more detailed illustration of the second category, derived from Figure 3-13. In this representation, $H(\cdot)$ is simplified as a sum block. Consequently, the output signal, $X(n)$, results from the summation of the signal of interest, $s(n)$, and the MA, $a(n)$. The operator $G(\cdot)$ denotes a measurement subsystem generates a reference signal, $d(n)$ for the input of $K(\cdot)$. $K(\cdot)$ generates $\hat{a}(n)$, an estimation of the MA, $a(n)$. Subsequently, $\hat{a}(n)$ is subtracted from the recorded signal.

Several assumptions are associated with this method:

1. The MA is not correlated with the signal of interest, $s(n)$.
2. The reference signal is correlated with the MA, $a(n)$.
3. The reference signal is not correlated with the signal of interest, $s(n)$.

The difference between the main input signal, $x(n)$, and the output, $\hat{a}(n)$, of the noise reduction system can be utilized as the error output, represented as $e(n)$, as shown in Equation (3-21):

$$e(n) = s(n) + a(n) - \hat{a}(n) \quad (3-21)$$

The mean square of $e(n)$ is given by Equation (3-22):

$$\begin{aligned} E[e^2] &= E[(s + a - \hat{a})^2] = \\ &= E[s^2] + E[(a - \hat{a})^2] + 2 E[s(a - \hat{a})] \end{aligned} \quad (3-22)$$

If $s(n)$ is not correlated with $d(n)$, Equation (3-22) simplifies to Equation (3-23):

$$E[e^2] = E[s^2] + E[(a - \hat{a})^2] \quad (3-23)$$

As the difference between $a(n)$ and $\hat{a}(n)$ approaches zero, the error output $e(n)$ can be considered the best least-squares estimate of the ECG signal, as shown in Equation (3-24). The effectiveness of noise reduction relies on the level of correlation between $d(n)$ and $a(n)$. Therefore, ensuring a high correlation between them is essential to suppress the noise [128].

$$e(n) \approx s(n) \quad (3-24)$$

This method can be categorized into two types. In the first type, there is an assumption that $K(\cdot)$ represents a known transfer function for estimating MA. In the second type, an adaptive noise filtering approach is employed to estimate MA. In this scenario, the correlation between the reference signal and MA becomes crucial.

3.7.4 First Type: $K(\cdot)$ Is Known

In the first type, the entire system is mathematically modeled, where $K(\cdot)$ represents a known transfer function containing certain unspecified parameters. Unspecified parameters in this method can be estimated using the reference signal and Block least-squares minimization. Equation (3-22) is then employed to mitigate MA. This technique is highly effective in eliminating MA if the model is accurately calculated; otherwise, it may not yield acceptable results. Serteyn et al. [41] utilized this method, demonstrating effectiveness in both simulation and lab setups. However, the proposed method does not completely eliminate the artifact under real-life conditions. Factors such as a simplified system model, thermal noise, and other artifacts like triboelectric effects and EMI induced by unaddressed motion may obscure R-peaks.

3.7.5 Second Type: Adaptive Noise Filtering

Active noise cancellation [129] or adaptive noise filtering [38] methods estimate the transfer function, $K(\cdot)$, between a reference signal and the MAs [37]. Essentially, by employing a reference signal that correlates with the MA present in the recorded ECG, the adaptive filter adjusts its coefficients to minimize the error signal, $e(n)$, as defined in Equation (3-23). This adjustment aligns the reference signal with the MA [66]. The recorded signal is subtracted from the mapped reference signal, resulting in an output with cleaner ECG waveforms [38]. This approach shows promise in MA removal due to its low computational complexity.

The coefficients of this nonlinear filter frequently change based on predefined conditions [126]. In cases where the characteristics of MAs change over time due to movement, adaptive filtering proves to be more effective than other methods. Its ability to adapt parameters facilitates better capture of evolving signal characteristics.

While adaptive filtering algorithms can be implemented with a single-channel input, achieving high filtering performance necessitates a reference signal that exhibits a strong correlation with the additive noise [37, 120, 125]. The limited correlation between the two signals often leads to more contamination of the desired ECG signal [38]. Moreover, alongside recording the ECG, simultaneous recording of a reference signal is essential [126].

The adaptive filter can be implemented using a variety of adaptive algorithms, with the most commonly employed ones being Least Mean Square (LMS), Normalized Least Mean Square (NLMS), and Recursive Least Squares (RLS) [37, 38, 97, 125]. Each of these approaches possesses its own set of advantages and disadvantages.

Many forms of reference signals, $d(n)$, have been employed for MA suppression, such as the measurement of skin stretching with optical sensors [130, 131], electrode motion using accelerometers [132, 133], deformation of electrodes [134], and the change in ETI [37, 38, 41, 66, 126, 129, 135, 136].

In a recent study, Ding et al. [128] introduced a novel reference signal using custom electrodes made of silver conductive fabric. Each electrode contained three layers: a rectangular layer of conductive material for acquiring ECG signals, a rectangular insulation layer above the previous layer, and a comb-tooth-shaped layer for acquiring the reference signal. This method showed good results; however, it adds one more signal acquisition channel. The main limitation of second category DSP methods is that they require additional sensors to measure a reference signal that correlates with motion and must be synchronized with the capacitive sensor [37, 41]. This solution may increase the complexity and power consumption of the recording system, and in some cases, their method is not automated [41], making it unsuitable for ambulatory monitoring, which is the primary goal of capacitive ECG measurements [37].

Among the mentioned reference signals, ETI seems a promising candidate. Although the first suggestion was to use an auxiliary capacitive sensor to track changes in the coupling impedance [137], other studies have shown better solutions that do not require additional sensors. ETI is a signal of significant interest since it exhibits a high correlation with MA, allowing for superior performance of beat detection algorithms compared to the use of other reference signals. Additionally, it is amenable to low-power circuit design since no additional sensor is required to produce ETI [38, 126]. The ETI signal can be recorded continuously and simultaneously with the ECG signal by sharing electrodes, injecting higher-frequency AC signals into the sensing electrodes, and amplifying the resulting voltage [66, 125]. Since the injected AC signals have spectral

contents outside the ECG band, they do not corrupt the ECG's morphology [38, 42]. This technique is also utilized in traditional ECG measurement systems employing gel or dry electrodes, but it has also been recently suggested for use in ECG measurement systems employing capacitively coupled electrodes [126]. In recent studies on capacitive electrodes, an injection signal has been employed for tasks such as channel selection [138], respiration observation, artifact localization [43], and impedance measurement in static conditions [139]. However, its use for artifact reduction or ECG reconstruction had not been explored until Serteyn et al. [140] conducted the first test in this regard. Eilebrecht et al. [139] then measured the static value of the coupling capacitance for different textiles and electrode designs. Buxi et al. [126] used an injection current at 20 kHz to monitor the ETI of wet and dry electrodes for different MAs. Torfs et al. [66] used a Howland current pump with very small current ranges to inject to the electrodes. In this measurement setup, the first indications of periodic MAs were seen, which could have been associated with heart activity. Current injection has been proposed for many wet and dry electrodes, too [125, 135, 136, 141]. Instead of injecting a current, another adaptive filtering approach injected voltage into capacitive electrodes to measure the ETI [41, 140, 142]. Demodulating the PLI allows for extracting a reference signal that reflects variations in coupling capacitance for adaptive MA removal, as proposed by Xu. et al. [37]. They conclude that the reference signal obtained by this technique can include components that reflect variation in the PLI amplitude in addition to the variation in the coupling impedance. This can lead to an overestimation or underestimation of the MAs. One important challenge is measuring the ETI signal without impacting the quality of biopotential signals and minimizing crosstalk [135, 143].

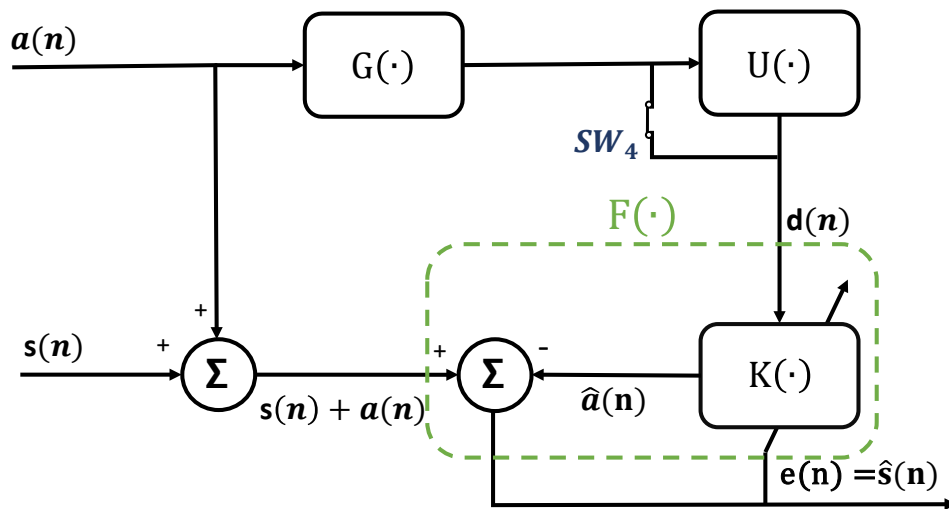


Figure 3-14: A general framework for artifact removal for reference-assisted Techniques.

3.7.6 Challenges of MA Reduction Using Adaptive Filtering with ETI as the Reference Signal

Among the studied methods for reducing MA, the combination of adaptive filtering with an ETI reference signal has received significant attention. However, literature highlights that unlike the clear and direct relationship between the impedance signal and motion pattern, the correlation between MA and ETI signals is not often strong and straightforward. As a result, efficiently subtracting MA becomes challenging [104]. Buxi et al. [126] investigated the relationship between MA and ETI for different artifacts, types of electrodes, and impedance signals. Their goal was to understand when ETI could effectively assist in reducing MA through algorithms. Their findings indicated that among the chosen electrodes, local electrode artifacts (such as pushing and pulling the electrode) had the highest correlation with MA. This was followed by local skin artifacts (like stretching, twist, skin), and then global artifacts (including actions like walking, jogging, jumping). Therefore, it becomes essential to understand the cause or mechanism of MA in order to identify a reference signal that is strongly connected to MA [120]. The ETI signal is usually thought to be purely capacitive in capacitive ECG measurement. Even materials like cotton or solder masks, which insulate well, show resistance in the range of a few Giga ohms. This is significantly lower than the input impedance of a common operational amplifier. Moreover, these materials exhibit some resistive characteristics within specific ECG frequency ranges [144]. Apart from the fully capacitive model, there are other impedance models of the ETI. One proposed by Akabane et al. [145], involves using a combination of a series resistor and a parallel arrangement of resistor and capacitor. Buxi et al. [126] studied the Bode-plot of the skin-electrode impedance. They introduced three different components (real part, imaginary part, and absolute impedance) to provide a comprehensive description of the impedance signal. Addressing the issue of limited correlation, Cömert and Hyttinen [104] focused on the frequencies used for impedance measurements. They noticed that impedance responses at various frequencies differed in the waveform when subjected to the same motion. In the realm of studying motion, higher-frequency impedance measurements displayed a stronger connection to motion compared to lower frequencies. At higher frequencies, impedance measurements turned out to be more sensitive to minor movements, thus delivering more accurate evaluations of applied motion across different motion levels. Additionally, these higher impedance frequencies could act as indicators of applied motion. They showcased that even though the correlation coefficients might be lower, higher frequencies exhibited stability in their relationship to the MA signal both in terms of time and frequency. They concluded that while impedance might

not directly predict the shape of the MA signal over time, it could anticipate the key frequency components of the MA signal. Furthermore, it serves as an effective predictor of the actual applied motion.

To facilitate discussion of the remaining aspects, a comparative table is employed to offer a comprehensive overview of the previous works, as depicted in Table 3-3. Serteyn et al. [41] applied the Block least-squares parameter estimation method to real-life data, achieving a reduction in artifact RMS amplitude by 9 dB. However, they noted instances of unclear visibility of R-peaks in certain sections. They suggested that remaining artifacts might stem from factors not addressed in their study or arise from the simplified electrical model they employed. In contrast, Torfs et al. [66] employed an LMS adaptive filter, resulting in an average reduction of 49% in the RMS content of the signal. They observed variations in the effectiveness of the capacitance impedance signal in correlation with different types of MAs. This finding highlights the importance of developing more sophisticated algorithms to fully take advantage of information from the capacitance impedance signal for effective MA reduction. In a similar study, Xu et al. [37] attempted to demodulate the PLI signal instead of injecting a signal to estimate ETI. They used an NLMS adaptive filter to mitigate MAs and claimed that their proposed method improved the system's SNR by an average of 1.2 dB, resulting in clearer visibility of R-peaks. However, they still observed high-amplitude MAs. They concluded that the reference signal obtained by this technique may encompass components reflecting variations in PLI amplitude, as well as variations in coupling impedance. This dual effect could potentially lead to an overestimation or underestimation of MAs. In the following discussion of ETI as the reference signal, He and Min [120] suggested that the ETI signal may not exhibit the highest correlation with the MA. As a result, they generated a novel synthesized reference signal. This synthesized signal combines skin-induced impedance behavior, skin "slope," and recovery "time constant" to effectively mitigate MA. To address this, an additional processing step, denoted as the $U(\cdot)$ block in Figure 3-14 was introduced. This step is designed specifically to enhance the correlation of the signal. In this scenario, the SW_4 component should be opened. Moreover, they addressed a key limitation of traditional LMS algorithms, the challenge of balancing convergence speed with convergence error. To overcome this trade-off, they introduced an enhanced LMS filter that incorporates both fast tracking and low convergence error components. This modification successfully navigated the delicate balance between speed and accuracy, yielding promising outcomes and be able to 7~15dB improvement on average in their system. But their experimental setup involved offline signal processing to adjust applied vertical forces to sensors, and they did not explore various artifact types in their study of MA. Recognizing the

low correlation between MA and ETI, Pholpoke et al. [38] used an additional layer of digital algorithms, BSS, in the backend to effectively reduce MA. They also highlighted the need for recording devices with higher input dynamic ranges (DR) to handle MAs. This requirement necessitates existing systems to use low gain in their amplification chains to prevent output saturation. To tackle this challenge, they implemented LMS filtering to generate a cancellation signal capable of nullifying MA near the system's input. For this design SW_3 in Figure 3-13 needs to be closed. By effectively suppressing MA, the signal could then undergo additional amplification without encountering output range saturation. In the field of using a more efficient method to tackle with different types of MA, Kim et al. [146] proposed a MA removal method employing more efficient techniques to address various types of MAs. Their approach utilized a two-stage cascade LMS adaptive filter. In the first stage, an LMS algorithm with analog feedback was employed to prevent signal saturation, similar to the technique used by Pholpoke et al. [38]. This aids in reducing the input dynamic range. For the second stage, an adaptive step-size LMS algorithm was used. This adaptive step-size algorithm facilitates rapid convergence to track large, sudden MAs while preserving the integrity of the ECG component. The filtering performance was evaluated based on heartbeat detection, measured by sensitivity (Se) and positive predictive value (+p), resulting in an improvement of 9.8% and 6.48% respectively.

Table 3-3 Comparison of Previous Works

Source	Methods for measuring ETI	Methods of MA Mitigation	Type of Experiments	Results
Serteyn et al. [41]	Voltage injection at a frequency of 1 kHz	•Reverse the transfer function. •Block least-squares parameter estimation	•Simulation •Lab Data •Real-Life Data ○Electrode Pushing	•Good results in simulation and lab experiments ○Achieved clear visibility of R-peaks. •Real-life data: ○Reduced artifact RMS amplitude by 9 dB ○Observed unclear visibility of R-peaks
Torfs et al. [66]	Current injection at a frequency of 10 kHz	•LMS adaptive filter	•Real-Life Data ○Electrode pushing/pulling and lateral motion ○Arm motion	•Acceptable results in push/pull motion •Not acceptable results in Arm motion •Reduced RMS content of the signal by an average of 49%
Xu et al. [37]	Demodulation of the PLI signal	•NLMS adaptive filter	•In-silico experiment •In-vivo experiment ○Subject seated on a chair with their trunk straight. ○Subject seated on the chair, oscillating their trunk ± 15 degrees forward and backward.	•Acceptable results in in-silico experiment •In-vivo experiment: ○High-amplitude MAs observed. Achieved clear visibility of R-peaks. ○1.1 dB improvement in SNR for the first test. ○1.3 dB improvement in SNR for the second test.
He and Min [120]	Current injection at a frequency of 5 kHz	•improved LMS filter ○Balances speed and accuracy	•Real-Life Data ○Electrode pushing/relaxing	7~15dB improvement on average (Performance metrics was not mentioned)
Pholpoke et al. [38]	Current injection at a frequency of 5 kHz	•Two stage MA mitigation ○1st-order low-pass filter ○Sign-sign LMS adaptive filter	•Real-Life Data ○Electrode pushing	-----
Kim et al. [146]	No information capable as they used database	•Two stage MA mitigation ○LMS adaptive filter feedback to analog circuit. ○Adaptive step-size LMS adaptive filter.	•Imec database	•Evaluated performance via heartbeat detection: ○9.8% improvement in sensitivity (Se) ○6.48% improvement in positive predictive value (+p)

3.8 Discussion and Future Directions

In capacitive ECG data loggers, it is evident that suboptimal circuit designs can introduce signal distortion, often misidentified as MAs. To address this issue, it is essential to carefully examine electrode construction and circuit design aspects, often overlooked in current literature. Rectifying these shortcomings will pave the way for a more comprehensive understanding of the origins of MAs. Presently, the definition and sources of MAs remain unclear. While there have been discussions on the study of MAs involving wet electrodes by introducing various artifacts to establish improved models, research efforts have predominantly centered around capacitive electrodes, given their growing demand in wearable telehealth monitoring systems. Consequently, most published works explore MAs, examining their amplitude and frequency characteristics across various applied artifacts in diverse ECG experiments utilizing capacitive electrodes. The ultimate goal is to present a reliable model for MAs.

Another related domain necessitating attention is DSP for MA removal. Although adaptive filtering, often utilizing the ETI as a reference signal, holds promise in mitigating this issue, it has yet to yield sufficient outcomes. Therefore, a more in-depth exploration of ETI is imperative and could serve as a main point for future research. Beyond solely relying on the capacitive model for skin-electrode impedance, there is room for investigating alternative models. Moreover, the circuit used for estimating the ETI requires further examination.

The efficacy of MA estimation through adaptive filtering significantly depends on the availability of a highly correlated "reference signal". While ETI is a widely accepted candidate, enhancing its correlation through pre-processing algorithms holds the potential for generating a more efficient reference signal. This approach has been adopted in studies involving wet and dry electrodes but remains unexplored in the context of capacitive electrodes. Additionally, using supplementary reference signals, such as accelerometer data, may hold promise for improving the SNR, a direction that merits investigation.

Another promising path for further research lies in the design of adaptive filtering itself. While current literature primarily concentrates on identifying reference signals that exhibit high correlation with MAs, designing adaptive filters capable of effectively mitigating MAs has received limited attention and deserves more research. Lastly Moreover, there are instances where combining DSP techniques with analog designs can potentially prevent amplifier saturation and signal loss, presenting another attractive area for future research.

It should be noted that besides traditional denoising techniques, there are other emerging approaches, such as machine learning and deep learning techniques, which are not as commonly cited in academic works. While deep learning techniques share certain characteristics with adaptive filters in the domain of ECG signal processing, they have primarily been utilized for tasks such as feature extraction and noise detection rather than direct ECG signal reconstruction. Although less frequently mentioned in the literature compared to traditional denoising techniques, the relevance of machine learning and deep learning methods in ECG denoising may increase in the coming years, particularly as research in this area continues to develop.

3.9 Conclusion

This review highlighted the significance of capacitive ECG measurement systems as a promising alternative for ECG measurement, offering non-intrusive long-term monitoring. However, the challenge lies in maintaining diagnostic accuracy comparable to hospital-grade systems. MAs have emerged as a critical issue in capacitive ECG measurement due to the variable impedance between the body and the electrode, along with existing interference sources. Despite being commonly acknowledged; the exact origins and definitions of MAs remain unclear. Addressing this gap, we reviewed existing models. Furthermore, this article studied state-of-the-art MA mitigation techniques, spanning analog circuits, electrode fabrication, and DSP methods. Emphasis has been placed on adaptive filtering using ETI as a reference signal, consistent with the approach of many recent articles. While advancements have been made in this field, challenges persist, warranting further research in several areas concurrently. These include synthesizing a reference signal more correlated with MAs using ETI or add other reference signals, optimizing mitigation methods for improved accuracy and speed, developing advanced techniques adaptable to various MAs, and enhancing the dynamic range of the system to enable higher gains, as evidenced in prior studies.

Chapter 4 Adaptive Motion Artifact Suppression in a Capacitive Single-Lead ECG Chest Strap Using Voltage Injection

4.1 Prelude

The content of this chapter is a copy of the article titled “Adaptive Motion Artifact Suppression in a Capacitive Single-Lead ECG Chest Strap Using Voltage Injection”, submitted to the peer-reviewed journal IEEE Transactions on Biomedical Circuits and Systems.

In Chapter 3, existing models of motion artifacts (MAs) were systematically reviewed, alongside state-of-the-art mitigation techniques spanning analog circuitry, electrode design, and digital signal processing (DSP). Particular emphasis was placed on adaptive filtering approaches that use electrode-tissue impedance (ETI) as a Reference Input Signal (RIS), aligning with recent trends in the literature.

Despite the notable progress documented in Chapter 3, several critical challenges remain. These include the need to synthesize RISs that are more strongly correlated with actual MAs, enhance the accuracy and efficiency of mitigation methods, and develop advanced filtering strategies adaptable to a wide range of motion scenarios. This chapter addresses the gaps identified in Chapter 3 and responds directly to Objective 3 as defined in Section 1.4. This chapter aims to model the MA behavior inherent to the customized single-lead capacitive ECG configuration. This single-lead configuration was selected due to its practicality for wearable ambulatory ECG monitoring, as it requires fewer electrodes compared to the conventional 12-lead ECG system, thereby improving patient comfort, simplifying electrode placement, and enhancing usability during daily activities. Subsequently, a low-complexity and highly effective voltage injection technique is proposed to extract an RIS with strong correlation to real MAs. Finally, the method’s performance is validated through extensive experimental evaluation across multiple performance metrics.

4.2 Abstract

With the increasing demand for real-time, long-term, and telemedicine-based electrocardiogram (ECG) monitoring, there is a growing trend towards sensors that ensure safety, comfort, accuracy, and continuous monitoring without requiring specialized assistance. Capacitive sensors, which measure ECG without direct skin contact, are a key innovation in this area. However, they are prone to motion artifacts (MAs) caused by body movements and physiological vibrations. To address this, we propose a capacitive single-lead chest strap for ECG monitoring across the torso, combined with an MA reduction algorithm based on a Reference Input

Signal (RIS), that is highly correlated with MAs. The RIS, which is measured simultaneously without extra sensors or electrodes, is fed into a Recursive Least Squares (RLS) adaptive filter to mitigate MAs. We demonstrate the performance of the proposed method using various evaluation metrics, including signal quality and three different correlations: MA vs. the RIS, estimated MA, and reconstructed ECG vs. the RIS. Additionally, we employ noise reduction metrics such as root mean square (RMS), standard deviation (STD) reduction, and signal-to-noise ratio (SNR) improvement for each R peak. Our results show promising improvements outperforming existing methods reported in the literature.

4.3 Introduction

Electrocardiogram (ECG) technology is widely used to detect abnormal heart rhythms, diagnose chest pain, and classify cardiovascular diseases (CVDs) [6, 8]. Real-time and long-term ECG monitoring is crucial for timely emergency care during the ‘Golden Hour’ to reduce mortality and for managing patients with specific CVDs [6, 11]. Additionally, telemedicine has become increasingly important in improving public health, especially in aging populations and underserved regions [13]. Effective telemedicine requires independent, remote ECG sensors that ensure safety, comfort, accuracy, and continuous monitoring without the need for specialized assistance.

Traditional gel-based Ag/AgCl electrodes, though commonly used in clinical and research settings, pose challenges in long-term wearability and user convenience [12, 18, 20, 21]. Capacitive electrodes offer a viable alternative by enabling ECG measurement without direct skin contact. They function through materials such as hair, fabric, insulation layers, or air, making them ideal for wearable devices [19]. Unlike conventional ECG systems that employ ten electrodes, ambulatory capacitive ECG systems typically operate with just two or three electrodes, improving the feasibility of continuous remote monitoring [27].

A major challenge in capacitive ECG systems is achieving diagnostic precision comparable to hospital-grade 12-lead ECGs [32]. Motion artifacts (MAs), the most significant source of interference, arise from variations in coupling capacitance due to body movements and physiological vibrations such as respiration and cardiac contraction [42, 43]. These movements typically occur within 0–20 Hz, encompassing respiration (0.1–2 Hz), general motion (0–10 Hz), and ballistocardiography vibrations (0–20 Hz) [37, 39–43]. In capacitive ECG systems, a DC voltage exists across the coupling capacitor. When the capacitance fluctuates due to motion, it modulates this DC voltage, generating an AC component at the frequency of capacitance variations; this AC voltage constitutes the MA [37]. Because MA frequencies overlap with the ECG bandwidth, simple frequency-

domain filtering methods are inadequate for artifact suppression. The DC voltage across the coupling capacitor originates from multiple sources, including triboelectric charge accumulation, electrodermal potentials, and DC bias currents from amplifiers [37, 41]. This mechanical-to-electrical transformation, known as microphonics, resembles the signal generation process in microphones [28]. Such artifacts can significantly compromise diagnostic accuracy, leading to misinterpretations of cardiovascular conditions, as seen in cases like "toothbrush tachycardia" [99].

Analog circuits partially mitigate these artifacts, but residual MAs must be addressed digitally [34]. Pure digital signal processing (DSP) techniques such as wavelet transforms, and blind source separation (BSS) present several limitations, as they rely on the unverified assumption of statistical independence between MAs and ECG signals, potentially leading to signal distortion [120]. Wavelet transforms, although effective for baseline wander or slowly varying noise, tend to perform poorly against rapidly time-varying motion artifacts unless coupled with an adaptive stage [122, 123]. BSS methods such as ICA assume that ECG signals and MAs are statistically independent and that a common noise source affects all channels. However, this assumption is invalid due to spatial variability in skin-electrode impedance across electrodes. Additionally, these methods require multiple recording channels, making them unsuitable for low-power wearable devices and relatively computationally intensive [118, 127]. Reference-assisted noise cancellation techniques, particularly adaptive filtering, have demonstrated promise in mitigating MAs with low computational complexity. These methods use an RIS correlated with MA to estimate the transfer function and minimize interference [37, 38]. By continuously adjusting filter coefficients, adaptive filtering effectively suppresses MA while preserving ECG integrity. However, its performance depends on key assumptions [128]: (1) MAs are uncorrelated with the ECG signal, (2) the RIS correlates with MA, and (3) the RIS does not interfere with ECG. Limited correlation between the RIS and MA can degrade filtering efficiency, necessitating a high-quality RIS [38].

Various adaptive algorithms, such as Least Mean Square (LMS), Normalized Least Mean Square (NLMS), and Recursive Least Squares (RLS), have been explored for MA suppression [37, 38, 97, 125]. RIS's investigated include skin stretching via optical sensors [130, 131], electrode motion via accelerometers [132, 133], electrode deformation [134], and electrode-tissue impedance (ETI) [37, 38, 41, 66, 126, 129, 135, 136]. ETI particularly stands out due to its strong correlation with MA, its ability to be recorded without additional sensors, and low power consumption [38, 126]. Recent studies employing high-frequency AC signal injection into electrodes have demonstrated ETI measurement alongside ECG without affecting ECG morphology [38,

42]. Such signals have been applied for electrode channel selection [138], respiration monitoring, artifact localization [43], and static impedance measurements [139]. However, their application for MA reduction or ECG reconstruction remained unexplored until Serteyn et al. [140] introduced voltage injection through a bias resistor using a simplified, unipolar capacitive electrode configuration. Despite promising simulation and laboratory results, their approach suffered limited effectiveness in real-life scenarios due to output signal attenuation. Xu. et al. [37] adopted a similar approach, employing 50 Hz demodulation (power line interference (PLI)) to generate an RIS. While innovative, inadequate preprocessing led to inaccuracies, as their RIS contained both PLI amplitude variations and coupling impedance fluctuations, potentially misrepresenting MAs. Torfs et al. [66] used a bipolar capacitive ECG system with a 180° out-of-phase injection signal to estimate ETI. However, their failure to explicitly model MA resulted in inconsistent correlations between the RIS and actual MA, limiting artifact suppression performance. Similarly, Buxi et al. [126] analyzed ETI via Bode plots instead of explicitly modelling MAs, while Lee et al. [147] and Pholpoke et al. [38] applied voltage and current injection methods, respectively, with encouraging results but still lacked comprehensive modeling and optimization. Despite these advancements, prior studies have inadequately addressed several critical issues: accurately modeling MA before deriving an RIS, optimizing the RIS extraction strategy, and ensuring maximal correlation with actual MAs. Practical aspects such as optimal electrode placement and wearing conditions have also received insufficient attention, and most studies use a single evaluation metric without exploring its suitability under varying MA scenarios.

To address these gaps, we present a capacitive single-lead ECG measurement system using cotton-covered electrodes integrated into a chest strap, laying the groundwork for wearable applications suitable for use over clothing, significantly improving comfort and practicality. We optimized the electrode design to achieve ECG signal quality comparable to wet electrodes under stationary conditions. Crucially, we accurately characterize MA within our bipolar capacitive ECG configuration prior to deriving the RIS, strategically selecting system parameters for controlled MA manipulation. An optimized, low-complexity, and highly effective voltage injection technique is developed to extract an RIS that exhibits strong correlation with actual MAs. We further conducted comprehensive evaluations using multiple performance metrics, demonstrating that tailored assessment approaches are required for different MA types and magnitudes.

The remainder of this paper is structured as follows: Section 4.4 describes the methodology for characterizing MA, capacitive electrode design, analog front-end, and DSP methods. Section 4.5 details the experimental

setup and data collection procedures. Section 4.6 presents and discusses our experimental findings. Section 4.7 provides a detailed discussion and outlines future research directions, and Section 4.8 concludes the paper.

4.4 System Design and Methodology

4.4.1 Motion Artifact Estimation in Differential Capacitive ECG Measurement Systems

One of the earliest and most fundamental equivalent circuits for capacitive electrodes was introduced by Ottenbacher and Heuer [94]. Later, Sersteyn et al. [41] expanded and refined this model, making notable advancements. They were among the pioneers in modeling the combined effects of DC voltages and capacitance variations. Their physical model and electrical equivalent circuit are shown in Figure 4-1, (a) and (b) respectively. This model has since been adopted in numerous studies [12, 37, 42, 100].

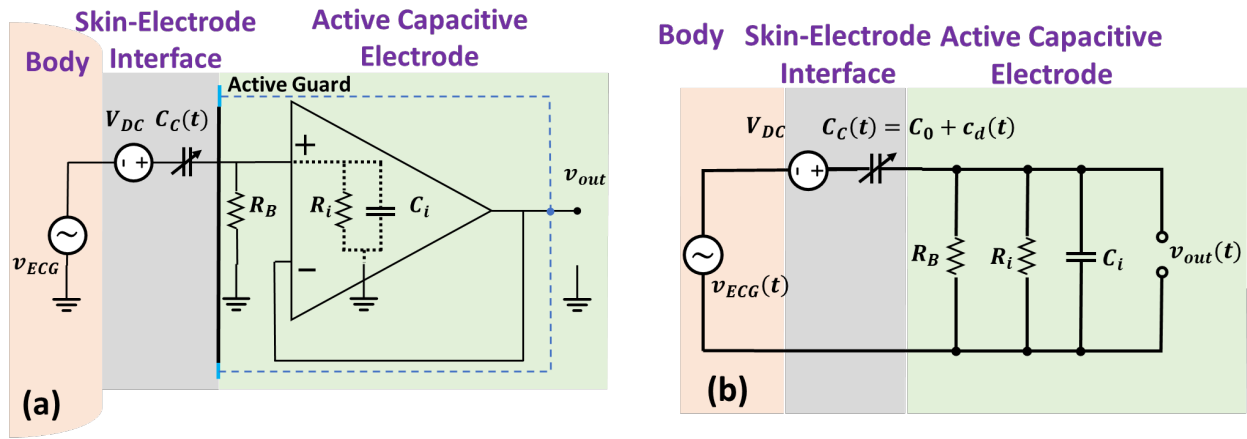


Figure 4-1 (a) Physical model of the capacitive electrode system. (b) Electrical equivalent circuit of the capacitive electrode system.

The ECG acquisition system, illustrated in Figure 4-1 (a), employs a widely used voltage follower/amplifier (VA) configuration utilizing an OpAmp as a buffer with ultra-high input impedance. The OpAmp is modelled with its input resistor, R_i and input capacitor, C_i . To mitigate the adverse effects of increased stray parasitic capacitance, active guarding is implemented, a well-established technique in capacitive biopotential measurements [89, 90]. Additionally, a high-value bias resistor, R_B , provides a bias current path for the OpAmp, preventing charge accumulation at the input front end [23, 30]. The leakage potential between the body's virtual ground and the system's reference node is denoted as V_{DC} [34], while the ECG signal is represented as $v_{ECG}(t)$. As shown in Figure 4-1 (b), the system incorporates a time-varying coupling capacitor, $c_c(t) = C_0 + c_d(t)$, formed between the electrode's plate and the body. Here, $c_c(t)$ consists of a constant capacitance component (C_0) and a dynamic component ($c_d(t)$), which varies due to motion [38, 147]. To quantify MA in this single-electrode setup, the output voltage influenced by V_{DC} , is determined using the

superposition theorem. This voltage represents the MA, can be denoted as $v_{out_{V_{DC}}}$, v_{MA} , or simply MA. The current flow through a variable capacitor is considered as $C(t) \frac{dV(t)}{dt} + V(t) \frac{dC(t)}{dt}$, where the first term accounts for voltage variations and the second term captures capacitance fluctuations due to motion [37, 41, 42, 102]. Applying Kirchhoff's current law (KCL) to the electrical equivalent circuit, we derive the differential equation in Equation (4-1). Transforming it into the Laplace domain, the MA component is expressed as $V_{MA}(s)$. Given that $C_0 \gg 2c_d(t)$, the equation simplifies to Equation (4-2), which characterizes the MA behavior in the system.

$$\frac{d[(V_{DC} - v_{MA}(t))(C_0 + c_d(t))]}{dt} = \frac{v_{MA}(t)}{R_B} + C_i \times \frac{dv_{MA}(t)}{dt} \quad (4-1)$$

$$V_{MA}(s) \approx C_d(s) \times V_{DC} \times R_B \times \frac{s}{sR_B[C_0 + C_i] + 1} \quad (4-2)$$

Similarly, the ECG signal can be obtained by determining the output voltage corresponding to $v_{ECG}(t)$. This voltage, $v_{out_{v_{ECG}}}$, is derived in the Laplace domain and expressed in Equation (4-3).

$$V_{out_{ECG}}(s) \approx V_{ECG}(s) \times R_B \times \frac{sC_0}{sR_B[C_0 + C_i] + 1} \quad (4-3)$$

In this study, we aim to model the overall MA, $v_{MA}(t)$, in a single-lead ECG system comprising two active capacitive electrodes (a single active capacitive electrode is shown in Figure 4-1) and an instrumentation amplifier, as depicted in Figure 4-2. The MA, $v_{MA}(t)$, is calculated by considering the differential-mode output of the system, as described by Equations (4-4) to (4-8). In this context, $V_{MA1}(s)$ and $V_{MA2}(s)$ represent the MA associated with each electrode in the Laplace domain, both of which are equivalent to $V_{MA}(s)$ in Equation (4-2). Here, C_0 denotes the constant component of the coupling capacitor, which is assumed to be identical for both electrodes. The terms $c_{d1}(t)$ and $c_{d2}(t)$ represent the time-varying components of the coupling capacitors for electrodes 1 and 2, respectively. Additionally, G_{amp} represents the gain of the instrumentation amplifier in differential mode. The transfer function $H(s)$, presented in Equation (4-7), is a first-order high-pass filter (HPF) with an angular cutoff frequency ω_0 , as given in (4-8). The constant K is nearly invariant, with frequency of variations of less than 0.5 Hz, as V_{DC} changes at this frequency [41]. The parameters K and ω_0 in Equations (4-5) and (4-8) are simplified under the assumption that $C_0 \gg C_i$.

$$V_{MA}(s) = G_{amp} \times [V_{MA1}(s) - V_{MA2}(s)] = K \times \Delta C_d(s) \times H(s) \quad (4-4)$$

With

$$K = \frac{G_{amp} \times V_{DC}}{(C_0 + C_i)} \xrightarrow{C_0 \gg C_i} K \approx \frac{G_{amp} \times V_{DC}}{C_0} \quad (4-5)$$

,

$$\Delta C_d(s) = C_{d1}(s) - C_{d2}(s) \quad (4-6)$$

And

$$H(s) = \frac{s}{s + \omega_0} \quad (4-7)$$

with

$$\omega_0 = \frac{1}{R_B[C_0 + C_i]} \xrightarrow{C_0 \gg C_i} \omega_0 \approx \frac{1}{R_B C_0} \quad (4-8)$$

Similarly, the overall $V_{out_{ECG}}(s)$ can be computed using Equation (4-9), which incorporates the same transfer function $H(s)$. In this equation, $\Delta V_{ECG}(s)$ represents the differential ECG signal measured between two points on the body, expressed in the Laplace domain.

$$V_{out_{ECG}}(s) = G_{amp} \times \Delta V_{ECG}(s) \times H(s) \quad (4-9)$$

Consequently, the total system output voltage is given by the sum of the ECG signal and the MA component as $v_{out}(t) = v_{out_{ECG}}(t) + v_{MA}(t)$. It can be shown that if $\omega_{ECG,min} \gg \omega_0$, where $\omega_{ECG,min}$ denotes the lower bound of the frequency range selected for the ECG signal, and both R_B and C_0 are sufficiently large, the effect of $H(s)$ becomes negligible. This is illustrated in the Bode plot of $H(s)$ shown in Figure 4-3. As $R_B = 10 \text{ G}\Omega$ and C_0 increases, the influence of $H(s)$ diminishes. For sufficiently large values of C_0 , particularly in the range of hundreds of picofarads, the magnitude response of $H(s)$ approaches unity within the ECG frequency range (0.67 Hz to 250 Hz), and the phase shift becomes negligible. This confirms that, with appropriately chosen R_B and C_0 , $H(s)$ has minimal impact and can be effectively disregarded in the given frequency range. Minimizing this effect ensures that the ECG signal remains unattenuated and free from distortion caused by the inherent high-pass filtering, thereby preserving its low-frequency components, as described by Equation (4-9). Furthermore, this simplification facilitates the mitigation of MA, the primary source of interference in $v_{out}(t)$. As a result, MA becomes linearly proportional to $\Delta C_d(t)$ with a constant factor K , as given in (4-4). By employing an adaptive filter and using $\Delta C_d(t)$ as the RIS, MA can be effectively estimated and subtracted from the contaminated ECG signal, significantly enhancing signal quality and yielding $v_{out}(t) \approx v_{ECG}(t)$.

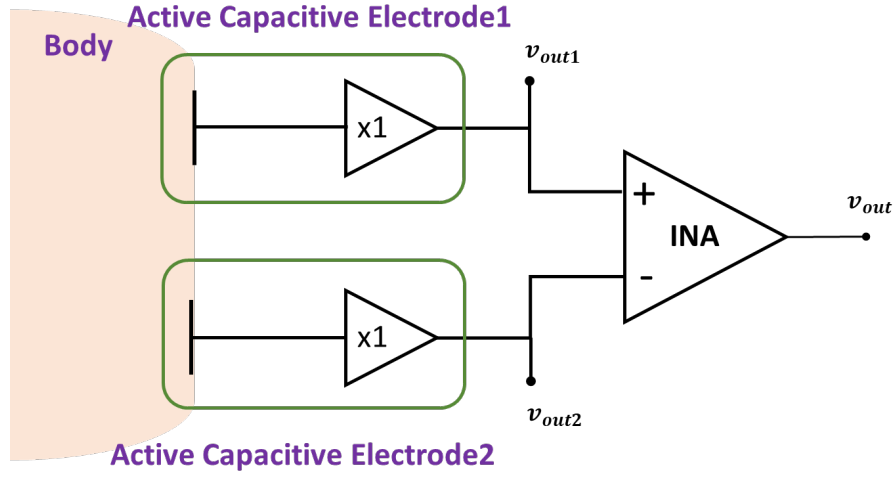


Figure 4-2 Schematic of the bipolar capacitive single-lead ECG measurement system.

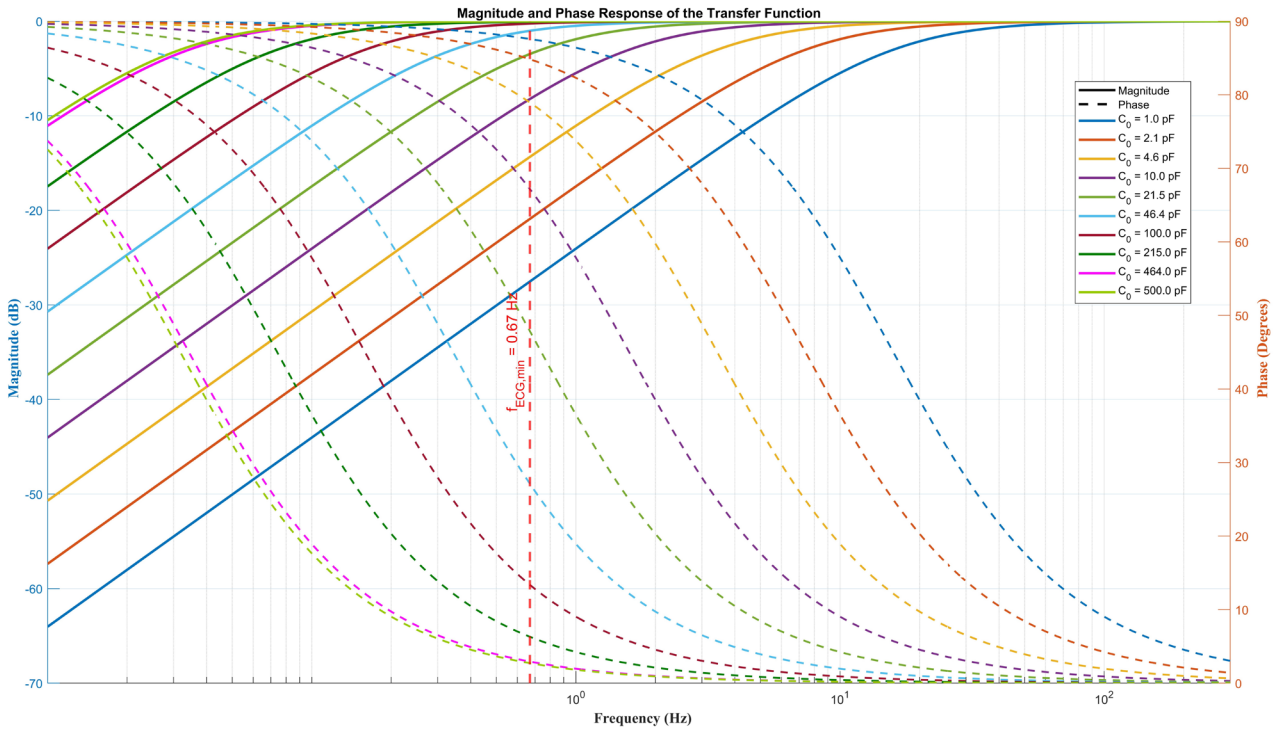


Figure 4-3 Bode plot of $H(s)$ for $R_B = 10 G\Omega$ with varying C_0

4.4.2 Design of Active Capacitive Electrodes with Enhanced Voltage Injection

The VA configuration shown in Figure 4-1 is employed in two active capacitive electrode designs. The LTC624x (Analog Devices, MA, USA) OpAmp is selected due to its ultra-low bias current (typical 0.2 pA), high input impedance ($R_{in} = 1 T\Omega$), and low input capacitance ($C_{in} = 3 pF$). To ensure proper operation, a high bias resistor of $R_B = 10 G\Omega$ is chosen. The proposed capacitive electrodes are circular, with a 30 mm diameter. To accommodate wearable ECG measurement, the sensing plate is conductive and is coated with a thin cotton fabric (thickness: $80 \mu m$, relative permittivity: 1.8). Given these parameters, the coupling capacitance, C_0 , is estimated to be approximately $140 pF$, as calculated using Equation (4-10).

$$C_0 = \epsilon_r \epsilon_0 \frac{A}{d} \quad (4-10)$$

A differential capacitive ECG was employed in this study with the configuration shown in Figure 4-2. Calculating $\Delta c_d(t)$ to estimate MA using an adaptive filter requires injecting a high-frequency signal into the electrodes. We initially analyzed this method by injecting the high-frequency signal into a single electrode; subsequent sections will address the differential configuration and the detailed calculation of $\Delta c_d(t)$.

There are two primary injection methods: voltage injection through the bias resistor, R_B , and current injection into each electrode using a current source. Current injection has been extensively explored in wet, dry, and capacitive electrodes due to its ability to stabilize output voltage against electrode impedance fluctuations [125, 135, 136, 141, 148]. However, this approach introduces considerable design complexity. A reliable current source requires high output impedance, stable operation under varying loads and minimal noise interference. Due to these challenges, we opted for voltage injection and improved its effectiveness by placing a capacitor, C_B , in parallel with the bias resistor, R_B , as illustrated in Figure 4-4. Using the superposition theorem, the transfer function between the injected voltage $v_{inj}(t)$ and the corresponding output voltage $V_{out_{inj}}(j\omega)$ is expressed by Equations (4-11) and (4-12), representing configurations before and after adding C_B , respectively. For simplicity, only the constant coupling capacitance component, C_0 , was considered under stationary conditions, with further simplifications assuming $C_0 \gg C_i$ and $C_0 \gg C_i + C_B$. The Bode plots of Equations (4-11) and (4-12), for $R_B = 10G\Omega$ and different values of C_0 are depicted in Figure 4-5(a) and (b) respectively. Figure 4-5(a) illustrates the original configuration, behaving as a first-order low-pass filter (LPF) with a -20 dB per decade attenuation. Given that the injected signal frequency is typically above 1 kHz (to avoid ECG bandwidth interference), significant signal attenuation occurs, approximately -77 dB at 1 kHz for $C_0 = 100pF$, leading to low SNR [41]. In contrast, Figure 4-5(b) shows the modified system, where high-frequency attenuation is effectively eliminated. At high frequencies, the magnitude response becomes frequency-independent, thereby enhancing stability and improving SNR. Specifically, the magnitude increases by approximately a factor of $(R_B \cdot C_B \cdot \omega)$ compared to the original configuration, significantly enhancing the robustness of the injected signal. Additionally, this improvement nearly eliminates phase shift at 1 kHz, ensuring the output signal is predominantly real-valued at high frequencies. Importantly, our injection current stays well below established safety limits. According to ANSI/AAMI ES1-1993, up to 10 μA of current injection is permissible at frequencies up to 1 kHz, with higher frequencies permitting greater currents. In our

design, based on the selected parameters, the injected current is calculated to remain within the nanoampere range, approximately 1000 times lower than the established safety limits, thus ensuring regulatory compliance and minimizing physiological effects. By adding a small capacitor ($C_B = 6.8pF$) the gain at 1 kHz improved by approximately 53 dB compared to the original configuration (reaching -24 dB for $C_0 = 100pF$). As C_B is significantly smaller than C_0 , the impact on the ECG signal integrity remains negligible, ensuring the preservation of ECG measurement quality.

$$G(j\omega) = \frac{V_{out_{inj}}(j\omega)}{V_{inj}(j\omega)} = \frac{1}{1 + R_B \cdot (C_i + C_0) \cdot j\omega} \xrightarrow{C_0 \gg C_i} G(j\omega) \approx \frac{1}{1 + R_B \cdot C_0 \cdot j\omega} \quad (4-11)$$

$$F(j\omega) = \frac{V_{out_{inj}}(j\omega)}{V_{inj}(j\omega)} = \frac{1 + R_B \cdot C_B \cdot j\omega}{1 + R_B \cdot (C_i + C_0 + C_B) \cdot j\omega} \xrightarrow{C_0 \gg C_i + C_B} F(j\omega) \approx \frac{1 + R_B \cdot C_B \cdot j\omega}{1 + R_B \cdot C_0 \cdot j\omega} \quad (4-12)$$

The designed electrode PCB is depicted in Figure 4-6(a), (b) and (c), illustrating its top view, cotton-covered bottom surface, and internal PCB layers, respectively. The PCB has a diameter of 36 mm, with a 30 mm diameter sensing area intentionally left uncovered by a solder mask to reduce insulation to only the thin cotton fabric layer. The PCB utilizes a four-layer design, where two driven guard layers placed in the middle layers minimize parasitic capacitances and displacement currents. These layers are connected to the buffer output, maintaining the guard at nearly the same potential as the sensing input, thereby reducing leakage currents and high-frequency noise coupling to optimize signal performance [149, 150]. Additionally, a guard ring around the sensing area, held at buffer output potential, further reduces parasitic capacitance and displacement currents, providing additional shielding against external noise and improving the stability of the capacitive measurement [151].

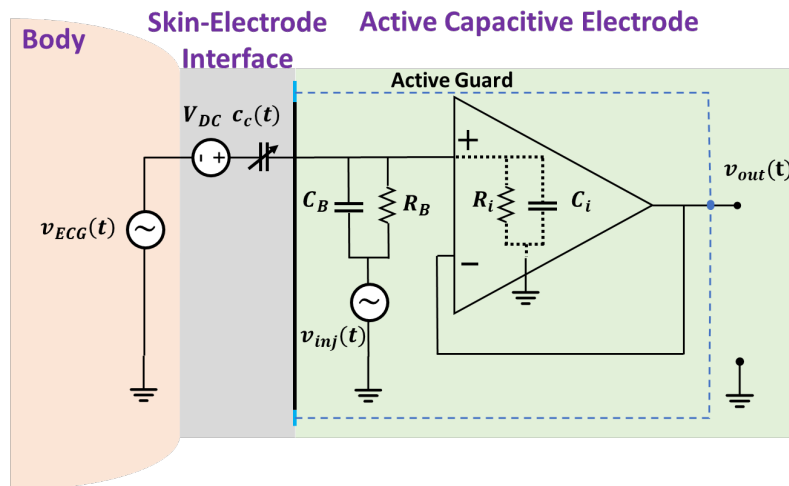


Figure 4-4 Modified voltage injection method with a parallel capacitor C_B to mitigate high-frequency attenuation.

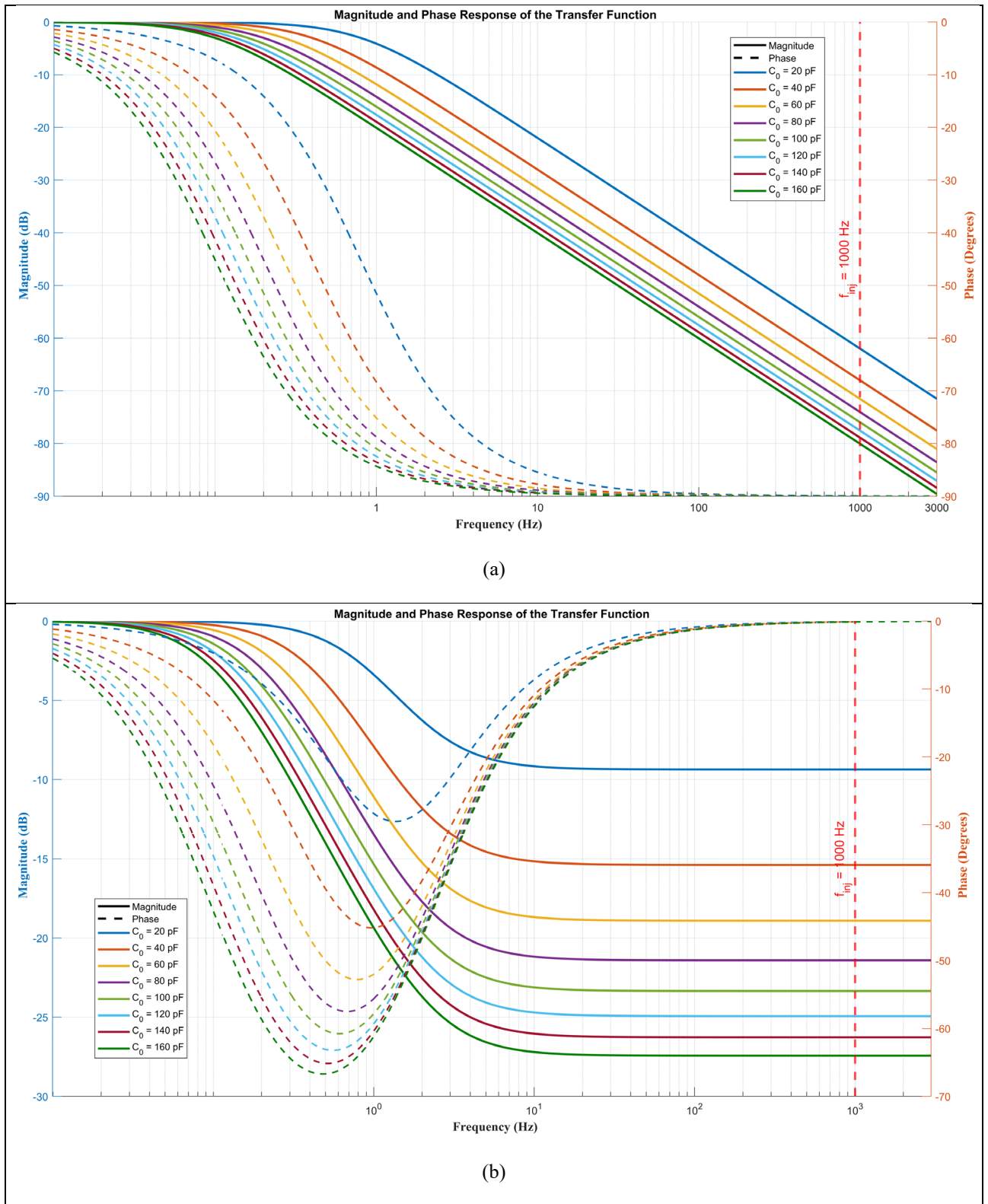


Figure 4-5 (a) Bode plot of the injection path transfer function for $R_B = 10G\Omega$ and varying C_0 . (b) Bode plot of the revised injection path transfer function for $R_B = 10G\Omega$, $C_B = 6.8pF$, and varying C_0 .

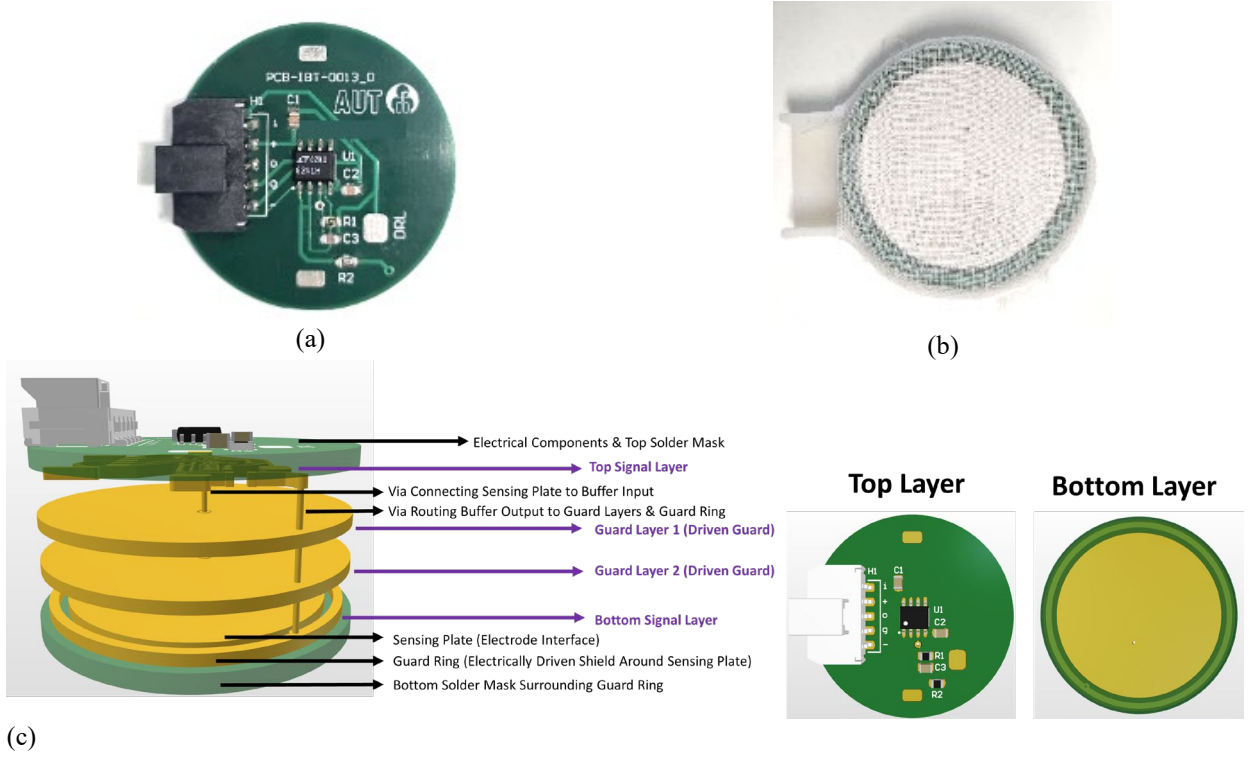


Figure 4-6 (a) Top side of the PCB. (b) Bottom side of the PCB with the cotton layer on the sensing side. (c) Four-layer structure of the PCB design.

4.4.3 Brief Discussion on MA and Electrode Design

Before proceeding further, it is essential to briefly revisit the calculation of MAs and clarify the design considerations behind our electrodes. Previously, Serteyn et al. [41] defined the angular frequency $\omega_0(t) = \frac{1}{R_B[C_i + c_c(t)]}$, given earlier in Equation (4-8). In their design $c_c(t)$ varied between 0.5 and 8 pF, owing to the smaller electrode size (approximately 2 cm²) and larger electrode-to-body distance (up to 3.5 mm). This configuration resulted in a relatively high cutoff frequency, within the ECG bandwidth, making the influence of the high-pass transfer function $H(s)$ (Equation (4-7)) significant. Consequently, they employed a block least-squares parameter estimation method to adaptively estimate $\omega_0(t)$, and related parameters. In contrast, our electrode design achieves significantly larger coupling capacitance (~140 pF), primarily due to an increased electrode surface area (~7 cm²) and minimized electrode-to-body separation, enabled by the chest strap configuration and a thin cotton fabric cover. Furthermore, selecting a high-value bias resistor ($R_B = 10\text{ G}\Omega$) effectively lowers the cutoff frequency far below the ECG's lowest frequency of interest (0.67 Hz). This reduction allows us to consider the impact of $H(S)$ negligible, thus simplifying the MA estimation and adaptive filtering processes. In a related approach, Lee et al. [147] used dry electrodes characterized by a different equivalent circuit model, setting their cutoff frequency at approximately 8 Hz ($\omega_0 = \frac{1}{R_D C_0}$), with

$R_D = 987.26\text{k}\Omega$ (skin-electrode contact resistance) and $C_0 = 15\text{nF}$. Compared to their design, our configuration yields a substantially lower cutoff frequency due to the significantly higher bias resistance and carefully optimized coupling capacitance, further reinforcing our decision to omit the influence of $H(S)$ within our capacitive ECG measurement system.

4.4.4 Analog Front-End Circuit Design

Figure 4-7 illustrates the proposed single-lead ECG system employing a three-electrode configuration. Two capacitive electrodes interface with the main board, feeding their output signals into an instrumentation amplifier configured in differential mode. This setup extracts a single-ended ECG signal by amplifying the differential voltage while effectively rejecting common-mode interference. The AD620 instrumentation amplifier (Analog Devices, MA, USA) was selected due to its high common-mode rejection ratio ($\text{CMRR} \geq 100\text{ dB}$ at a gain of 20 dB) and adjustable gain. For optimal balance between amplification and noise rejection, the amplifier gain was set to 20 dB. Additionally, a first-order LPF, as recommended by the AD620 datasheet, was implemented at the amplifier input, with a differential cutoff frequency of approximately 3 kHz, ensuring proper handling of injected signals below this threshold. A third (wet) electrode was placed on the body to provide a stable ground reference, further enhancing common-mode noise rejection and signal stability.

4.4.4.1 High-Frequency Signal Injection for $\Delta c_d(t)$ Estimation Using Bias Capacitor (C_B)

To estimate the difference between the time-varying components of the coupling capacitances, $\Delta c_d(t)$, a high-frequency voltage is injected through the parallel combination of R_B and C_B into each electrode, as depicted in Figure 4-7. Previous studies have explored injecting either 180°-out-of-phase sinusoidal signals or in-phase sinusoidal signals into the electrodes, represented as $v_{inj1}(t) = \pm v_{inj2}(t) = A_{inj} \sin(2\pi f_{inj}t)$. Using the defined transfer function from Equation (4-12) at high frequencies (approximated as $\frac{C_B}{C_0}$) and replacing C_0 with the actual coupling capacitance $C_c(t)$ under normal motion conditions, the differential-mode output voltage is obtained as shown in Equation (4-13):

$$v_{out_{inj}}(t) = G_{amp} \times v_{inj}(t) \times \left[\frac{C_B}{c_{c1}(t)} \pm \frac{C_B}{c_{c2}(t)} \right] \quad (4-13)$$

where the "+" sign corresponds to 180°-out-of-phase injection, the "-" sign corresponds to in-phase injection, and G_{amp} represents the gain of the instrumentation amplifier. However, when employing 180°-out-of-phase injection, the output voltage is proportional to the sum rather than the difference of electrode impedances.

Thus, isolating and calculating $\Delta c_d(t)$ becomes impossible, as the differential contribution cancels out. Torfs et al. [66] previously explored 180°-out-of-phase sinusoidal current injection into electrodes to estimate the ETI reference signal for adaptive filtering. However, their approach neglected explicit modeling of MA within the system, resulting in an RIS that inconsistently correlated with actual MA, alternating between positive and negative correlations. In contrast, in-phase sinusoidal voltage injection allows accurate estimation of $\Delta C_d(t)$. Consequently, the differential-mode output voltage can be accurately expressed by Equation (4-14):

$$v_{out_{inj}}(t) = G_{amp} \times v_{inj}(t) \times \left[\frac{C_B}{c_{c1}(t)} - \frac{C_B}{c_{c2}(t)} \right] = G_{amp} \times v_{inj}(t) \times y(t) \quad (4-14)$$

4.4.4.2 Influence of Phase Shift Between the Injected Voltage and the Output Voltage

An important aspect overlooked in previous studies using bipolar electrode configurations [38, 147] is the phase shift (φ) between the injected voltage $v_{inj}(t)$ and the output voltage $v_{out_{inj}}(t)$. In a unipolar system with a single capacitive electrode, this phase shift is negligible. However, in a differential (bipolar) system, a notable phase shift φ emerges, typically approaching either 0° or 180°. While the magnitude of this shift can be compensated through adaptive filtering, its sign directly impacts the estimation of $\Delta c_d(t)$. Therefore, correcting this sign variation before applying adaptive filtering is essential, as conventional filters generally do not account for this issue. From Equation (4-14), two conditions arise:

If $c_{c2}(t) > c_{c1}(t)$, then $\frac{C_B}{c_{c1}(t)} > \frac{C_B}{c_{c2}(t)}$, leading to $y(t) > 0$ and $\varphi = 0^\circ$

If $c_{c2}(t) < c_{c1}(t)$, then $\frac{C_B}{c_{c1}(t)} < \frac{C_B}{c_{c2}(t)}$, leading to $y(t) < 0$ and $\varphi = 180^\circ$

By substituting $c_{c1}(t)$ and $c_{c2}(t)$ from Equation (11), the output voltage in is rewritten as Equation (4-15):

$$v_{out_{inj}}(t) = G_{amp} \times v_{inj}(t) \times \left[\frac{C_B}{c_{d1}(t) + C_0} - \frac{C_B}{c_{d2}(t) + C_0} \right] \times e^{j\varphi} \quad (4-15)$$

Considering $C_0 \gg c_{d1}(t), c_{d2}(t)$, Equation (4-15) simplifies further to Equation (4-16):

$$v_{out_{inj}}(t) = -v_{inj}(t) \times \left[\frac{C_B \times G_{amp}}{C_0^2} \right] \times \Delta c_d(t) \times e^{j\varphi} \quad (4-16)$$

This equation illustrates an amplitude modulation (AM) structure, represented succinctly as Equation (4-17):

$$v_{out_{inj}}(t) = m(t) \times v_{inj}(t) \quad (4-17)$$

where

$$m(t) = - \left[\frac{C_B \times G_{amp} \times A_{inj}}{C_0^2} \right] \times \Delta c_d(t) \times e^{j\varphi} \quad (4-18)$$

Here, $m(t)$ is the message signal representing low-frequency variations of $\Delta c_d(t)$, while $v_{inj}(t)$ acts as the high-frequency carrier. In AM, extracting $m(t)$ involves demodulating $v_{out_{inj}}(t)$ and isolating its real component, yielding the final expression for $\Delta c_d(t)$ as Equation (4-19).

$$\Delta c_d(t) = -\frac{Re\{m(t)\} \times C_0^2}{G_{amp} \times A_{inj} \times C_B} \quad (4-19)$$

In Equation (4-19), calculating $\Delta c_d(t)$ explicitly depends on C_0 , which remains unknown. However, since our primary objective is estimating the MA signal described in Equation (4-4) and C_0 is a constant not affecting time-dependent variations, it is sufficient to directly extract the real part of $m(t)$ from Equation (4-18) without explicitly determining C_0 . Thus, we define the extracted signal as the RIS, $v_{ref}(t)$ as defined in Equation (4-20).

$$v_{ref}(t) = -Re\{m(t)\} \quad (4-20)$$

4.4.5 Digital System Design

The block diagram of the digital processing system is illustrated in Figure 4-8. Initially, the analog output signal, $v_{out}(t)$, is digitized by an analog-to-digital converter (ADC), producing the digital signal $v_{out}[n]$. The digital signal is subsequently processed in two parallel channels:

- **ECG Channel**

In this path, $v_{out}[n]$ is passed through an LPF (Block 1-1) to isolate the ECG signal while retaining MAs. The LPF's cutoff frequency is selected based on the target ECG frequency range. Subsequently, to eliminate DC offset, the filtered signal undergoes an HPF (Block 1-2). The resulting output contains both the ECG ($v_{out_{ECG}}[n]$) and MA ($v_{MA}[n]$) signals, which serve as the primary input for adaptive filtering.

- **Impedance Channel**

In this path, $v_{out}[n]$ is filtered by a band-pass filter (Block 2-1), around the injection frequency f_{inj} with an adjustable bandwidth. This bandwidth is selected considering the MA frequency range, typically below 20 Hz. This process isolates the injected signal, yielding $v_{out_{inj}}[n]$.

- **Demodulation (Block 2-2):** The extracted signal, $v_{out_{inj}}[n]$ is demodulated to recover the message signal, $m[n]$.
- **Extraction of the RIS (Block 2-3):** The real part of $m[n]$ is inverted, resulting in the RIS $-Re\{m[n]\}$, as previously defined in Equation (4-20).

- **Final Filtering (Blocks 2-4 & 2-5):** To eliminate high-frequency noise while preserving MAs, $-Re\{m[n]\}$ is passed through an LPF (Block 2-4) with a cutoff frequency typically set below 20 Hz. Subsequently, an HPF (Block 2-5) removes any residual DC offset, generating the final RIS $v_{ref}[n]$ for adaptive filtering.

At this stage, both essential inputs, $v_{out_{ECG}}[n] + v_{MA}[n]$ (the contaminated ECG signal) and $v_{ref}[n]$ (the RIS), are prepared. These inputs are then fed into the adaptive filtering algorithm (Block 3), allowing effective MA estimation and removal, ultimately reconstructing a clean ECG signal.

The filter blocks used in this study are summarized in Table 4-1. To ensure numerical stability and computational efficiency, higher-order filters were implemented as cascaded stages rather than single high-order filters. This approach simplifies design and enhances stability. For Block 3, the classical RLS algorithm was selected for motion artifact cancellation in non-stationary ECG signals. As the primary goal was to develop an RIS highly correlated with MAs, a simple yet effective third-order RLS filter with a forgetting factor of $\lambda = 1$ was employed. This configuration showed excellent stability and rapid convergence across all experiments.

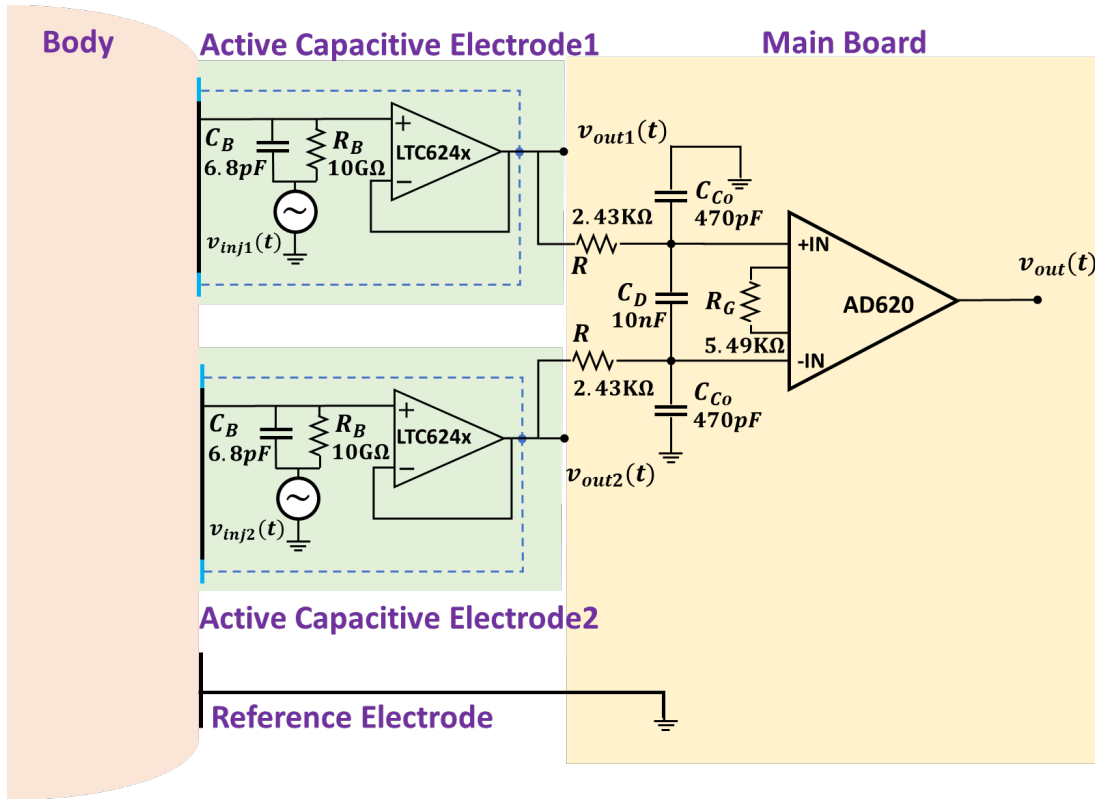


Figure 4-7 Analog front-end (AFE) configuration, with two capacitive electrodes interfacing with the main board

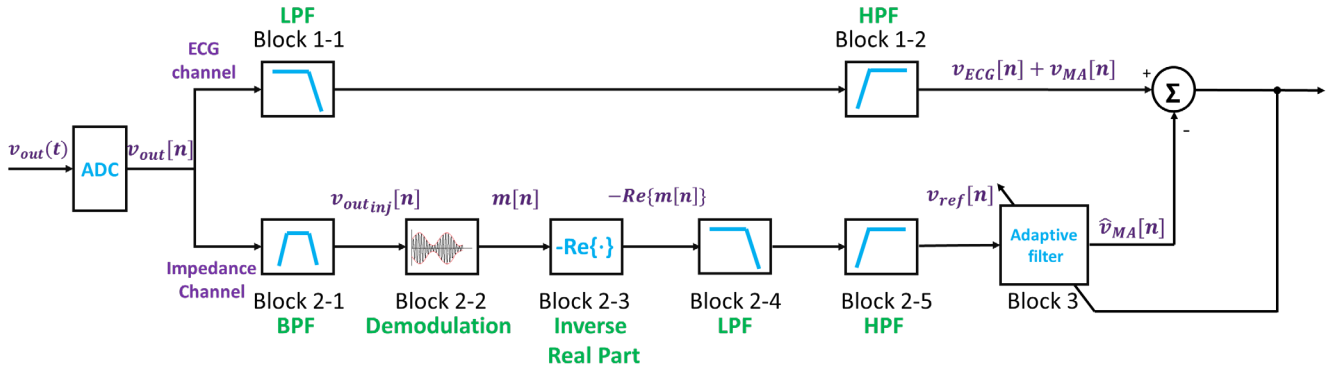


Figure 4-8 Block diagram of the digital processing system

Table 4-1 Summary of filter blocks and signal processing stages used in the system design.

Block(s)	Key parameters
1-1	Butterworth, 4 th order, $f_c = 40 \text{ Hz}$, $4 \times$ cascaded
1-2	Butterworth, 1 th order, $f_c = 0.05 \text{ Hz}$, $1 \times$ cascaded
2-1	Butterworth, 2nd order, $f_c = 1 \text{ k Hz}$, $\text{BW} = 100 \text{ Hz}$, $10 \times$ cascaded
2-2 & 2-3	Hilbert transform pair, Extracts analytic signal; computes envelope & instantaneous phase $\rightarrow$ real (message) component
2-4	Butterworth, 4 th order, $f_c = 10 \text{ Hz}$, $4 \times$ cascaded
2-5	Butterworth, 1 th order, $f_c = 0.05 \text{ Hz}$, $1 \times$ cascaded

4.5 Experimental Setup and Data Collection

To develop a wearable capacitive ECG measurement system, we designed a single-lead chest strap that can be positioned at various locations on the torso. The chest strap is made of an elastic material to ensure both comfort and a secure fit for the subject. The system comprises two sensing active electrodes (capacitive dry electrodes covered with a cotton layer) and a passive gel electrode serving as the reference, typically placed on the right lateral abdomen. Our primary objective was to inject a high-frequency signal into the sensing active electrodes to explore the feasibility of simultaneously acquiring ECG and RISs, aiming to derive an RIS highly correlated with MAs. Since achieving this objective requires a stable and well-defined reference, we opted for a galvanic reference electrode instead of a technically feasible and fully non-contact approach. Figure 4-9 (a), (b), and (c) respectively depict the reverse side of the chest strap, its front side, and the strap as worn by a participant. The participant is a healthy woman, aged between 30 and 40 years, with no known history of CVDs.

A battery-powered main board was developed to (1) power the active electrodes, (2) collect their outputs and feed them to an instrumentation amplifier, and (3) inject high-frequency signals. For injection, an NI 9263 module (16-bit, 100 kHz) generated two in-phase 1 kHz sine waves (10 V), routed to the electrodes. This module allowed adjustment of frequency, amplitude, and waveform during prototyping. The resulting single-ended output was digitized using an NI 9239 module (24-bit, 50 kHz). Both modules were housed in an NI

cDAQ-9178 chassis, enabling synchronized acquisition, channel expansion, and real-time streaming. All data were processed offline after logging.

We implemented all DSP algorithms mentioned in Figure 4-8 in MATLAB (Version 24.2.0.2712019 (R2024b), MathWorks, Inc.), running on Microsoft Windows 11 Enterprise. This setup provided a robust environment for filtering, demodulation, and adaptive filtering implementation.

4.6 Key Findings and Results

In this section, additional experiments were conducted using alternative setups, distinct from the optimized proposed system, to validate our approach. Each setup is described before presenting the corresponding results.

4.6.1 Simultaneous ECG Measurement Using Capacitive and Wet Electrodes at Two Torso Locations

To evaluate the performance of our capacitive ECG system, we recorded signals from the lower and upper chest of a stationary subject using both standard buffered wet electrodes and capacitive electrodes embedded in a chest strap. As shown in Figure 4-10, the acquired signals exhibited clear PQRST waveforms, confirming high signal fidelity. The correlation and mean squared error (MSE) between capacitive and wet electrodes were 0.988 and 0.024 for the lower chest and 0.947 and 0.104 for the upper chest, respectively. These results demonstrate that despite the fabric-covered interface, capacitive electrodes provide signal quality comparable to wet electrodes, enabling seamless ECG monitoring through clothing.

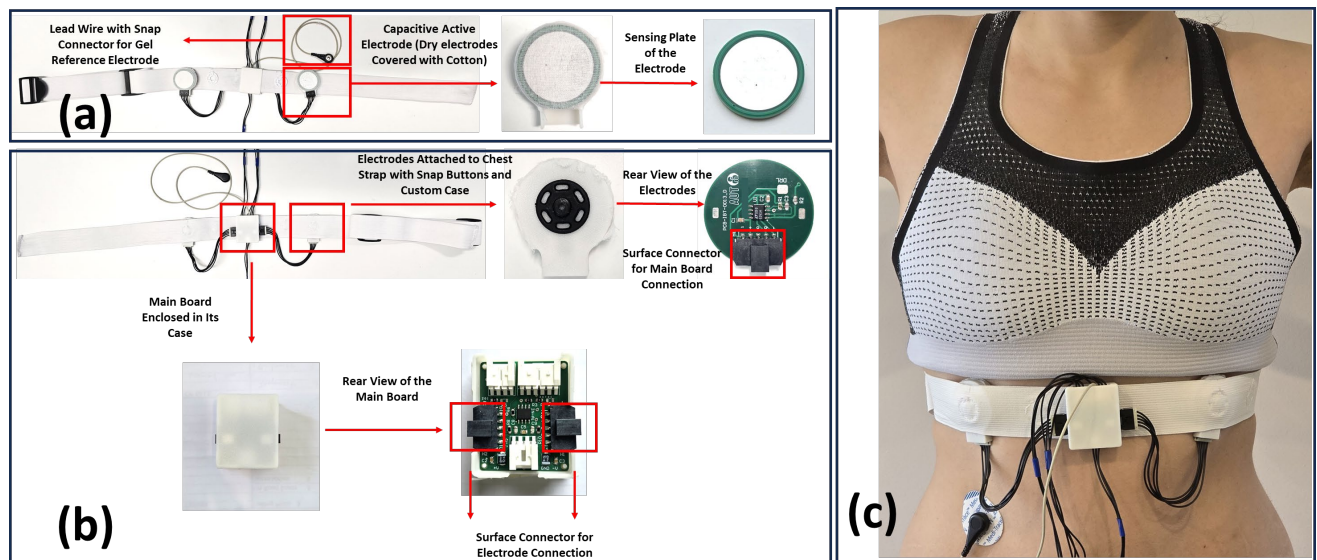


Figure 4-9 (a) Reverse side of the chest strap, (b) Front side of the chest strap, and (c) Strap worn by the participant.

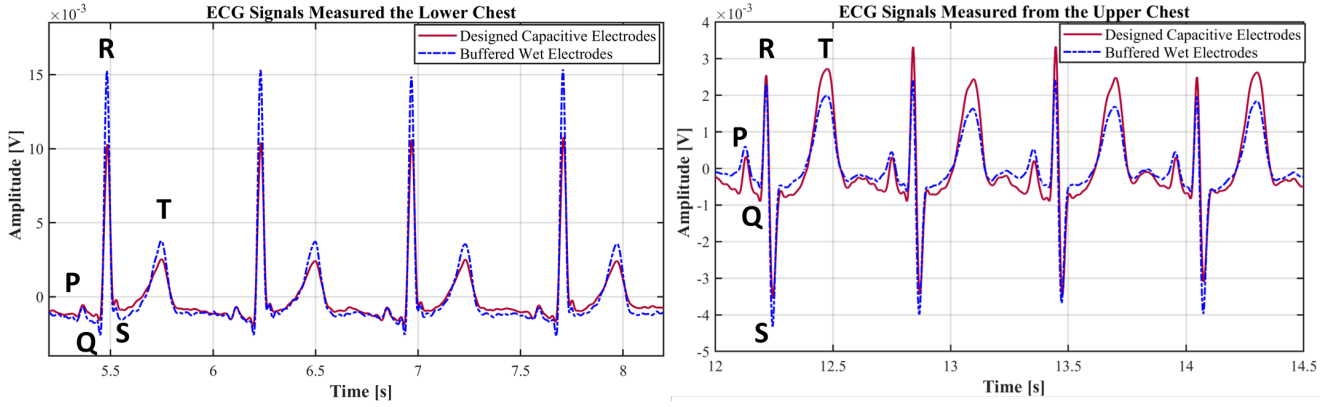


Figure 4-10 ECG signals recorded from the lower and upper chest of a stationary subject using standard buffered wet electrodes, and capacitive electrodes embedded in a chest strap

4.6.2 Selection of In-Phase vs. 180° Out-of-Phase Injection

In this experiment, we simultaneously inject two multi-tone signals into each electrode, as described by Equations (4-21) and (4-22). Specifically, we apply in-phase sine signals (9 V amplitude at 1 kHz) and 180° out-of-phase sine signals (1 V amplitude at 600 Hz) for comparative analysis.

$$v_{inj1}(t) = 9\sin(2\pi 1000t) + \sin(2\pi 600t) \quad (4-21)$$

$$v_{inj2}(t) = 9\sin(2\pi 1000t) - \sin(2\pi 600t) \quad (4-22)$$

The results of this experiment are presented in Figure 4-11. Electrode 1 and electrode 2 are pressed alternately every 20 seconds, generating MAs as shown in the first plot. In addition to the applied MAs, respiratory-related artifacts are also evident in the signal. Our observations indicate that the amplitude of respiratory artifacts varies across experiments, influenced by factors such as electrode placement, as breathing-induced chest expansion is more pronounced in certain areas, strap tightness, and possibly the elasticity of the chest strap, despite its inherent flexibility. The second plot displays the filtered and inverted real part of the message signal with in-phase injection, denoted as $v_{ref}(t)$ in Equation (4-20). Visual inspection reveals a strong correlation between this signal and the MAs. To quantify this correlation, the cross-correlation over a 3-second window is calculated in the third plot, demonstrating a consistently high positive correlation. This correlation is notably higher in the presence of MAs, as compared to other parts of the ECG signal, where the QRS complex is present, as was expected. The third plot shows the filtered real part of the message signal with 180° out-of-phase injection. This signal corresponds to the expression $G_{amp} \times A_{inj} \times \left[\frac{C_B}{c_{c1}(t)} + \frac{C_B}{c_{c2}(t)} \right]$, as previously described in Equation (4-13). In contrast to the in-phase case, the correlation with the MAs is less pronounced. The calculated cross-correlation for this signal in the last plot further supports this observation. The peaks in this plot are consistently unidirectional, with their direction not changing in sync with the MA direction.

Interestingly, the peaks sometimes exhibit positive and sometimes negative deflections, indicating a weaker, more variable correlation with the MAs.

4.6.3 Importance of Selecting the Real Part of the Message Signal, $m[n]$

In this experiment (Figure 4-12), data was recorded using the final configuration described in Section 4.5. Electrode 1 and Electrode 2 were pressed alternately every 10 seconds, with their respective activations labelled as “1” and “2” in the plot. Examining the magnitude of the message signal, we observe the following behavior:

- **Section A:** Since $c_{c1}(t) > c_{c2}(t)$, the magnitude of the message signal is directly proportional to $\Delta c_d(t)$.
- **Section B:** After pressing Electrode 2, $c_{c2}(t)$ increases, approaches $c_{c1}(t)$, and eventually surpasses it. Consequently, the magnitude of the message signal fluctuates, being proportional to $\Delta c_d(t)$ in some regions and to $-\Delta c_d(t)$ in others.
- **Section C:** Releasing Electrode 2 restores the condition $c_{c1}(t) > c_{c2}(t)$, similar to Section A.
- **Section D:** A behavior similar to Section B occurs once again.
- **Section E:** A special case occurs when, before pressing either electrode, $c_{c1}(t) = c_{c2}(t)$. Pressing either electrode causes it to exceed the other in capacitance. In this section, regions labeled “a” correspond to proportionality with $\Delta c_d(t)$, whereas regions labeled “b” correspond to proportionality with $-\Delta c_d(t)$.
- **Section F:** The pattern observed for Electrode 2 in Section B now occurs for Electrode 1, again causing the magnitude of the message signal to fluctuate between $\Delta c_d(t)$ and $-\Delta c_d(t)$.
- **Section G:** The overall polarity of the system is reversed, with $c_{c2}(t) > c_{c1}(t)$, making the magnitude of the message signal proportional to $-\Delta c_d(t)$.

Although the magnitude captures overall signal variations, it fails to preserve sign information, which is crucial for distinguishing positive and negative $\Delta c_d(t)$. This issue becomes particularly problematic in cases like Sections B and F, where rapid sign reversals may occur. In contrast, the real part of the message signal, as shown in the second plot, maintains sign consistency, ensuring a correct interpretation of MA variations. Since adaptive filtering can compensate for magnitude variations but cannot correct fast sign inversions, utilizing the real part of the signal is essential to preserve the correct polarity of $\Delta c_d(t)$ and enable effective MA estimation.

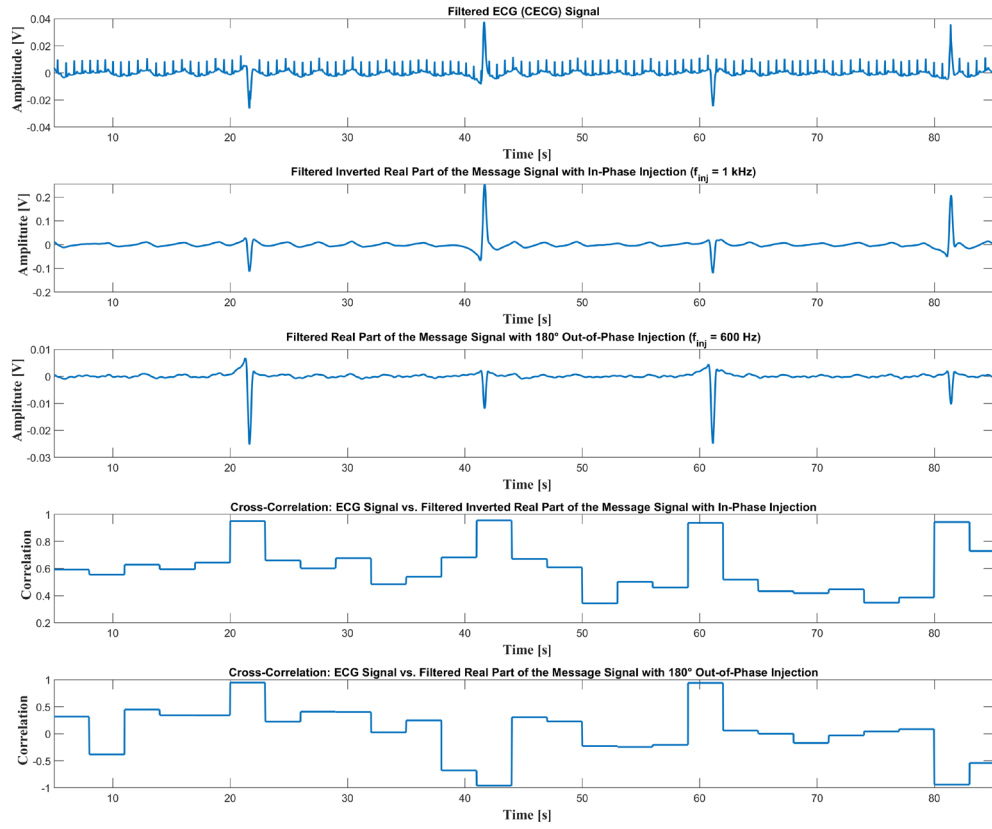


Figure 4-11 Experiment results showing the injection of two multi-tone signals into the electrodes

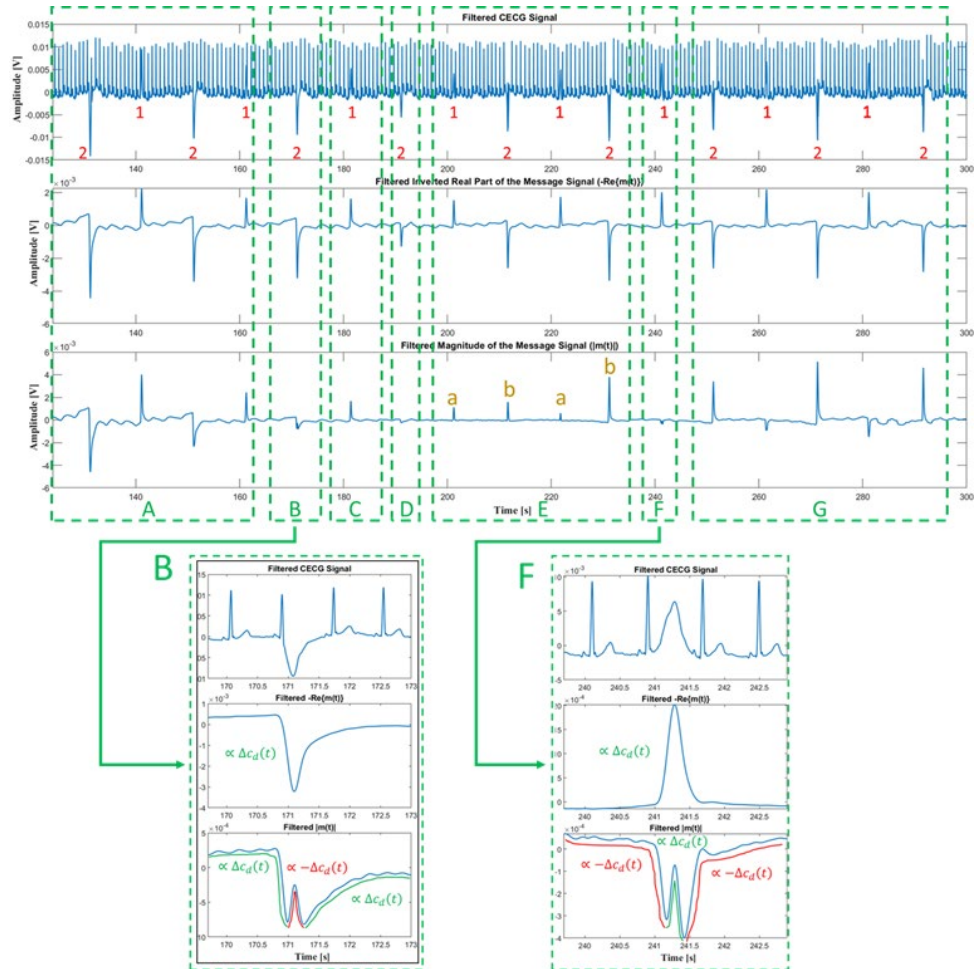


Figure 4-12 Experiment demonstrating the behavior of the magnitude and real parts of the message signal during electrode press cycles.

4.6.4 Evaluation Metrics

To evaluate the noise reduction performance of various signal-processing techniques, both subjective and objective methods are commonly employed. Subjective methods rely on expert assessment of ECG signal quality through signal visualization, while objective methods use mathematical metrics to eliminate human bias. Since subjective evaluation is widely accepted in clinical practice [97, 152, 153], we visually examined the denoised ECG signals to confirm waveform reconstruction. Additionally, multiple objective metrics were used, as no single metric sufficiently captures noise reduction performance. These metrics are relative to factors such as the type of experiment, the severity of MA, and the specific filtering approach used. The chosen methods include:

4.6.4.1 Signal Visualization

We examined the entire ECG signal to observe overall trends and artifacts. Additionally, zoomed-in sections were analyzed to compare $d[n]$, with its high-pass filtered version $d_{HPF0.67}[n]$ and $e[n]$. This detailed view allows for a more precise evaluation of how different processing methods affect waveform reconstruction in artifact-prone regions.

4.6.4.2 Correlation Analysis

Due to the absence of a separately extracted MA from $d[n]$, refining the correlation analysis requires alternative approaches. Common methods include: (i) windowed correlation analysis over fixed time intervals [66], (ii) low-pass filtering $d[n]$ (2–5 Hz) to isolate MA by suppressing high-frequency ECG components [66, 154], though this method can distort the true MA waveform and is therefore less effective, and (iii) computing correlation within detected MA regions [147]. To ensure a more comprehensive evaluation, we adopted a variable window strategy, applying correlation analysis both within MA-affected regions and adjacent segments. The following correlation assessments were performed:

- $d[n]$ vs. $v_{ref}[n]$ (CORR1): Expected to be higher in regions where MA is dominant.
- $d[n]$ vs. $\hat{v}_{MA}[n]$ (CORR2): Expected to be higher than the previous correlation, reflecting the adaptive filter's ability to map $v_{ref}[n]$ to the actual MA.
- $e[n]$ vs. $v_{ref}[n]$ (CORR3): Expected to be significantly lower, indicating effective MA mitigation.

4.6.5 Noise Reduction Metrics

- **Root Mean Square (RMS) & Standard Deviation (STD)**

To quantify noise reduction between $d[n]$ and $e[n]$, We computed the RMS and STD within a 2-second window. This approach is particularly effective in the presence of high MA levels.

- **Signal-to-Noise Ratio (SNR)**

Following Xu et al. [37], we calculated SNR using $20 \log \frac{v_{pp}}{v_n}$ where v_{pp} is the peak-to-peak amplitude of each R peak, and v_n represents noise within the surrounding intervals $[t(i-1) + 300 \text{ ms}, t(i) - 75 \text{ ms}]$ and $[t(i) + 75 \text{ ms}, t(i) + 250 \text{ ms}]$, ensuring the exclusion of QRS complexes and covering a heart rate range of 30–200 bpm. Unlike Xu et al., who used the maximum amplitude in these intervals, we modified v_n to the RMS value. RMS better represents overall noise energy, improving robustness in segments with fluctuating noise levels.

4.6.6 Experimental Validation

To evaluate the proposed method, we designed three controlled experiments that systematically introduced MAs by applying manual pushing and pulling forces on electrodes. These actions changed the dielectric thickness between the electrode and skin, directly influencing the coupling capacitance, as described by Equation (4-10). This ensured disturbances primarily originated from coupling capacitance variations, thus minimizing other confounding factors. The results of these experiments are comprehensively illustrated in Figure 4-13 to Figure 4-24.

4.6.6.1 Experiment 1: Impact of Pressing Electrode 1 Each 5 seconds

In this experiment, Electrode 1 was manually pressed every 5 seconds. The chest strap was loosely fastened to intensify fluctuations in $c_{c1}(t)$ and $c_{c2}(t)$, enhancing both motion- and respiration-induced artifacts. This configuration significantly impacted ECG components, including R-peaks. Results (Figure 4-13 to Figure 4-17) demonstrate successful MA mitigation, clearly restoring suppressed R-peaks and removing baseline drift. In contrast, applying a 0.67 Hz HPF failed to recover these peaks and introduced additional signal distortion. Analysis of $v_{ref}[n]$ (Figure 4-13) reveals clear proportionality to $\Delta c_d(t)$. Upward peaks in $v_{ref}[n]$ indicated pressing Electrode 1, while MA appeared inversely correlated with $v_{ref}[n]$. This inverse relationship suggests a negative V_{DC} in Equation (4-4) as other parameters are positive. CORR1 consistently exceeded 0.8 in MA regions except around R-peaks, confirming a strong inverse correlation. CORR2 closely matched CORR1 in absolute terms, validating the adaptive filter's efficacy. Post-mitigation, CORR3 significantly decreased, indicating effective artifact removal. Performance metrics confirmed substantial improvements.

RMS and STD showed positive enhancement in all 2-second windows, with maximum reductions of 4.16 dB (38.05%) in RMS and 4.11 dB (37.73%) in STD. Overall RMS and STD improvements were 1.58 dB (15.97%) and 1.39 dB (14.19%), respectively. SNR analysis revealed significant improvements around reconstructed R-peaks, with the highest enhancement reaching 17.9 dB and an overall average improvement of 4.75 dB (56.99%).

4.6.6.2 Experiment 2: Alternating Electrode Pressing

In this experiment, the induced MA was unintentionally lower than in previous experiments, as the electrodes were pulled only slightly to maintain continuous contact. Electrodes 1 and 2 were alternately pressed every 10 seconds. Results (Figure 4-18 to Figure 4-22) indicate that most MA segments were successfully mitigated. However, the fourth segment retained minor residual artifacts, indicating potential room for further adaptive filtering improvements.

Similar to Experiment 1, upward and downward peaks in $v_{ref}[n]$ corresponded to pressing Electrodes 1 and 2, respectively, and its negative correlation with the MA reinforced the indication of negative V_{DC} . CORR1 was slightly lower compared to Experiment 1, attributed to lower MA intensity. CORR2 confirmed the strong correlation between $v_{ref}[n]$, and MAs, while CORR3 markedly decreased after mitigation, emphasizing effective artifact suppression. Performance metrics aligned with qualitative findings. RMS and STD remained nearly unchanged in unaffected segments but showed substantial improvement in affected regions, peaking at 1.24 dB (13.3%). Overall RMS and STD improvements were 0.119 dB (1.29%) and 0.12 dB (1.31%), respectively. SNR improvements were lower due to initially smaller MAs but remained notable, with maximum enhancements of 4.24 dB (36.8%) and 4.49 dB (33.1%), averaging 0.27 dB (2.07%).

4.6.6.3 Experiment 3: Alternating Electrode Pulling

Results (Figure 4-23 to Figure 4-27) demonstrated successful MA mitigation across all segments. Interestingly, the directionality of peaks in $v_{ref}[n]$ differed from the previous experiments, with upward peaks now indicating pulling of Electrode 2, implying a positive V_{DC} . This observation contrasts with findings by Lee et al. [147], who consistently reported inverse correlation using dry electrodes. Our results suggest that electrode-body contact continuity may affect V_{DC} 's sign, a phenomenon requiring further investigation.

CORR1, CORR2, and CORR3 exhibited similar patterns to Experiment 2, albeit with lower correlations due to weaker MAs and higher ECG amplitudes. Pearson correlation reached 0.8186 for CORR1. Given the

minimal MA intensity, RMS and STD values for original and mitigated signals closely matched, and negative improvements in some segments indicated these metrics might be less sensitive when MAs are minimal. Overall RMS and STD reductions were negligible (0.001% and 0.02%, respectively). SNR values showed minor variations due to low MA amplitude, with maximum improvement reaching 3.08 dB (14.7%), and an overall negligible improvement of 0.02 dB (0.16%).

A comparative summary of the three experiments is presented in Table 4-3, highlighting key differences in MA intensity, V_{DC} sign, and performance metrics.

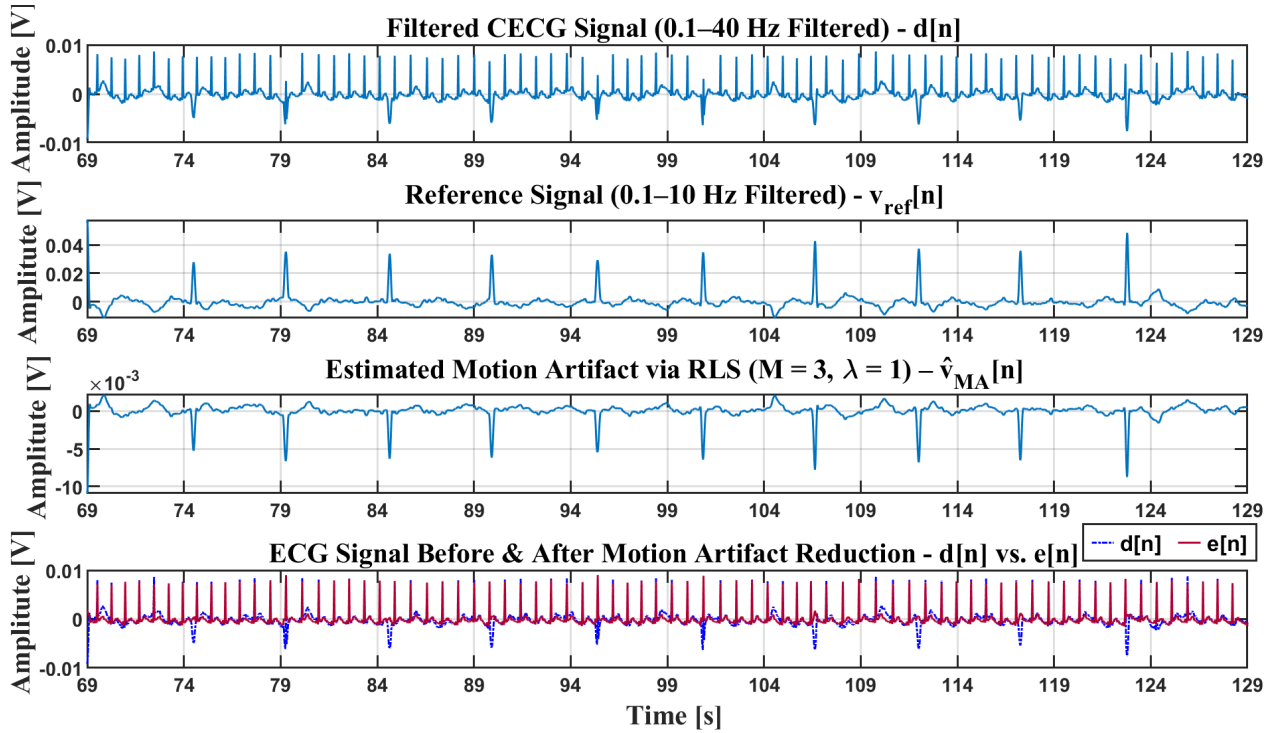


Figure 4-13 (Experiment 1): Signals $d[n]$, $v_{ref}[n]$, $\hat{v}_{MA}[n]$, ($d[n]$ and $e[n]$) over the full time window.

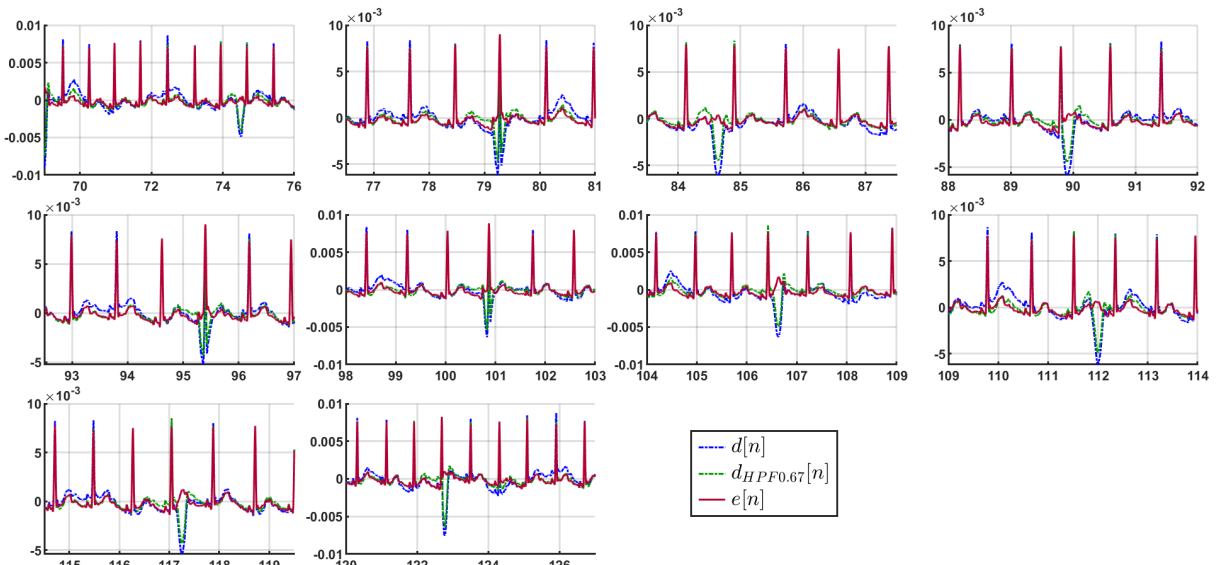


Figure 4-14 (Experiment 1): Zoomed view of the MA segments showing $d[n]$, $e[n]$, and the 0.67 Hz high-pass filtered $d[n]$, highlighting the removal of low-frequency components.

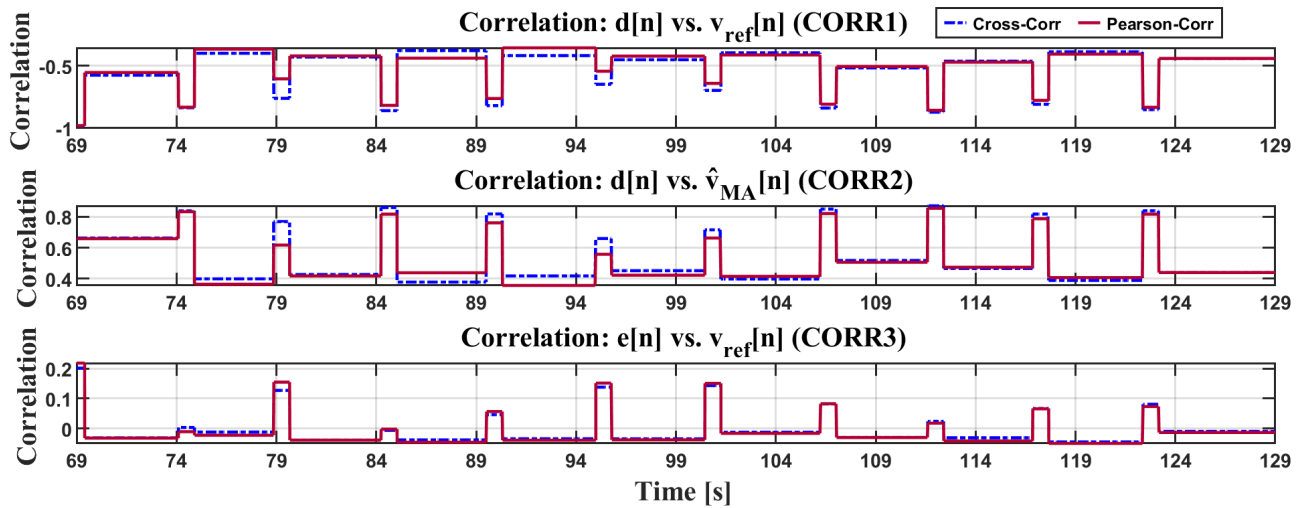


Figure 4-15 (Experiment 1): Correlation analysis (normalized cross-correlation and Pearson correlation). CORR1, CORR2, and CORR3 are shown in each plot, respectively.

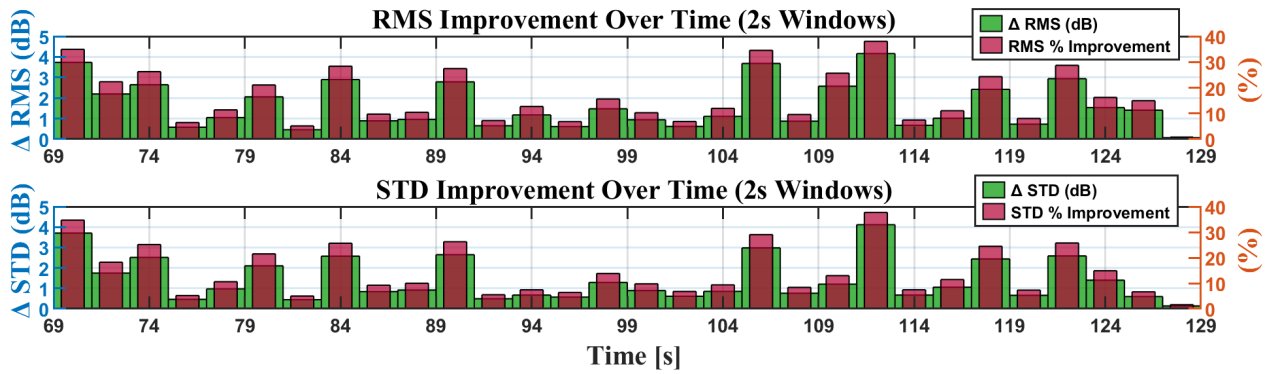


Figure 4-16 (Experiment 1): Noise reduction metrics based on the reduction in dB and percentage for RMS and STD, respectively.

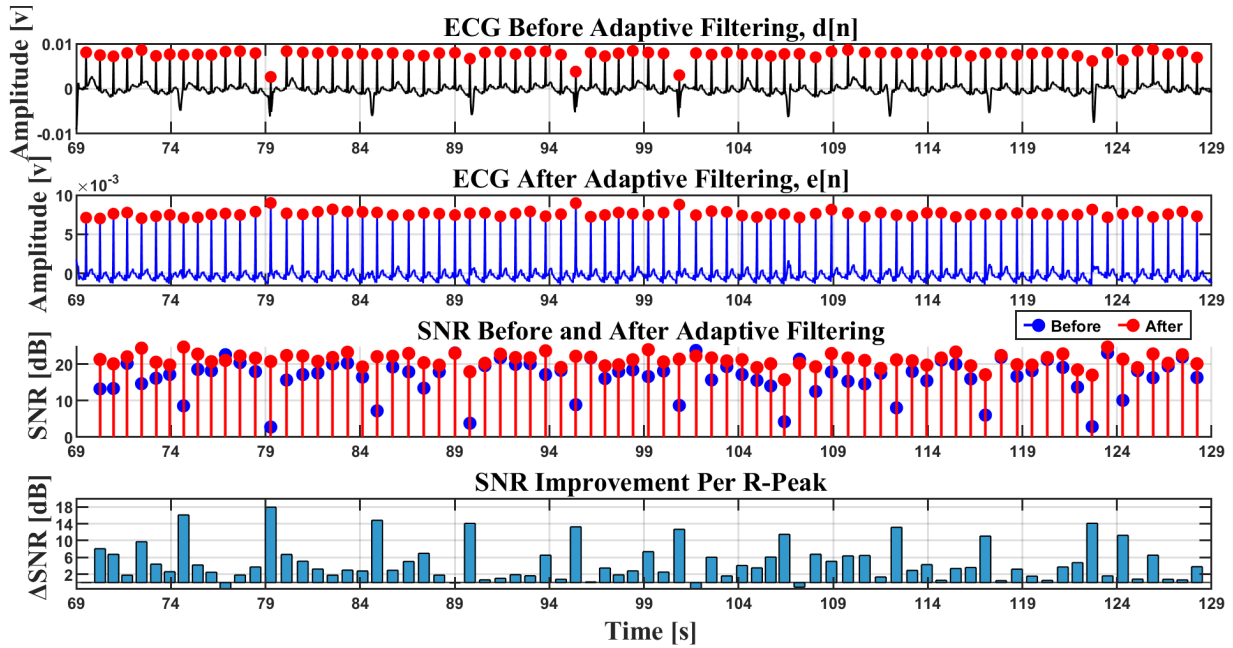


Figure 4-17 (Experiment 1): Noise reduction metrics based on improvement in dB and percentage for SNR per R peak.

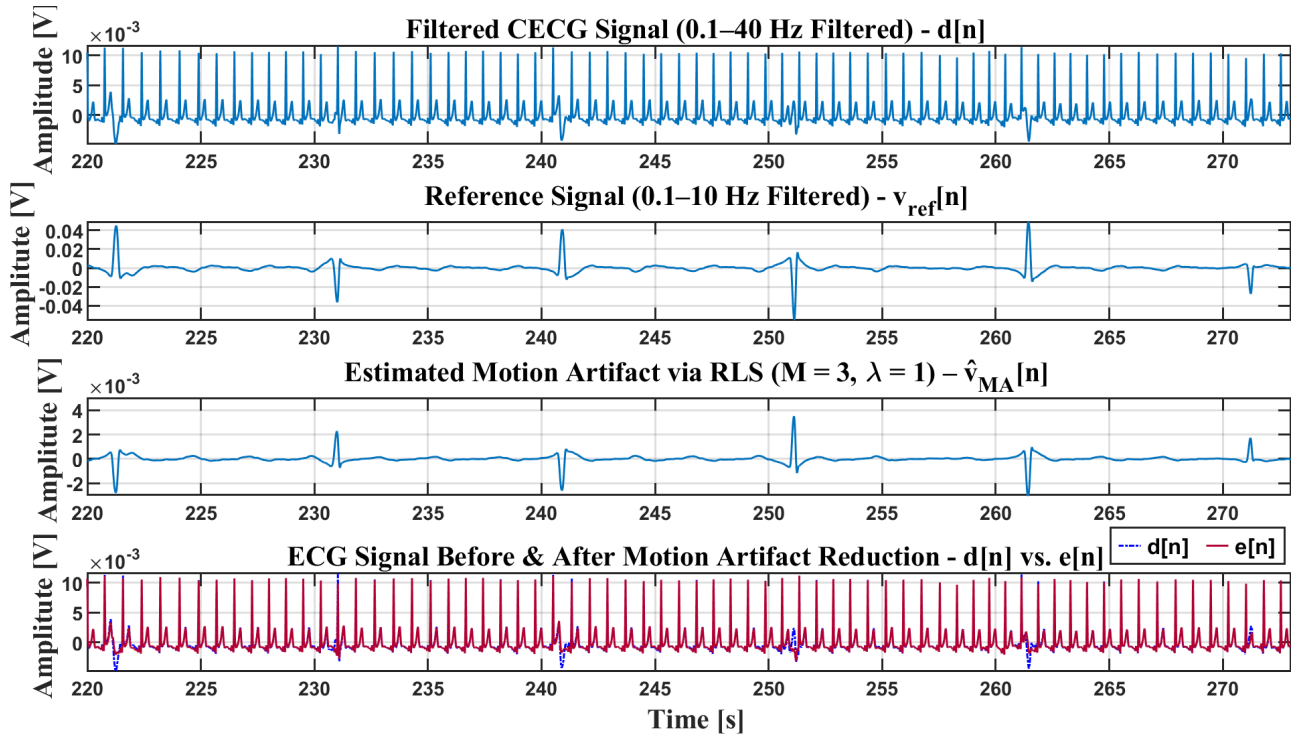


Figure 4-18 (Experiment 2): Signals $d[n]$, $v_{ref}[n]$, $\hat{v}_{MA}[n]$, ($d[n]$ and $e[n]$) over the full time window.

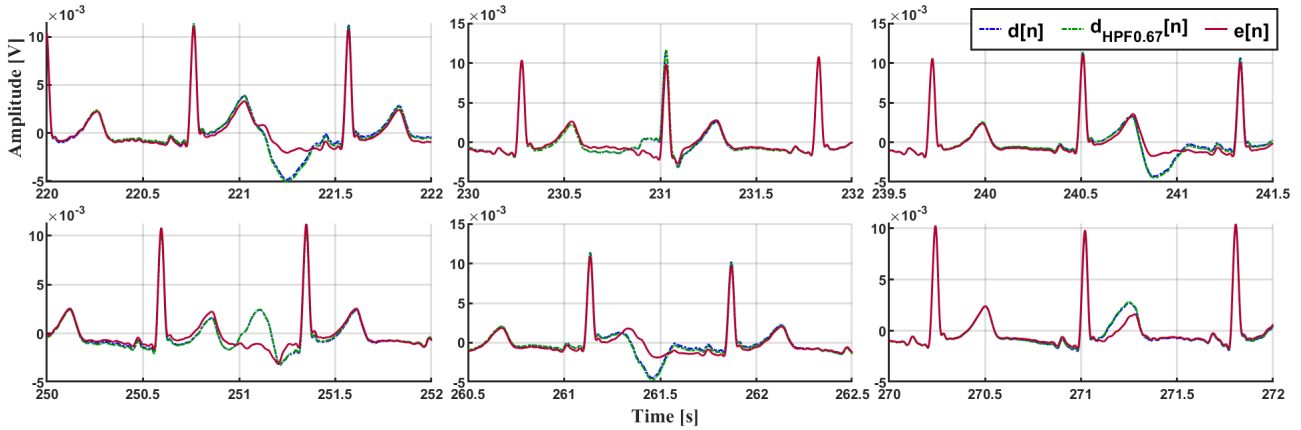


Figure 4-19 (Experiment 2): Zoomed view of the MA segments showing $d[n]$, $e[n]$, and the 0.67 Hz high-pass filtered $d[n]$, highlighting the removal of low-frequency components.

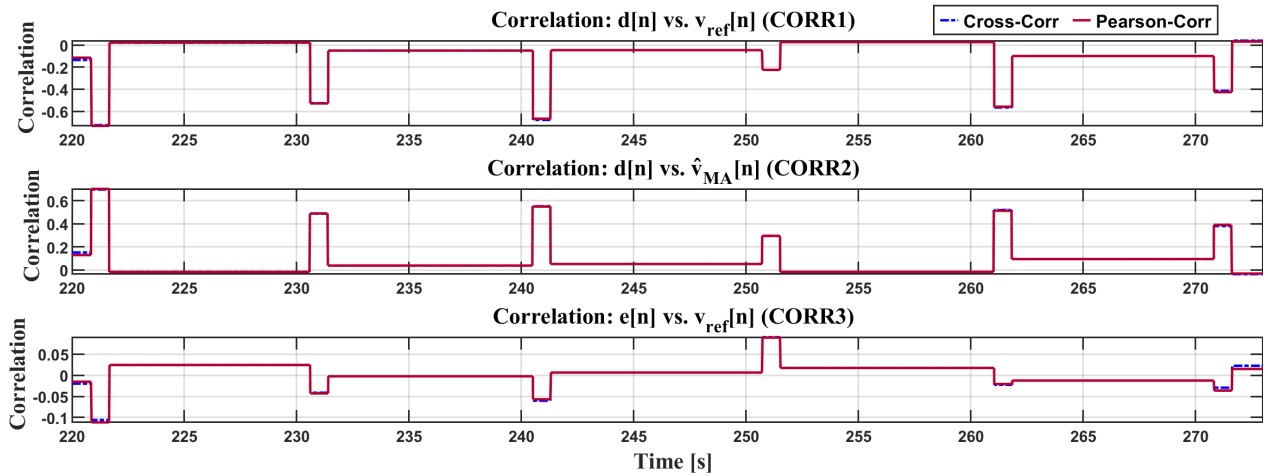


Figure 4-20 (Experiment 2): Correlation analysis (normalized cross-correlation and Pearson correlation). CORR1, CORR2, and CORR3 are shown in each plot, respectively

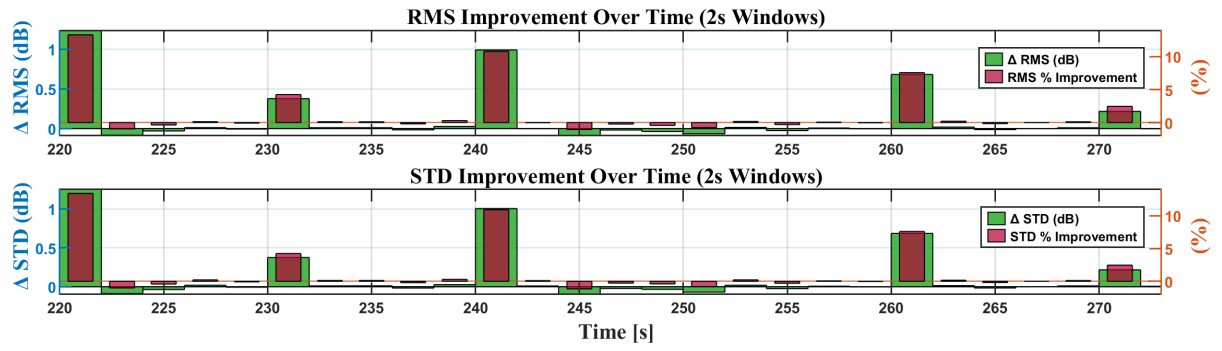


Figure 4-21 (Experiment 2): Noise reduction metrics based on the reduction in dB and percentage for RMS and STD, respectively.

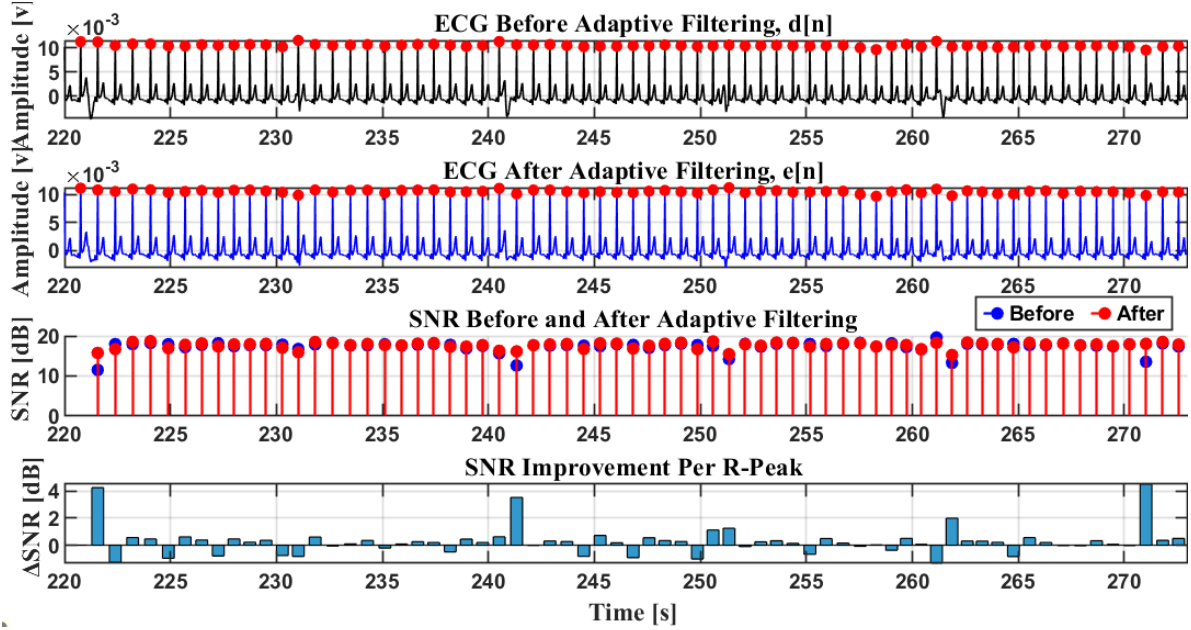


Figure 4-22 (Experiment 2): Noise reduction metrics based on improvement in dB and percentage for SNR per R peak.

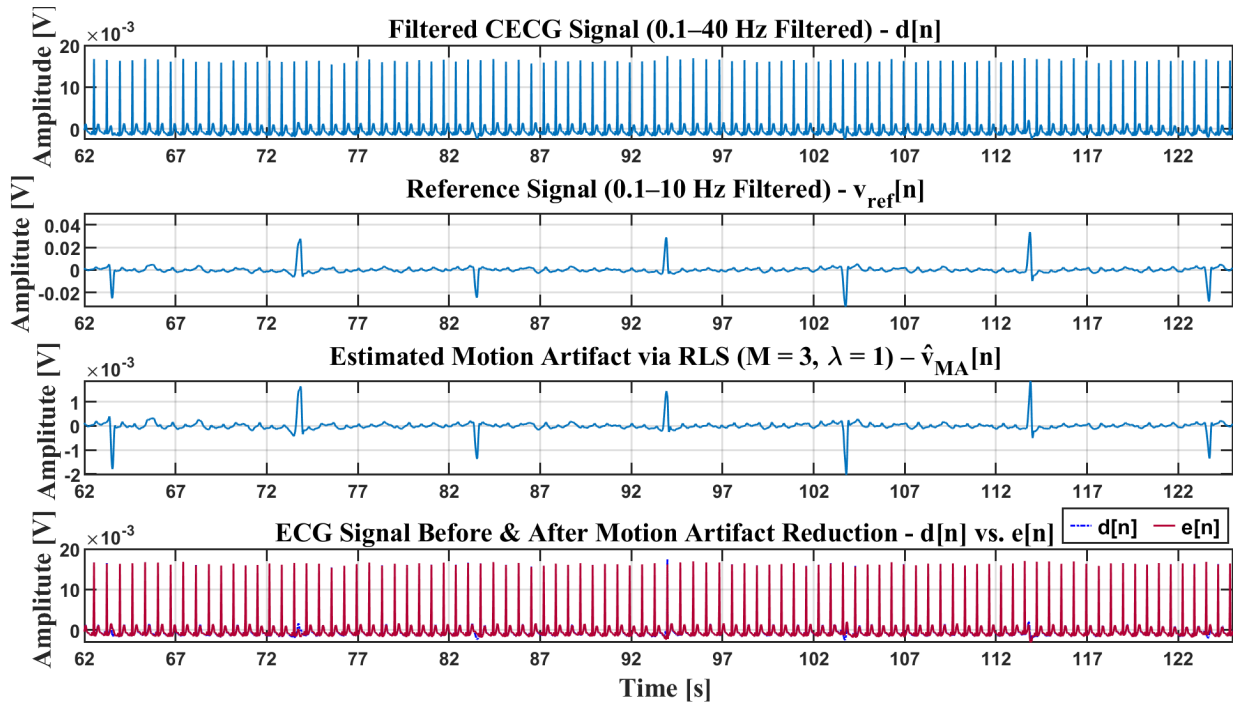


Figure 4-23 (Experiment 3): Signals $d[n]$, $v_{ref}[n]$, $\hat{v}_{MA}[n]$, ($d[n]$ and $e[n]$) over the full time window.

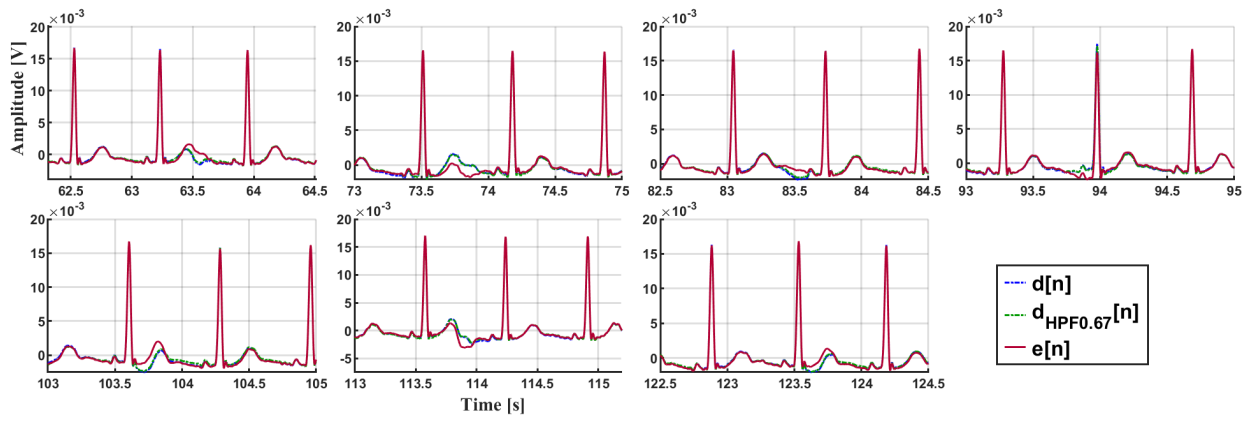


Figure 4-24 (Experiment 3) : Zoomed view of the MA segments showing $d[n]$, $e[n]$, and the 0.67 Hz high-pass filtered $d[n]$, highlighting the removal of low-frequency components.

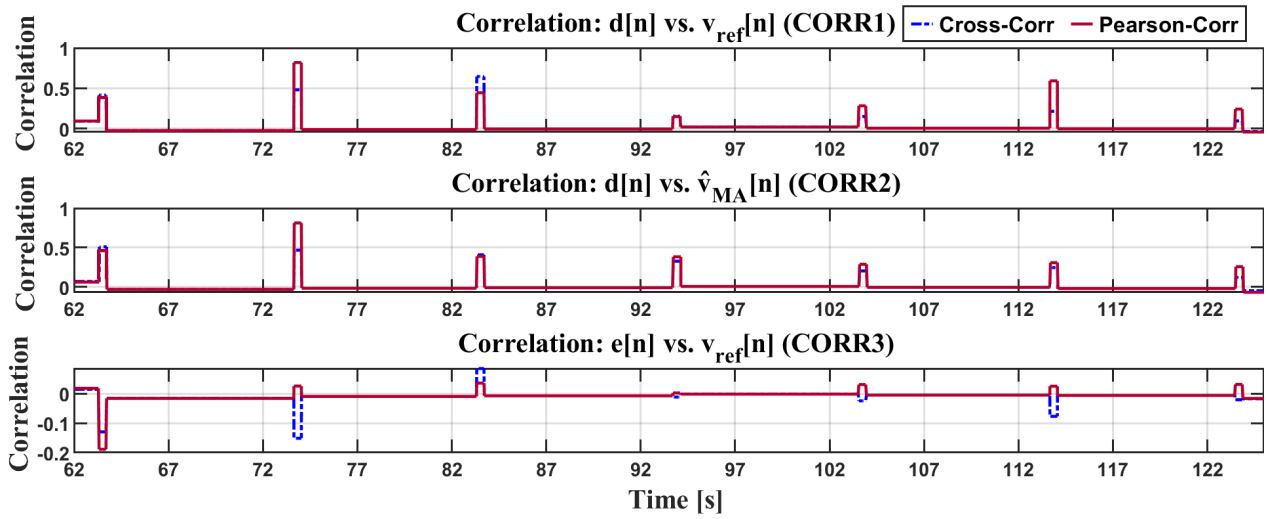


Figure 4-25 (Experiment 3): Correlation analysis (normalized cross-correlation and Pearson correlation). CORR1, CORR2, and CORR3 are shown in each plot, respectively.

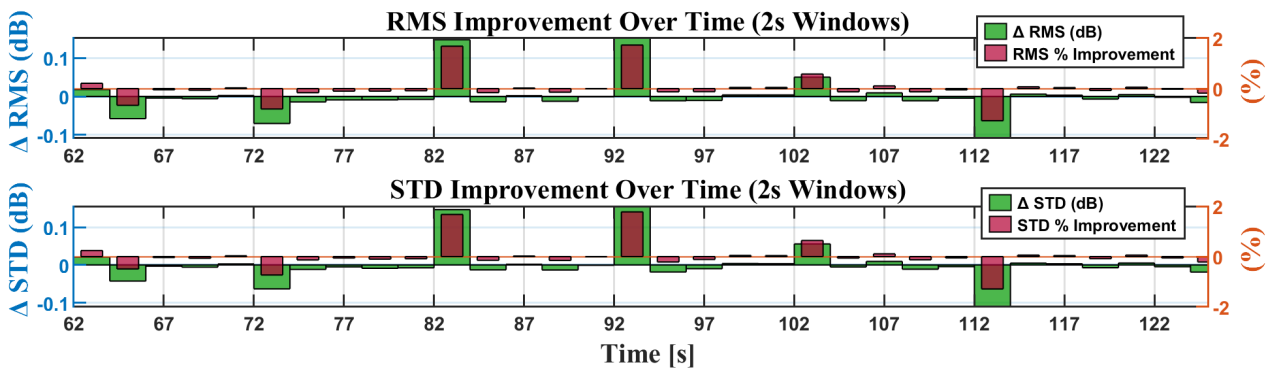


Figure 4-26 (Experiment 3): Noise reduction metrics based on the reduction in dB and percentage for RMS and STD, respectively.

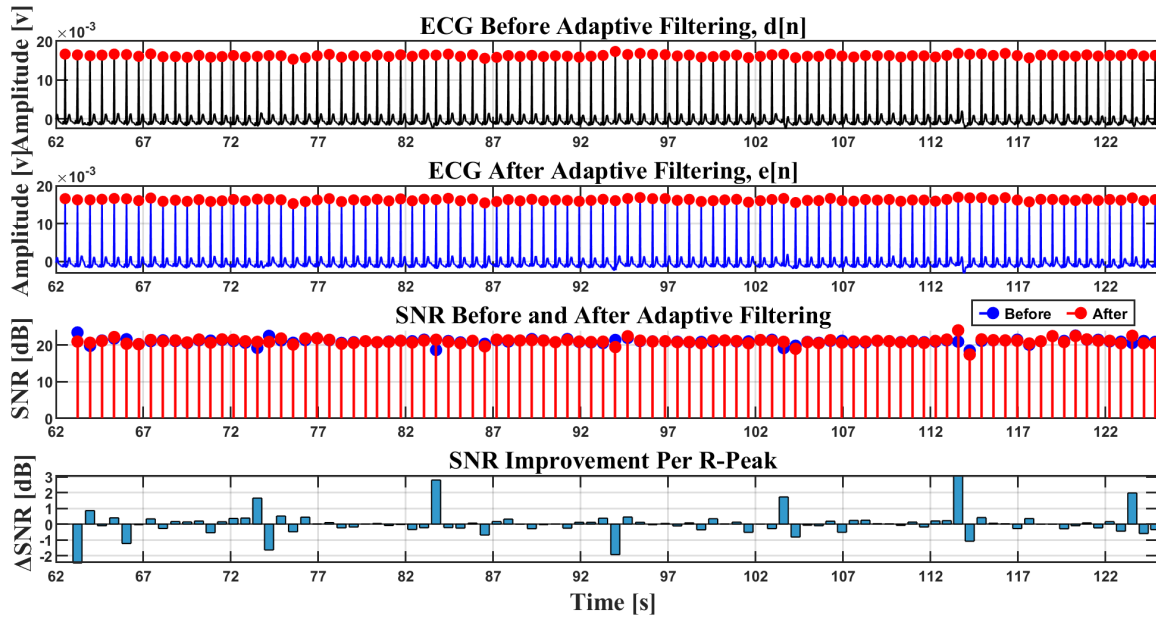


Figure 4-27 (Experiment 3): Noise reduction metrics based on improvement in dB and percentage for SNR per R peak.

Table 4-2 Experimental conditions, MA intensity, correlation strength, and performance gains ($\downarrow$ reductions, $\uparrow$ improvements) in RMS, STD, and SNR.

Exp.	MA Type	MA Intensity	Max CORR1 (QRS-free)	V_{DC} Polarity	Peak RMS $\downarrow$	Peak STD $\downarrow$	Peak SNR $\uparrow$	Overall RMS/STD $\downarrow$	Overall SNR $\uparrow$
1	Press Electrode 1 every 5s	High	0.81	-	4.16 dB (38.05%)	4.11 dB (37.73%)	17.9 dB (650%)	15.97% / 14.19%	4.75 dB (56.99%)
2	Alt. press every 10 s	Moderate	0.72	-	1.24 dB (13.3%)	1.25 dB (13.4%)	4.49 dB (33.1%)	1.29% / 1.31%	0.27 dB (2.07%)
3	Alt. pull every 10 s	Low	0.82	+	0.147 dB (1.7%)	0.15dB (1.7%)	3.08 dB (14.7%)	0.001% / 0.02%	0.02 dB (0.16%)

4.7 Discussion and Future Direction

Comparing this study with previous works is challenging due to differences in evaluation methodologies, system architectures, and research stages. While some studies rely on subjective assessments, others employ objective metrics, complicating direct comparisons. Additionally, differences exist in electrode types, front-end circuitry, and digital processing. Variations also arise from the diverse stages of research and development (R&D), ranging from simulations and preliminary in-vivo testing to fully integrated tape-out implementations. Another crucial factor is the variability in MAs applied across studies. Some researchers induce controlled MAs using mechanical presses or manual manipulations, whereas others simulate realistic conditions such as walking or jogging. Data collection duration, persistence of artifacts, and volunteer cooperation can all significantly impact the outcomes, as previously noted by He and Min [120]. Given these complexities, several studies, including Lee et al. [147], have opted to use feature comparison tables instead of direct performance

comparisons. The present study adopted a similar strategy, summarizing key features of the proposed system relative to advanced studies in Table 4-3. The comparative analysis primarily focuses on studies using ETI as an RIS; however, due to the limited research employing capacitive electrodes, we also included relevant studies using dry electrodes. In studies 1–4, the magnitude of MAs was substantially higher than in the method proposed here, leading to significantly lower ECG signal quality. Specifically, R-peaks were indistinguishable in studies 1 and 2, whereas only the R-wave remained visible in studies 3 and 4. In contrast, the proposed method achieved ECG quality comparable to wet electrodes under stationary conditions, clearly preserving all PQRST waves. Furthermore, even in scenarios involving induced MAs, the proposed mitigation approach maintained nearly all waveform components, consistently validated by multiple evaluation metrics indicating enhanced signal quality. In study 5, which also utilized dry electrodes, MAs were effectively suppressed and R-peaks successfully reconstructed, although not all ECG components were fully retained. Study 6 reported high-quality ECG signals with all waves visible; however, their system employed dry electrodes and followed a fundamentally different design compared with the system reported here.

Although the results of this study confirm the effectiveness of the proposed RIS for MA suppression in capacitive ECG measurements, further investigation is required to (1) verify the technique across a wider spectrum of motion patterns, (2) validate its performance among more participants, and (3) refine the adaptive-filter design to eliminate the residual artifacts that were observed. The present work primarily examined artifacts resulting from electrode pressing and pulling, directly affecting coupling capacitance. Expanding experiments to encompass a broader range of motion scenarios is essential to thoroughly understand the correlation between various MA types and the derived RIS. Additionally, while the classical RLS adaptive filter effectively reduced MAs, residual artifacts persisted in certain instances, highlighting the potential benefits of further optimization or exploration of advanced adaptive filtering algorithms. Another limitation is the small sample size, this proof-of-concept evaluation involved a single participant; however, limited cohorts are common in early-stage studies, and four of the six comparison works in Table 3 were likewise validated with only one subject. Larger, multi-participant trials are therefore required to obtain statistically significant results and to generalize the proposed methodology.

Table 4-3 Comparison of key features between this study and state-of-the-art ETI-based MA reduction studies.

Reported Work	1-Serteyn et al. [41]	2-Torfs et al. [66]	3-Xu et al. [37]	4-He and Min [120]	5-Pholpoke et al. [38]	6-Lee et al. [147]	7-The proposed work
Electrode configuration	1 active + 1 passive ref. ¹	2 active + 1 passive ref. ¹	2 active + 1 passive ref. ²	Passive wet / dry ³	Wearable system ⁴	2 dry active + 1 ref. ⁵	2 active + 1 passive ref. ⁶
MA quantified?	Yes	No	Yes ⁷	Yes	Yes	Yes	Yes
RIS Measurement Method	1 kHz voltage-injection via bias R	10 kHz 180° out-of-phase current to each sensor	PLI-signal demodulation	5 kHz current-injection ⁸	5 kHz in-phase current to each sensor	1 kHz voltage-injection via ref. ⁹	1 kHz in-phase voltage-injection to each sensor ¹⁰
MA-suppression algorithm	TF inversion + block LS	LMS	NLMS	Improved LMS	Two-stage estimation MA	LMS	RLS
Experiments	Simulation, lab data, real-life, electrode pressing	Press / pull, lateral, arm-motion	In-silico; seated trunk $\pm 15^\circ$	Electrode press / relax	Electrode press	Arm-lift, walking, jogging	Press / pull electrodes
Participants (n)	1	1	5	5	1	1	1
Evaluation Metrics	RMS	CORR1, RMS, STD	SNR (per R)	RMS or STD ¹¹	Qualitative ¹²	CORR1-3, MSE (vs. GT ECG)	CORR1-3, RMS, STD, SNR (per R)
ECG Waves Observed / Lost in MA Sections	R peaks obscured at times; P/QRS/T peaks lost	R peaks obscured at times; P/QRS/T peaks lost	Only visible R-peaks	Only R-peaks visible	R-peaks visible; other waves often lost	Most waves preserved	Most waves preserved

¹ Wearing conditions not specified.

² Subjects wore a T-shirt with an elastic band securing the electrodes (reference in hand).

³ Electrodes placed on arm, leg, abdomen for some volunteers. However, the exact number of electrodes used was not specified.

⁴ Type of wet/dry electrodes not detailed. Wearing conditions not specified.

⁵ Electrodes sewn into conductive fabric (Lead I–III).

⁶ Cotton-coated electrodes on a chest strap, position adjustable.

⁷ MA calculated, but its correlation with the reference was not analyzed.

⁸ After ETI acquisition, the authors derived a more MA-correlated RIS by combining slope and recovery-time processing.

⁹ ETI further processed using slope calculation and a LPF; slope parameter tuned per trial.

¹⁰ Real part of the ETI (message signal) used as RIS.

¹¹ Paper reports MA-removal effect without naming specific metrics; inferred as RMS/STD.

¹² No quantitative evaluation metrics reported.

Abbreviations: *ref.* – reference electrode; *ETI* – electrode-tissue interface; *GT* – ground truth; *TF* – transfer function; *LS* – least square

4.8 Conclusion

This study proposes a capacitive single-lead ECG measurement system integrated into a chest strap, along with an MA-reduction algorithm. The performance of the capacitive ECG system, using the proposed chest strap, was evaluated by comparing the quality of the ECG signal in a stationary condition with that of a buffered ECG electrode setup placed on two parts of the torso. Excellent signal quality was obtained, with all ECG waves visible, a correlation coefficient > 0.947 , and an MSE < 0.104 , indicating negligible MA interference. To address the presence of MAs in ECG signals acquired using the proposed chest strap, we designed an MA-reduction algorithm grounded in a thorough analysis of MA-generation mechanisms specific to our capacitive system. Our findings reveal that optimizing the capacitive electrodes to exhibit a higher coupling capacitance and selecting a higher bias-resistor value can significantly enhance ECG-signal quality. Moreover, this design choice also leads to a stronger correlation between the MA and the RIS, facilitating effective MA reduction. We further introduced a bias capacitor to improve the efficiency of the voltage-injection process through the bias resistor, simplifying the system while maintaining performance. The analysis showed that injecting high-frequency in-phase signals into each electrode, along with using the real part of the demodulated signal as the RIS, is necessary for effective MA reduction. Three experiments involving electrode-pushing and -pulling motions confirmed that the affected ECG segments were effectively reconstructed. Detailed comparisons before and after reconstruction, and against a 0.67 Hz HPF, demonstrated the superiority of the adaptive approach. CORR1 remained robust across all experiments, CORR2 closely matched CORR1, and CORR3 consistently showed MA reduction. RMS, STD, and per-peak SNR improvements (17.9 dB / 650.2 %, 4.24 dB / 36.8 %, and 2.8 dB / 15 %) further validated the approach.

The results demonstrate that the proposed system fulfils the study objectives of precise MA characterization, optimized RIS derivation, and multi-metric validation, thereby advancing capacitive ECG monitoring. Nevertheless, this proof-of-concept evaluation was limited to a single participant and three controlled MA scenarios, and minor residual artifacts were observed in some parts. Future work will therefore include more participants, a broader spectrum of motion patterns, and further optimization of the adaptive-filter architecture to eliminate the remaining artifacts and enhance generalizability.

Chapter 5 Motion Artifact Reduction in a Wearable Capacitive ECG System

Using an Electrode-Tissue Impedance-Based Reference and a Novel Adaptive Filter

5.1 Prelude

The content of this chapter is a copy of the article titled “Motion Artifact Reduction in a Wearable Capacitive ECG System Using an Electrode-Tissue Impedance-Based Reference and a Novel Adaptive Filter”, submitted to the peer-reviewed journal Biomedical Signal Processing and Control, published by Elsevier.

In Chapter 4, it was confirmed that the proposed capacitive ECG system successfully achieved the objectives of the study by enabling accurate motion artifact (MA) characterization, efficiently deriving a Reference Input Signal (RIS) highly correlated with actual MAs, and demonstrating robust performance through comprehensive validation using multiple evaluation metrics. However, the evaluation conducted in Chapter 4 was limited to a single participant and considered only three controlled motion artifact scenarios. Additionally, minor residual artifacts were still observed in certain segments, highlighting the need for further refinement and validation.

To address these limitations, this chapter responds directly to Objective 4, as defined in Section 1.4. This chapter expands the validation by evaluating the extracted RIS across two comprehensive sets of experiments involving multiple participants (three in total) to assess system robustness and generalizability. These experiments included five distinct motion scenarios in the first set and four realistic daily activity scenarios in the second set, simulating typical chest-strap usage conditions. By incorporating multiple participants and diverse experimental conditions, this study explicitly investigates the robustness and consistency of RIS extraction and highlights existing limitations in adaptive filtering techniques. The limitations of existing adaptive filters (AFs) are evaluated. Based on this analysis, a novel adaptive filtering algorithm, the Variable Step-Size Least Mean Square with Correlation-Power Boosting (VSS-LMS-CPB), is proposed. The overall system performance is thoroughly assessed across the same experimental scenarios, and the effectiveness of the proposed AF is carefully compared against several established adaptive filtering techniques.

5.2 Abstract

Motion artifacts (MAs) remain a major challenge in capacitive ECG measurement systems, despite being well studied. Adaptive noise cancellation (ANC), using an adaptive filter (AF) driven by a motion-correlated

Reference Input Signal (RIS), offers a promising solution. Among various RIS sources, those based on electrode-tissue impedance (ETI) show strong potential; however, limited research has investigated ETI-based RIS extraction in capacitive setups, and few studies validate performance across diverse experimental scenarios and participants.

This study presents a single-lead capacitive ECG system that simultaneously acquires ECG and a highly correlated ETI-based RIS using a chest strap configuration. To overcome the limitations of existing AFs, we introduce a novel algorithm, Variable Step-Size LMS with Correlation-Power Boosting and automatic step size adaptation (VSS-LMS-CPB). The complete system was evaluated across two experimental sets (nine trials involving three participants), including both controlled and realistic motion scenarios. Performance was assessed using correlation and root mean square (RMS) metrics. Additionally, the proposed algorithm was benchmarked against seven established AFs to validate its effectiveness. Overall, the system demonstrated robust MA suppression across varied conditions.

5.3 Introduction

Motion artifacts (MAs), a well-known phenomenon, remain the most significant challenge in capacitive electrodes. They arise from variations in the coupling capacitance formed between the body and electrode due to body movements and physiological vibrations [42, 43]. In capacitive ECG systems, a DC voltage exists across the coupling capacitor. When motion alters the capacitance, it modulates this DC voltage, generating an AC component at the frequency of variation, this AC signal constitutes the MA [37]. The DC voltage originates from multiple sources, including triboelectric charge accumulation, electrodermal potentials, and DC bias currents from amplifiers [37, 41].

These artifacts can severely compromise diagnostic accuracy and even lead to misinterpretation of cardiovascular conditions [34]. Their frequency range, which typically spans from 0.01 to 100 Hz, overlaps with essential ECG components such as the P wave, QRS complex, and T wave. This overlap makes it challenging to suppress MAs without distorting critical clinical information [6]. Moreover, due to their non-stationary nature, MAs cannot be effectively removed using fixed-coefficient filters. As a result, advanced adaptive algorithms are essential for suppressing these artifacts while preserving ECG fidelity [118, 146].

Advanced techniques such as wavelet transform, empirical mode decomposition, and blind source separation have been explored to overcome the limitations of conventional filters in removing MAs from ECG signals.

Although these methods enhance signal decomposition, they often require high computational power and memory, thus limiting their practicality in low-power, real-time systems [155].

An alternative approach is adaptive noise cancellation (ANC), which uses a Reference Input Signal (RIS) and an adaptive filter (AF) to estimate and subtract the MA. AFs are particularly well-suited for wearable ECG systems due to their ability to operate in non-stationary environments with low computational and power demands. Unlike traditional filters, they require no prior knowledge of signal or noise characteristics and can dynamically adjust to input changes, making them highly effective in scenarios where noise varies unpredictably [97, 154].

The effectiveness of ANC depends on both the AF's performance and the quality of the RIS, which must correlate well with MAs while remaining uncorrelated with the ECG to prevent further interference [38].

Various types of RISs have been explored for MA suppression, including skin stretch measured by optical sensors [131], electrode motion captured via accelerometers [132, 133], electrode deformation [134], changes in electrode-tissue impedance (ETI) [37, 38, 41, 66, 120, 126, 136, 147], and additional electrodes with specific structures and configurations [26, 128]. However, RISs from accelerometers and motion sensors often correlate poorly with actual MA, as body movement does not always cause electrode displacement, and electrode-skin impedance varies spatially and temporally. Electrodes may remain stable during motion, making accelerometer data an unreliable proxy for MAs [118]. Even advanced AFs have failed to fully eliminate MAs when using such low-correlation inputs [156].

By contrast, ETI has demonstrated stronger correlation with MAs and has outperformed accelerometer-based systems in comparative studies [37, 157]. Its key advantage is that it can be derived without additional sensors, making it well-suited for low-power designs and a promising RIS for wearable ECG applications [14, 22]. Several studies have investigated ETI extraction for both dry and capacitive electrodes, but many failed to ensure that the extracted ETI component was proportional to the actual MAs by correctly modeling the MA in their system, which is an essential criterion often overlooked [37, 66]. Furthermore, limited research has assessed ETI in the context of capacitive electrodes, particularly under varied experimental conditions and across different participants.

Various adaptive algorithms have been investigated for MA estimation, particularly Least Mean Square -based methods such as Least Mean Square (LMS), Normalized LMS (NLMS), and enhanced LMS variants, as well as more advanced approaches like Recursive Least Squares (RLS) [37, 38, 97, 125]. Each offers unique

advantages and drawbacks, often trading off between convergence speed, stability, and computational complexity. Key limitations include the use of fixed step sizes, inconsistent performance across and within experiments, poor adaptability to fluctuating RIS-MA correlation, and difficulty tracking abrupt, high-amplitude artifacts. Furthermore, in the context of capacitive electrodes, few studies have evaluated AF performance across diverse experimental conditions.

Against this backdrop, this study aims to: (1) develop a method for extracting an ETI-based RIS highly correlated with MA; (2) evaluate the extracted RIS across two sets of experiments simulating daily chest strap use in three participants; (3) investigate the limitations of existing AFs and propose a novel algorithm to address them; (4) assess the proposed filter's performance across the same experimental conditions; and (5) compare its effectiveness with several existing linear and nonlinear AFs. The remainder of this paper is organized as follows: Section 5.4 reviews related work on adaptive filtering for MA suppression. Section 5.5 presents the system design and the proposed VSS-LMS-CPB algorithm. Section 5.6 describes the experimental setup, signal characterization, evaluation metrics, and results. Section 5.7 discusses the findings and future work. Section 5.8 concludes the manuscript.

5.4 Background and Related Work

5.4.1 Adaptive Filtering Techniques for Motion Artifact Suppression

The standard ANC architecture shown in Figure 5-1 involves two input signals: the primary input $d(n)$, which contains the desired ECG signal contaminated with MA, and the RIS, $x(n)$. Ideally, $x(n)$ should be strongly correlated with the MA component and uncorrelated with the underlying ECG signal [158]. The degree of correlation between RIS and noise critically determines ANC effectiveness; low correlation may lead to spurious contamination in the reconstructed ECG [38]. The AF continuously updates its coefficients, aiming to minimize the error between estimated and actual MA, thus isolating the clean ECG signal [159]. For linear AFs, the output $y(n)$ is computed as the inner product between the tapped-delay vector of the reference signal $\mathbf{x}(n) \in \mathbb{R}^M$ and the adaptive weight vector $\mathbf{w}(n) \in \mathbb{R}^M$ at time n , as given by Equation (5-1). The ANC output $e(n)$, representing the reconstructed ECG, is computed using Equation (5-2). Different adaptive filtering algorithms differ primarily in their weight-update equations, such as Equation (5-3). The specific form of this update equation significantly influences the filter's convergence behavior and ECG reconstruction quality.

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (5-1)$$

$$e(n) = d(n) - y(n) \quad (5-2)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + y(n) \cdot e(n) \quad (5-3)$$

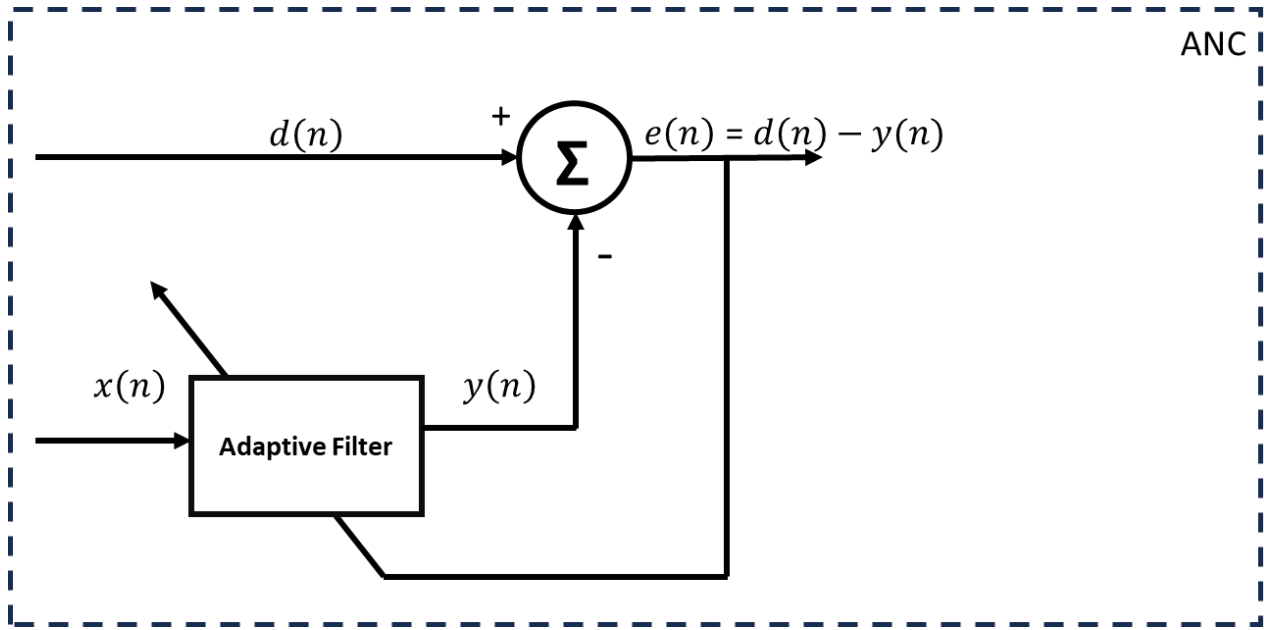


Figure 5-1. Standard ANC architecture.

The LMS algorithm is a widely adopted adaptive filtering method due to its simplicity, robustness, and ease of hardware implementation. It has been extensively applied to ECG MA removal [66, 147, 160, 161], performing reliably in non-stationary environments like ECG signal processing [162]. LMS iteratively updates filter coefficients using a stochastic gradient descent approach, aiming to minimize the mean squared error (MSE), as expressed in Equation (5-4), where the step size μ is a critical parameter controlling convergence speed and steady-state error [163–167]. However, LMS has notable limitations: a smaller μ yields stable yet slow convergence, while a larger μ accelerates convergence at the cost of higher residual error and potential instability [161, 166–168]. Additionally, LMS performance can degrade in the presence of high-frequency components or substantial gradient variance, potentially causing unstable coefficient updates [155].

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \cdot \mathbf{x}(n) \cdot e(n) \quad (5-4)$$

To overcome the limitations of fixed step-size LMS, Variable Step-Size LMS (VSS-LMS) algorithms have been introduced, dynamically adjusting their learning rate to enhance convergence speed and numerical stability. Among the earliest and most widely used variants are NLMS and Error-Normalized LMS (ENLMS), both frequently applied in biopotential applications [37, 154, 164, 166, 168, 169]. NLMS adapts the step size

by normalizing it to the power of the input signal $x(n)$ as shown in Equation (5-5), while ENLMS normalizes it to the power of the error signal $e(n)$, as expressed in Equation (5-6).

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\varepsilon + \mathbf{x}(n) \cdot \mathbf{x}(n)^T} \cdot \mathbf{x}(n) \cdot e(n) \quad (5-5)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\varepsilon + e(n)^2} \cdot \mathbf{x}(n) \cdot e(n) \quad (5-6)$$

These variants offer improved stability in the presence of fluctuating signal amplitudes and generally exhibit greater robustness and real-time performance compared to standard LMS [164, 168, 170]. A key advantage of ENLMS, as noted in [164], is that its step-size becomes independent of both input power and filter length, enabling more flexible filter behavior. However, ENLMS can become unstable in high-noise conditions, where large error fluctuations cause erratic adaptation [11]. In ECG applications, this limitation is amplified because $e(n)$ includes cardiac features such as R-peaks, leading to step-size spikes during QRS complexes and potential distortion of signal morphology. Despite their advantages, both NLMS and ENLMS become less effective during intense or abrupt MAs. During large MAs, the normalized step-size becomes too small, reducing the filter's ability to track fast, high-amplitude changes [146].

To overcome the trade-off between rapid convergence and low steady-state error inherent to traditional LMS and normalized LMS filters, some more advanced VSS-LMS algorithms have been proposed. These approaches dynamically adjust the step-size ($\mu(n)$) according to instantaneous characteristics of the input and error signals, thereby enhancing tracking performance, particularly under varying MA intensities common in ECG monitoring [118, 146, 171–173]. The general form of VSS-LMS weight update is presented in Equation (5-7). In ECG artifact mitigation applications, VSS-LMS configurations vary widely, with adaptations tailored to specific signal conditions and artifact types. Some implementations emphasize fast convergence for abrupt disturbances, while others focus on stability to preserve ECG morphology.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n) \cdot \mathbf{x}(n) \cdot e(n) \quad (5-7)$$

Among the various VSS-LMS variants, one notable class includes gradient-based algorithms. The Gradient-based Variable Step-Size LMS (GSVS-LMS) algorithm stands out by incorporating a nonlinear relationship between step-size and the error signal $e(n)$. GSVS-LMS further optimizes $\mu(n)$ by directly exploiting gradient information from the AF coefficients. Compared to earlier variable step-size approaches, GSVS-LMS achieves superior convergence speed, lower steady-state error, and greater resilience to interference, significantly enhancing overall ECG signal reconstruction quality in challenging, artifact-rich environments [165, 167]. One

well-known implementation of GSVS-LMS is the GASS-LMS algorithm proposed by Mathews and Xie [174], which uses a gradient-adaptive mechanism to update the step-size. The GASS-LMS equations, shown in Equations (5-8), update $\mu(n)$ based on the interaction between the instantaneous error and a smoothed gradient tracker $\psi(n)$, which accumulates recent error-weighted input vectors. This formulation enables real-time tracking of signal dynamics, providing improved responsiveness to nonstationary MAs.

$$\begin{aligned}\mu(n+1) &= \mu(n) + \rho \cdot e(n) \cdot \mathbf{x}^T(n) \cdot \psi(n) \\ \psi(n+1) &= \beta \cdot \psi(n) + e(n) \cdot \mathbf{x}(n)\end{aligned}\tag{5-8}$$

However, LMS and its variants are not the only adaptive filtering methods used for ECG artifact mitigation. More advanced algorithms, notably RLS and Kalman filtering, have also been explored [154, 155]. RLS recursively updates its coefficient vector via the matrix-inversion lemma, achieving rapid convergence even with highly correlated inputs [154, 163]. Its iterative parameter equations are given in (5-9). While RLS offers superior convergence performance compared to LMS-based filters, it also introduces higher computational complexity and stability concerns, especially in hardware-constrained systems. Strategies such as adaptive control of the forgetting factor λ have been proposed to improve performance under dynamic conditions, though at the cost of increased computational overhead [155, 159].

$$\begin{aligned}\mathbf{w}(n+1) &= \mathbf{w}(n) + \mathbf{k}(n) \cdot e(n) \\ \mathbf{k}(n) &= \frac{\mathbf{P}(n-1) \cdot \mathbf{x}(n)}{\lambda + \mathbf{x}^T(n) \cdot \mathbf{P}(n-1) \cdot \mathbf{x}(n)} \\ \mathbf{P}(n) &= \frac{1}{\lambda} [\mathbf{P}(n-1) - \mathbf{k}(n) \cdot \mathbf{x}^T(n) \cdot \mathbf{P}(n-1)]\end{aligned}\tag{5-9}$$

Kalman filters, while theoretically optimal for linear-Gaussian models, demand intensive matrix operations and accurate state-space descriptions; consequently, they remain impractical for low-power wearable ECG systems with unknown or non-stationary dynamics [155].

In addition to linear adaptive algorithms, non-linear methods such as Kernel AFs (KAFs) particularly Kernel Least Mean Squares (KLMS) and its normalized variant (NKLMS) have recently been applied to ECG artifact removal [175]. Unlike linear filters, NKLMS generates its output $y(n)$ via non-linear kernel evaluations between the current input $x(n)$ and past inputs stored in a pruned dictionary D as shown in (5-10). KAF-based methods demonstrate superior performance in removing complex, nonlinear artifacts and preserving critical biopotential features, such as ECG QRS complexes or EEG oscillations, which linear filters often distort [175,

176]. These gains, however, come with higher computational cost and slower convergence; normalization and dictionary sparsification are commonly applied to mitigate both issues [176, 177]. Notably, well-tuned linear algorithms can sometimes match kernel methods' effectiveness; one study reported LMS achieving the lowest MSE for general ECG artifacts, with RLS outperforming it only for narrowband interference [177]. Consequently, the computational overhead of KAFs must be justified when targeting resource-constrained wearable applications.

$$y(n) = \sum_{i=1}^{|\mathcal{D}|} \alpha_i \cdot k(x_n, x_i)$$

$$k(x_n, x_i) = \exp\left(-\frac{(x_n - x_i)^2}{2\sigma^2}\right) \quad (5-10)$$

$$\alpha_n = \frac{\mu \cdot e(n)}{\sum_{i=1}^{|\mathcal{D}|} k^2(x_n, x_i) + \varepsilon}$$

Beyond single-stage ANC methods, multi-stage ANC configurations have been introduced to further reduce residual MAs [118, 127]. Despite their improved artifact suppression, these multi-stage methods increase computational complexity and require careful tuning to avoid physiological signal distortion. Their performance also varies with movement type, demanding additional post-processing to maintain consistent ECG quality [127].

An alternative approach, known as convex adaptive filtering, combines two adaptive filters, typically one designed for fast convergence and the other for high accuracy, to achieve a better balance between convergence speed and steady-state error, as presented in Equation (5-11). Recent studies have shown the effectiveness of dynamically mixing outputs from multiple filters [120, 159]. For instance, combining fast and slow LMS filters has demonstrated rapid convergence alongside low steady-state mis adjustment, providing a practical trade-off between computational complexity and performance.

$$y(n) = \lambda \cdot y_1(n) + (1 - \lambda) \cdot y_2(n) \quad (5-11)$$

5.4.2 Limitations of Conventional Adaptive Filtering Approaches

Across the diverse range of adaptive filtering techniques explored in the literature, most efforts focus on resolving the classic trade-off between convergence speed and stability. However, a critical yet often overlooked factor is the potentially low correlation between the RIS and MA. This misalignment may result from electrode displacement, variability at the skin-electrode interface, or complex body-electrode dynamics.

To address this, Ghaleb et al. [118] introduced a correlation-weighted adaptation scheme, where the filter update is modulated by the correlation between accelerometer signals and the ECG. This mechanism reduces adaptation intensity when motion and artifacts are poorly aligned, helping preserve ECG morphology. Kim et al. [146] aimed to address both low correlation and low step-size issues during high-intensity MA segments by adjusting the step size based on the standard deviation of $x(n)$ and $d(n)$ over the last half-cycle of the estimated heart rate. This interval was selected to avoid R-peaks and preserve clean ECG morphology. While innovative, this method has two key limitations: (1) during intense MAs, R-peak detection and heart-rate segmentation may fail; and (2) if MAs occur within excluded intervals, significant artifacts may be overlooked. Despite these advances, no existing solution fully integrates all critical challenges into a unified framework. Based on our analysis, the most pressing limitations include: (1) fixed step-size usage; (2) inconsistent performance across experiments; (3) intra-experiment MA variability; (4) poor adaptation under fluctuating RIS-MA correlation; and (5) failure to track abrupt, high-amplitude MAs. To overcome these, we propose a Variable Step-Size LMS with Correlation-Power Boosting (VSS-LMS-CPB) algorithm, which is designed to enhance adaptive filtering robustness across diverse and challenging ECG scenarios. The method is detailed in Section 4.4.

5.5 System Design and Methodology

5.5.1 Hardware Architecture for Concurrent ECG and RIS Acquisition

Figure 5-2 illustrates the proposed capacitive single lead ECG system designed for simultaneous ECG and ETI acquisition using a three electrode configuration. Each of the two active capacitive electrodes is connected to an ultra low bias current operational amplifier (LTC624x, Analog Devices, USA; $I_{bias} \approx 0.2 \text{ pA}$) and a $10 \text{ G}\Omega$ bias resistor, R_B , in a voltage follower configuration [38, 41, 44, 66]. These electrodes feed into an instrumentation amplifier (AD620, Analog Devices, USA) configured for differential input. This setup, optimized for a 20 dB gain, provides strong common-mode rejection ($\text{CMRR} \geq 100 \text{ dB}$) and clean single-ended ECG output. A first-order low-pass filter ($\text{cutoff} \approx 3 \text{ kHz}$), as recommended in the AD620 datasheet, is added at the input to manage injected signal frequencies. A third wet electrode serves as the body reference, enhancing stability and common-mode suppression. The capacitive electrodes, which are 30 mm in diameter and coated with 80 μm cotton ($\epsilon_r \approx 1.8$), are designed for wearable use, with a coupling capacitance (C_0) of $\sim 140 \text{ pF}$, estimated via $C_0 = \epsilon_r \epsilon_0 \frac{A}{d}$.

For robust ETI measurement, a 6.8 pF capacitor, C_B is placed in parallel with R_B , introducing a zero in the system's transfer function that prevents attenuation and ensures frequency-independent behavior at high frequencies. This configuration improves the gain of output voltage in response to the injected voltage at 1 kHz by ~ 53 dB without affecting ECG integrity, as C_B is much smaller than the formed coupling capacitor between body and skin, C_c , thereby resolving injection issues noted in prior studies [38, 41, 66].

The system output $v_{out}(t)$, derived via superposition, comprises ECG, DC offset (as described in Section 5.3, V_{DC}), and injected high-frequency signals, v_{inj} , represented respectively as $v_{out_{ECG}}(t)$, $v_{out_{V_{DC}}}(t)$ (referred to as MA) and $v_{out_{inj}}(t)$ in Equations (5-13) to (5-15). The coupling capacitor C_c , includes a constant component C_0 (assumed equal across electrodes) and dynamic motion-induced terms $c_{d1}(t)$ and $c_{d2}(t)$ [38, 147]. The instrumentation amplifier gain is denoted G_{amp} . A NI 9263 module (16-bit, 100 kHz) was used to generate two in-phase 1 kHz sine waves with 10 V amplitude in this study. The systems transfer function $H(j\omega)$, defined in Equation (5-16), behaves as a first-order high-pass filter with a cutoff at $\frac{1}{R_B C_0}$. Given $C_0 \approx 140$ pF, and high R_B , the cutoff frequency falls well below the ECG band (≥ 0.67 Hz), rendering $H(j\omega)$ negligible not only for ECG components but also in facilitating accurate MA estimation by adaptive filtering.

$$v_{out}(t) = v_{out_{ECG}}(t) + v_{out_{V_{DC}}}(t) + v_{out_{inj}} = v_{out_{ECG}}(t) + \text{MA} + v_{out_{inj}} \quad (5-12)$$

$$V_{out_{ECG}}(j\omega) = G_{amp} \times \Delta V_{ECG}(j\omega) \times H(j\omega) \quad (5-13)$$

$$V_{out_{V_{DC}}}(j\omega) = K \times \Delta C_d(j\omega) \times H(j\omega) \quad (5-14)$$

$$V_{out_{inj}}(j\omega) = -V_{inj}(j\omega) \times \left[\frac{C_B \times G_{amp}}{C_0^2} \right] \times \Delta C_d(j\omega) \times e^{j\phi} \quad (5-15)$$

with

$$K \approx \frac{G_{amp} \times V_{DC}}{C_0}, \Delta C_d(j\omega) = C_{d1}(j\omega) - C_{d2}(j\omega) \text{ and } H(j\omega) = \frac{j\omega}{j\omega + \frac{1}{R_B C_0}} \quad (5-16)$$

Based on Equation (12), the injected signal frequency (1 kHz) lies well above the ECG bandwidth, allowing straightforward separation via filtering. In contrast, the MA component overlaps with the ECG spectrum, making basic filtering ineffective and necessitating reference-based removal. As shown in Equation (5-14), MA is proportional to coupling capacitance variation $\Delta c_d(t)$, making it a suitable RIS.

From the modulation structure in Equation (4-17), derived from Equation (5-15), demodulating the amplitude-modulated output $V_{outinj}(j\omega)$ isolates its low-frequency envelope $m(t)$, as shown in Equation (7). While Equation (4-18) theoretically reconstructs $\Delta c_d(t)$ from $m(t)$, the unknown constant C_0 prevents exact computation. However, since C_0 is time-invariant, $m(t)$ remains directly proportional to $\Delta c_d(t)$ and is thus usable as an RIS.

A remaining challenge is resolving the phase shift φ between the injected and output signals. In differential configurations, imbalance in coupling capacitances c_{c1} and c_{c2} can induce a shift, typically 0° or 180° , which alters the polarity of $\Delta c_d(t)$. While AFs handle magnitude variations, polarity inversion has been overlooked in prior studies [38, 66, 147]. In this work, the real part of $m(t)$, which retains proportionality to $\Delta c_d(t)$, is selected as the RIS, as expressed in Equation (4-20).

$$v_{outinj}(t) = m(t) \times v_{inj}(t) \quad (5-17)$$

where

$$m(t) = - \left[\frac{C_B \times G_{amp} \times A_{inj}}{C_0^2} \right] \times \Delta c_d(t) \times e^{j\varphi} \quad (5-18)$$

$$RIS = -Re\{m(t)\} \quad (5-19)$$

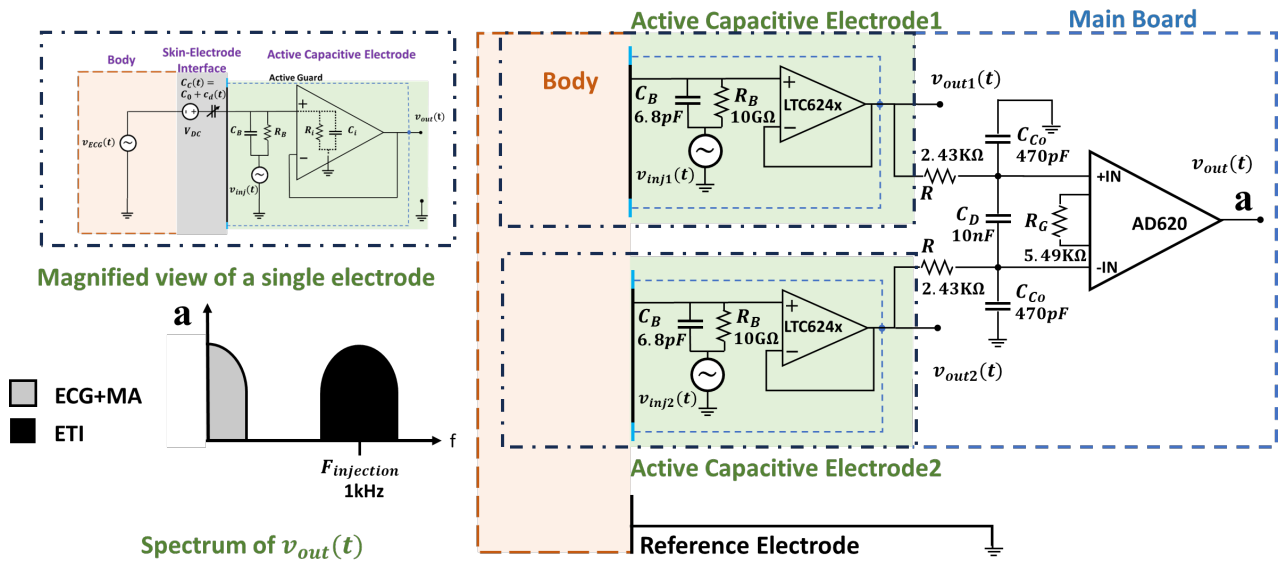


Figure 5-2. Proposed single-lead capacitive ECG system enabling simultaneous ECG and ETI acquisition via a three-electrode setup, with corresponding output voltage spectrum.

Following the acquisition, $v_{out}(t)$ is digitized using an NI 9239 module (24-bit, 50 kHz), and all subsequent processing is performed offline in MATLAB (R2024b, Version 24.2.0.2712019, MathWorks, Inc.) on Microsoft Windows 11 Enterprise. The processing pipeline is outlined in Figure 5-3.

The digitized signal, $v_{out}[n]$, is downsampled to 1 kHz to improve computational efficiency. As shown in the block diagram, a series of filters extracts the two input signals, $d[n]$ and $y[n]$, for the ANC block. The proposed AF then estimates the MA, $y[n]$, which is subtracted from $d[n]$ to reconstruct the clean ECG signal, $e[n]$.

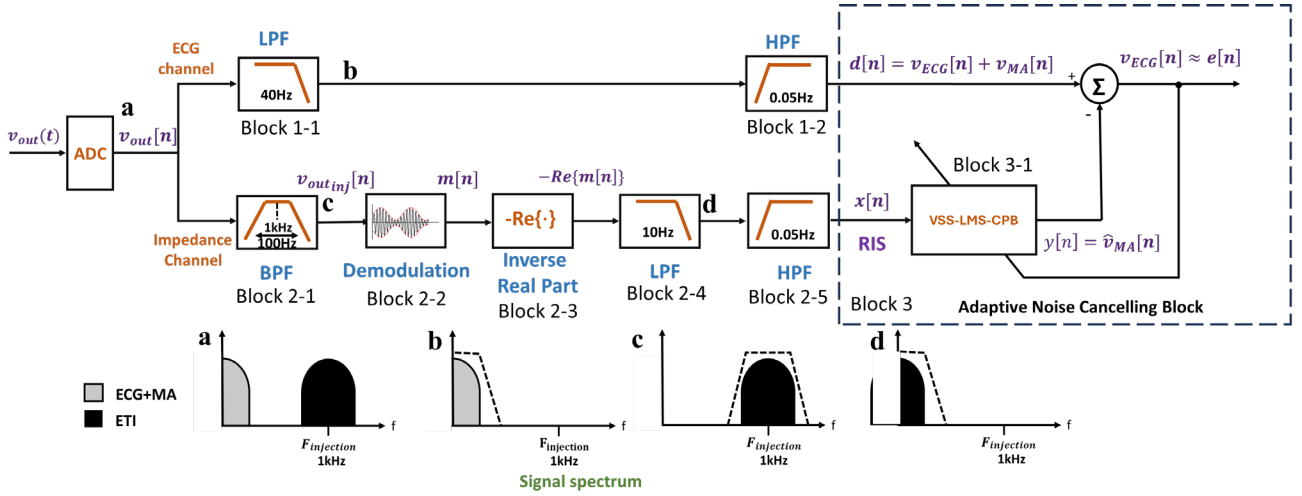


Figure 5-3. Digital signal processing pipeline and corresponding spectrum

5.5.2 Proposed Adaptive Algorithm: Variable Step-Size LMS with Correlation-Power Boosting (VSS-LMS-CPB)

To address the gap regarding adaptive algorithms identified in Section 5.4, a new algorithm, VSS-LMS-CPB, is proposed. Its structure follows that of the LMS filter introduced in Section 5.4, with the filter order set to ten. Unlike classical LMS, it dynamically adapts the step size $\mu(n)$, as defined in Equation (5-20), instead of using a fixed value.

$$\mu(n) = \mu_0 \cdot \left(1 + \log_{10} \left(1 + 2 \left(\frac{P_{x_{now}}}{P_{x_{avg}} + \varepsilon} \right)^2 \right) \right) \cdot c(n)^2 \quad (5-20)$$

5.5.2.1 Correlation-Power Boosting Mechanism

Initially, μ_0 was defined as a constant baseline step size, with selective boosting applied during intense motion. The RIS, $x(n)$ was chosen for power monitoring, as $d(n)$ and $e(n)$ contain ECG morphology (e.g., R-peaks), making them unreliable for isolating motion-related variations. However, relying solely on $x(n)$'s power can lead to unnecessary distortion. To address this, a two-part multiplicative boosting structure is introduced:

- a) Logarithmic power-based boosting
- b) Squared correlation factor

These terms are combined as $\mu(n) = \mu_0 \cdot (1 + a \cdot b)$, where the “1 +” ensures the step size defaults to μ_0 under low-motion, low-correlation conditions, while enabling proportional amplification during high-motion, high-correlation periods.

5.5.2.1.1 Logarithmic Power-Based Boosting

This term uses the ratio between the instantaneous RIS power $P_{x_{now}}$ and its exponentially smoothed average $P_{x_{avg}}$, defined as $(\frac{P_{x_{now}}}{P_{x_{avg}} + \varepsilon})$. The average power is updated recursively via exponential smoothing, as shown in Equation (5-21). Squaring the ratio and multiplying by two emphasize significant motion bursts while attenuating minor fluctuations. Embedding this term in a base-10 logarithmic function serves to:

- Compress the dynamic range to avoid excessive boosts during strong motion,
- Provide a smooth, differentiable response that allows moderate yet effective sensitivity adjustment, and
- Ensure the function remains positive and defined, even when $P_{x_{now}} \approx 0$, due to the “1 +” term.

The small constant ε in the denominator ensures numerical stability and desensitizes the ratio to negligible fluctuations when $P_{x_{now}} \ll \varepsilon$.

This boosting mechanism offers low complexity, low memory usage, and strong responsiveness to transient motion events.

$$P_{x_{avg}} = (1 - \alpha) \cdot P_{x_{avg}} + \alpha \cdot P_{x_{now}} \quad (5-21)$$

5.5.2.1.2 Squared Pearson Correlation Integration

To ensure the filter responds only when motion is both strong and causally affecting the ECG, the squared Pearson correlation coefficient is used, as defined in Equation (5-22). It is computed over a symmetric sliding window centered at index n . Squaring the correlation amplifies strong associations and suppresses weak or noisy ones, preserving ECG features like the QRS complex.

Even without modeling the artifact waveform, a strong correlation between $x(n)$ and $d(n)$ statistically indicates MA presence, making $c(n)^2$ a reliable motion indicator. This mechanism is effective in two key cases: (1) when RIS fluctuations are uncorrelated noise, and (2) when RIS amplitude is high but its effect on the ECG is minimal. In both cases, the resulting low correlation appropriately reduces $\mu(n)$.

$$c(n)^2 = [\text{corr}(x(n), d(n))]^2 \quad (5-22)$$

5.5.2.2 Automatic Adaptation of μ_0

Experimental analysis across participants and scenarios revealed that while Correlation-Power Boosting enables dynamic step-size adjustment, the baseline μ_0 must also be tuned to account for inter-experiment variability. Initially requiring manual tuning, this approach proved inconsistent and impractical due to significant RIS amplitude and power differences caused by:

- Variations in the constant component C_0 , influenced by chest strap tightness
- Differences in $\Delta c_d(t)$, driven by motion type and intensity

μ_0 is initially set to a high value, μ_{max} for fast convergence [166, 167]. A threshold γ acts as a trigger, indicating when the current RIS power, $P_{x_{now}}$, is significant enough to initiate tracking. If $P_{x_{now}} > \gamma$, the algorithm monitors the maximum RIS power, $P_{x_{max_now}}$, over the next second. As outlined in Equation (5-23), μ_0 is adaptively updated, bounded by μ_{max} , if the current and previous maximum powers differ by a factor of β . Otherwise, μ_0 remains unchanged. It is held constant until the next significant variation in power is detected.

Finally, the value of $P_{x_{max_old}}$ is updated to the value of $P_{x_{max_now}}$.

$$\mu_0(n) = \begin{cases} \min\left(\frac{\mu_{init}}{P_{x_{max_now}}}, \mu_{max}\right), & \text{if } \frac{P_{x_{max_now}}}{P_{x_{max_old}}} \geq \beta \text{ or } \frac{P_{x_{max_old}}}{P_{x_{max_now}}} \geq \beta \\ \mu_0(n-1), & \text{otherwise} \end{cases} \quad (5-23)$$

The proposed algorithm retains a constant offset μ_0 for stability, scales it using Correlation-Power Boosting, and automatically adapts μ_0 in response to significant RIS power shifts. This mechanism ensures μ_0 remains responsive to RIS power dynamics, delivering robust, adaptive performance within and across experiments, participants, and conditions.

5.6 Experimental Methodology and Results

5.6.1 Measurement Configuration and Participant Details

To enable wearable capacitive ECG monitoring, a custom single-lead chest strap was developed using stretchable elastic fabric for secure placement and user comfort. Although the strap can be worn at various torso locations, it was consistently positioned around the lower thorax, approximately at the level of the seventh to ninth ribs, to standardize measurements. The system includes two cotton-coated active capacitive electrodes for comfort and insulation, and a passive wet electrode placed on the right lateral abdomen as a stable reference. Figure 5-4 (a–c) shows the front and reverse views of the chest strap and its application on a participant.

Experiments were conducted with three healthy adult volunteers (two males, one female), aged 25–40, with no known cardiovascular conditions.

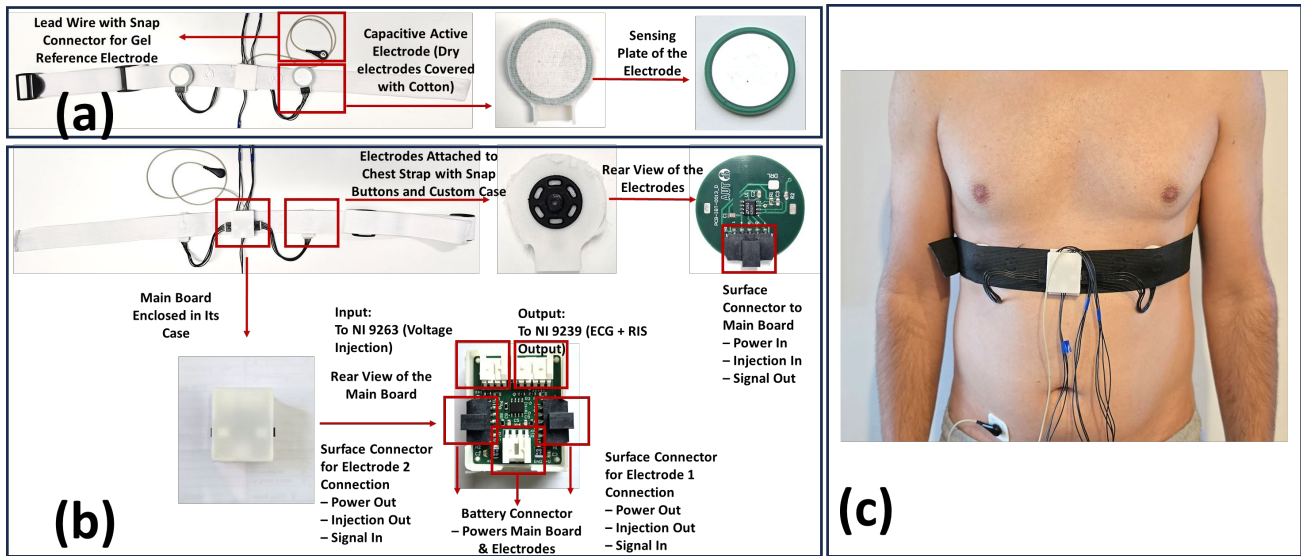


Figure 5-4. (a) Front view of the chest strap; (b) Reverse view showing the electrode layout; (c) Application of the chest strap on a participant.

5.6.2 Experimental Protocol and Motion Induction Design

Two sets of experiments were conducted to evaluate the proposed MA suppression method. Table 5-1 summarizes the first set, consisting of controlled artifacts commonly seen in wearable capacitive ECG systems. In Experiments 2 and 3, motion was applied directly to the electrodes, while in Experiments 4 and 5, MAs were induced by manipulating the skin beneath the electrode interface. To test the algorithm's robustness against electrode-specific interference, motion was alternated between Electrode 1 and Electrode 2 every 10 seconds, ensuring consistent skin contact without full detachment.

Table 5-2 presents the second set, simulating realistic upper body movements such as running, arm swings, and torso twists. These activities are common during wearable ECG use and are known to introduce motion induced noise. For each experiment in both sets, a continuous 100-second ECG segment was extracted and analyzed under each motion condition.

Table 5-1. Summary of Experiment Set 1: Controlled artifacts commonly encountered in wearable capacitive ECG systems.

Exp.	MA induced	Interval
1	Sitting on a chair with the subject's trunk straight	----
2	Pushing electrodes	10s
3	Pulling electrodes	10s
4	Rotational skin movement around the electrode	10s
5	Stretching skin around electrode	10s

Table 5-2. Summary of Experiment Set 2: Simulated upper-body movements inducing realistic MAs during wearable ECG use.

Exp.	Activity (MA induced)
1	Up and down arms wing motion
2	Upper body run motion (arms swinging)
3	Straight punch motion
4	Upper body twist motion

5.6.3 Frequency Characteristics of Body Movement and RIS Signals

Body movements relevant to wearable ECG systems typically fall within the 0–20 Hz range, covering respiration (~0.1–2 Hz), general motion (~0–10 Hz), and ballistocardiograph activity (~0–20 Hz) [37, 39–43]. In this study, since the RIS is modulated by such movements, both the RIS and resulting MAs are expected to share similar spectral content.

To quantify this, the raw RIS signal (before low- and high-pass filtering, as shown in Figure 5-3) was analyzed across participants and experiments. It was first high-pass filtered at 0.1 Hz to remove baseline drift while retaining motion components. Power spectral density (PSD) was estimated using Welch’s method (2 s Hamming window, 50% overlap, 65,536-point FFT). RIS dominant frequencies are defined as the frequency below which 95% of the cumulative linear-scale PSD resided.

Table 5-3 summarizes the dominant frequency ranges observed across all experiments. The experiments are grouped according to those listed in Table 5-1 (Exp. 1–5) and Table 5-2 (Exp. 1–4), with recordings collected from three participants for each condition. Each cell shows the frequency band (in Hz) that contains the dominant RIS power for a given experiment and participant. Across all these recordings, 95% of RIS power remained below 5 Hz, well within the ECG band (<40 Hz). Consequently, conventional analog filtering cannot isolate MAs without compromising ECG fidelity.

These insights guided the design of Block 2-4 in Figure 5-3, where a digital low-pass filter with a 10 Hz cutoff was implemented. This preserves the full MA spectrum (<5 Hz) while rejecting higher-frequency interference.

Table 5-3. Dominant frequencies in the RIS across participants and experiments.

Table Number	Table 1					Table 2			
Exp.	1	2	3	4	5	1	2	3	4
Participant 1	0-0.778 Hz	0-3.738 Hz	0-3.128 Hz	0-1.419 Hz	0-1.541 Hz	0-1.037 Hz	0-1.083 Hz	0-1.510 Hz	0-0.869 Hz
Participant 2	0-0.900 Hz	0-3.768 Hz	0-3.021 Hz	0-1.739 Hz	0-3.204 Hz	0-1.617 Hz	0-1.480 Hz	0-1.708 Hz	0-1.281 Hz
Participant 3	0-0.885 Hz	0-4.623 Hz	0-3.524 Hz	0-2.304 Hz	0-3.555 Hz	0-1.968 Hz	0-1.037 Hz	0-0.793 Hz	0-0.793 Hz

5.6.4 Performance Evaluation Metrics

The performance of the proposed mitigation method was evaluated using correlation and root mean square (RMS) analysis.

5.6.4.1 Correlation Analysis

Correlation analysis employed a variable windowing strategy tailored to each experiment's artifact characteristics. For the controlled experiments listed in Table 5-1 (Experiments 2-5), which involved intermittent motion, correlations were computed over motion-contaminated segments to allow localized assessment. In contrast, Experiment 1 in Table 5-1 (stationary position) and all experiments in Table 5-2 (Experiments 1-4) involved continuous upper-body movements, which made it difficult to identify distinct clean segments. For these cases, a fixed 5-second window was applied after low-pass filtering $d[n]$ at 5 Hz to attenuate high-frequency ECG components [66, 154].

Two correlation metrics were used:

- **CORR1:** Absolute Pearson correlation between the contaminated ECG $d[n]$ and RIS $x[n]$. High values indicate strong RIS-MA alignment, validating the RIS extraction.
- **CORR2:** Absolute Pearson correlation between the reconstructed ECG $e[n]$ and $x[n]$. A notable drop from CORR1 reflects successful MA suppression by the AF.

5.6.4.2 Delta Root Mean Square (RMS) Metric

To quantify noise reduction, the change in RMS between $d[n]$ and $e[n]$, denoted as delta RMS, was calculated using 2-second windows before and after filtering.

5.6.4.3 Quantitative Results

Performance outcomes, including CORR1, CORR2, and delta RMS, are summarized in Figure 5-5 to Figure 5-7. Rather than relying solely on mean or median values, box plots with overlaid scatter points were used to

visualize the distribution across selected intervals. Each box shows the median, interquartile range, and extrema, with mean values marked in black. To ensure a comprehensive evaluation, both correlation and delta RMS were used, as they capture different aspects of signal quality: CORR1 reflects the degree of similarity between the RIS and MAs and is thus more informative in high-MA scenarios; CORR2 indicates filter effectiveness and consistency of suppression; and delta RMS quantifies the magnitude of noise reduction, especially in motion-dense segments. Recognizing that no single metric fully reflects ECG quality, especially under low-MA conditions where visual inspection remains essential, multiple measures were employed.

CORR1 scatter plots reflect the degree of alignment between the RIS and MA. High CORR1 values, often clustering near 1, indicate strong correlation, especially in segments with large MAs relative to ECG amplitude. However, in low-artifact conditions (e.g., Table 1–Exp. 1 for Participants 1 and 2, and some intervals in Exp. 2–4), CORR1 becomes less meaningful.

In contrast, CORR2 consistently validates filter effectiveness. Lower medians and tighter interquartile ranges, compared to CORR1, indicate both reduced correlation and consistent artifact suppression. Notably, large CORR1-to-CORR2 drops in high-MA conditions reflect strong filtering, whereas minimal differences in low-CORR1 cases confirm the filter’s limited action or indicate negligible artifacts.

delta RMS plots mirror the correlation plots in format. Scatter point height reflects noise reduction. The visual scale of delta RMS differs across experiments to reflect varying MA intensities. Higher delta RMS values generally correspond to stronger suppression in regions with high MA content, as suppression magnitude is naturally influenced by artifact strength. Points around zero correspond to baseline periods with minimal motion, often overlapping with low-CORR1 regions. Experiments in Table 5-1, featuring periodic disturbances, show lower delta RMS overall, with elevated points appearing approximately every 10 seconds, reflecting induced motion (~10% of each 100-second trial). Average delta RMS during active intervals is summarized in Table 5-4 (Exp. 2–5, Table 5-1). In contrast, experiments in Table 5-2 show persistently elevated delta RMS due to continuous motion.

For each experiment in each table, the results of the participant with the highest mean CORR1 and delta RMS values are summarized below, highlighting the most prominent filtering effect and MA presence. The results are presented separately for each table and its corresponding experiment below:

Table 1:

- Exp1 (Seated): Respiration and minor motion were the only artifact sources. In order, Participant 2 exhibited the most prominent respiratory-induced MAs, likely due to electrode placement, while effects were minimal for Participants 1 and 3 (CORR1 = 0.866, CORR2 = 0.107, delta RMS = 0.422 dB).
- Exp2 (Pushing) and Exp3 (Pulling) showed the most substantial improvements in order, confirming effective MA detection and removal (Exp2: CORR1 = 0.789, CORR2 = 0.311, delta RMS = 1.91 dB; Exp3: CORR1 = 0.614, CORR2 = 0.203, delta RMS = 0.43 dB).
- Exp4 (Skin Rotation) and Exp5 (Stretching) demonstrated lower performance in order, with moderate to strong suppression under more persistent motion (Exp4: CORR1 = 0.382, CORR2 = 0.150, delta RMS = 3.14 dB; Exp5: CORR1 = 0.697, CORR2 = 0.382, delta RMS = 11.12 dB).

Table 2:

- In order of intensity, upper-body twists (Exp3: CORR1 = 0.886, CORR2 = 0.120, delta RMS = 2.61 dB), torso rotation (Exp2: CORR1 = 0.807, CORR2 = 0.113, delta RMS = 1.41 dB), and straight punches (Exp4: CORR1 = 0.745, CORR2 = 0.143, delta RMS = 1.03 dB) demonstrated robust filtering under high-motion conditions.
- Wing-like arm motion (Exp1: CORR1 = 0.415, CORR2 = 0.208, delta RMS = 1.50 dB) resulted in moderate suppression.
- Overall performance for Participant 1 in Table 5-2 was consistently lower than others, likely due to individual factors such as body posture or movement execution, electrode coupling, and body shape. These can affect how motion translates into capacitive changes and artifact levels. Unobserved variables may also have contributed to the reduced CORR1 and delta RMS values.

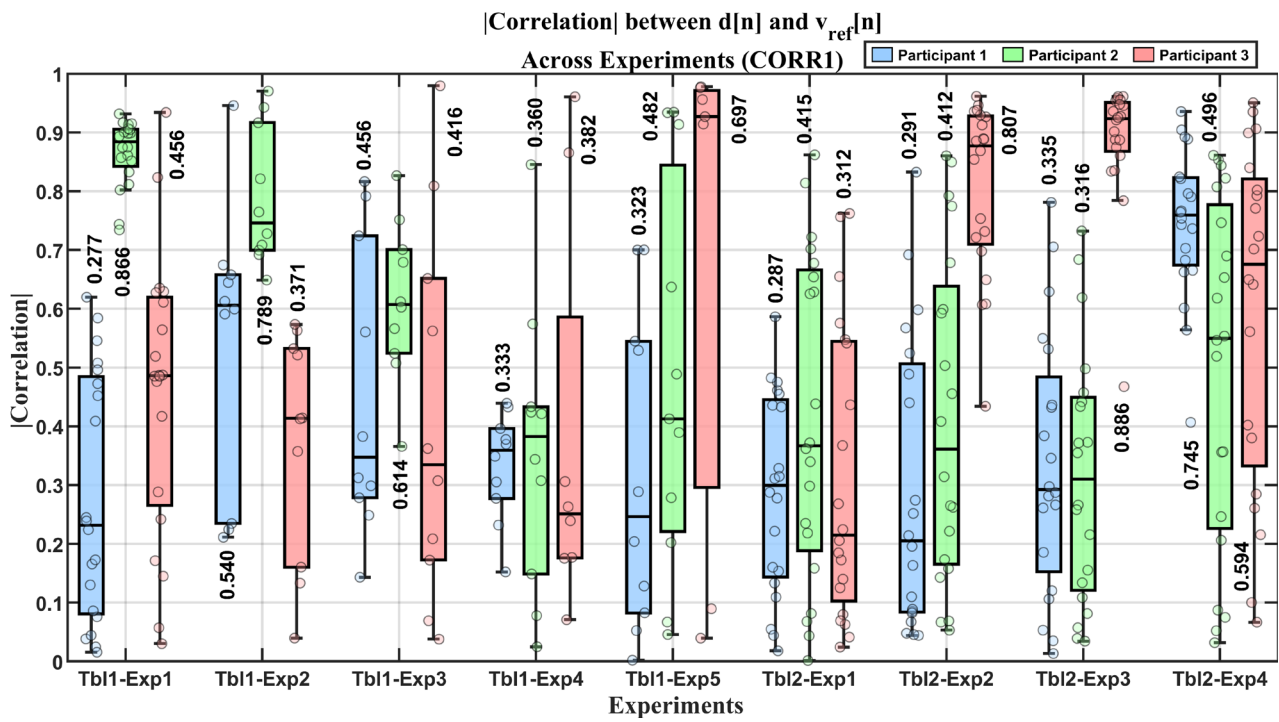


Figure 5-5. CORR1 box plots across experiments and participants, indicating correlation between the raw ECG and RIS. Higher values reflect stronger MA presence; lower values suggest minimal motion contamination.

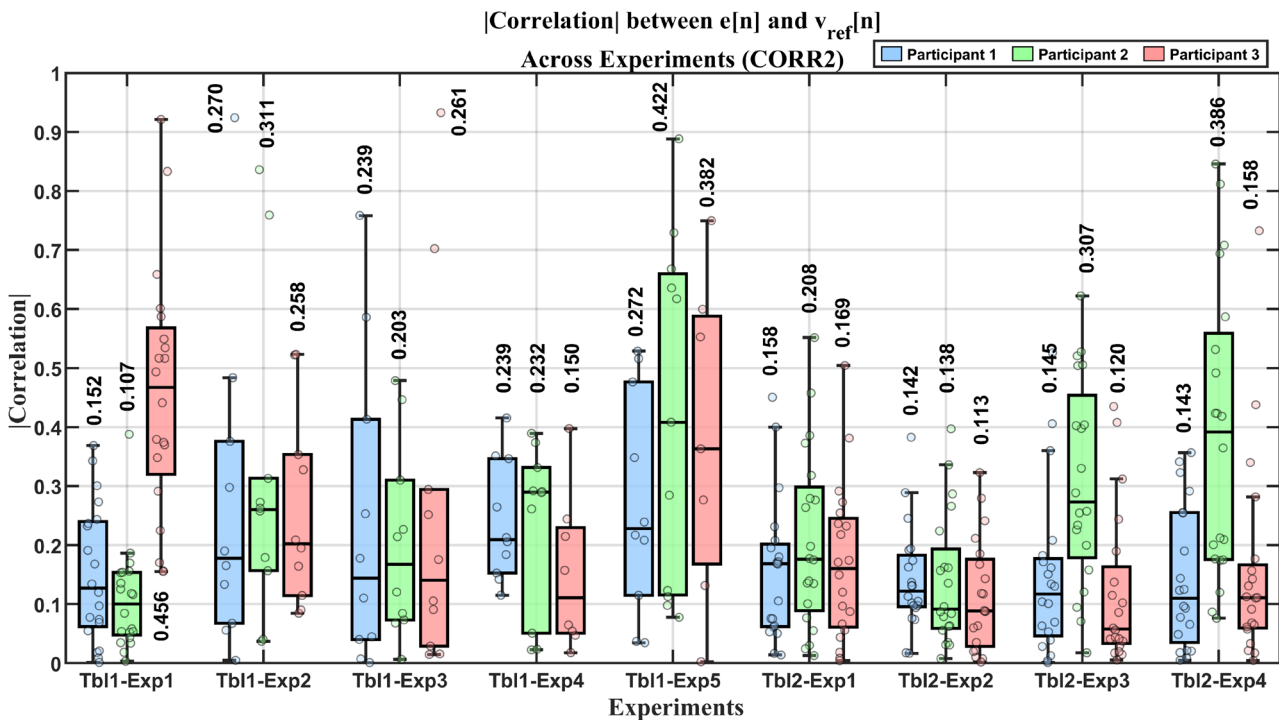


Figure 5-6. CORR2 box plots across experiments and participants, indicating correlation between the reconstructed ECG and RIS. Lower values indicate more effective filtering and reduced MA content.

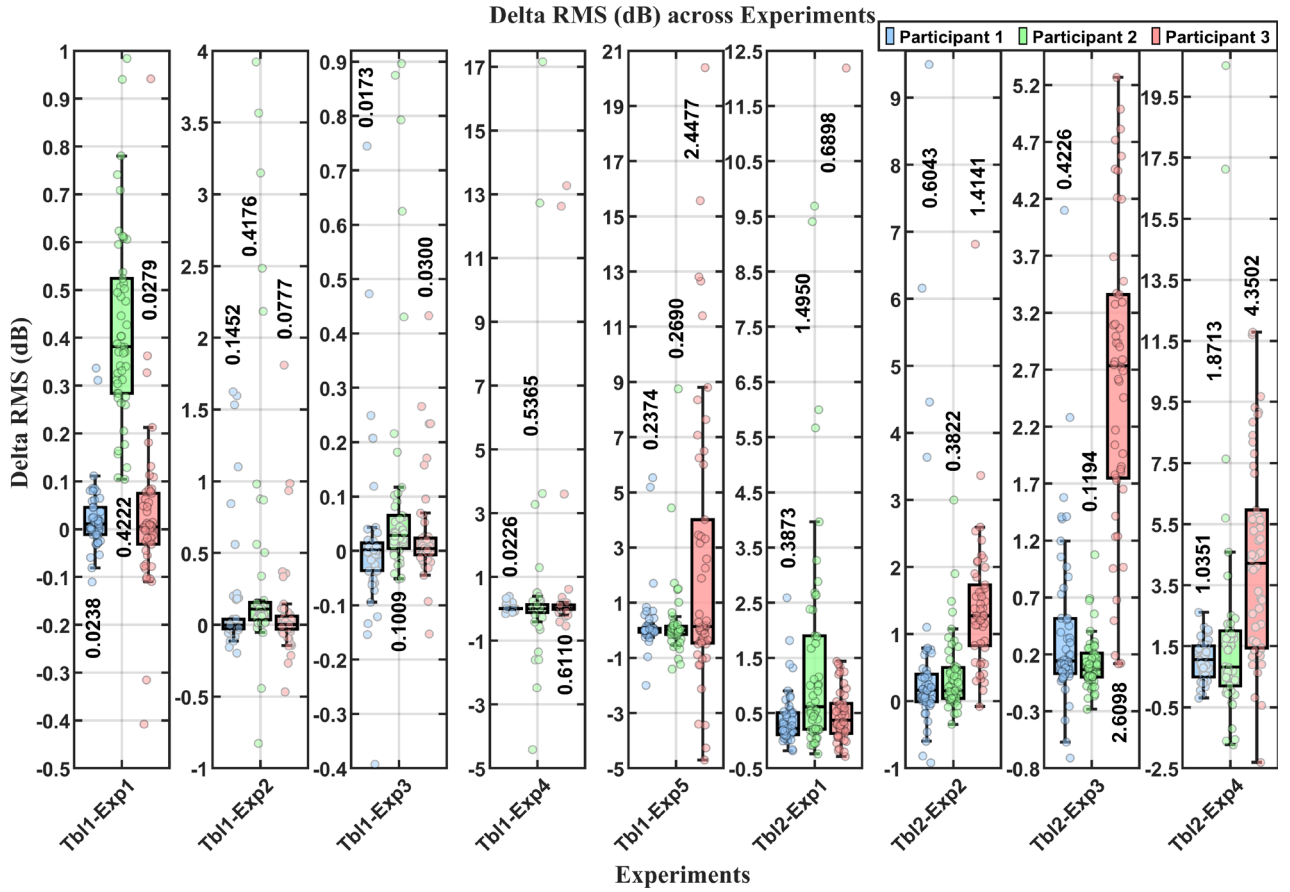


Figure 5-7. Delta RMS box plots across experiments and participants, quantifying the reduction in signal power after filtering. Higher values indicate stronger suppression in high-MA conditions, while values near zero correspond to baseline periods with minimal motion.

Table 5-4. Average delta RMS during active intervals for Table 1 experiments (Exp. 2–5).

Table Number	1			
Exp.	2	3	4	5
Participant 1	0.80 dB	0.21 dB	0.16 dB	1.63 dB
Participant 2	1.91 dB	0.43 dB	3.99 dB	2.05 dB
Participant 3	0.53 dB	0.18 dB	3.14 dB	11.12 dB

5.6.4.4 Performance Comparison with State-of-the-Art Adaptive Filters

To benchmark the proposed adaptive algorithm, seven well-known AFs including LMS, NLMS, ENLMS, RLS, NKLMS, GASS, and Convex-LMS (introduced in Section 5.4) were applied to the dataset, representing diverse filter families. All filters were implemented with an order of ten, using representative parameter values that ensured fair and stable performance across experiments. Comparative results are illustrated quantitatively using delta RMS box plots (Figure 5-8 to Figure 5-16) and qualitatively through selected signal plots (Figure 5-17 to Figure 5-25). The dataset included nine distinct motion experiments across three participants, as detailed in Table 1 and Table 2. For qualitative assessment, one signal plot was selected per experiment, each showing a zoomed-in segment from a specific participant to highlight a particular MA condition or filtering

behavior. The notation (Tblx–Expx–Px) indicates the table number, experiment number, and participant number associated with each plot. Each signal plot includes: (1) raw MA-contaminated ECG $d[n]$; (2) the extracted RIS $x[n]$; (3) ECG before/after filtering with the proposed method; and (4) ECG before and after filtering with one selected comparison algorithm from the benchmarked AFs. RIS plots also illustrate MA correlation and amplitude variation across participants, emphasizing the need for adaptive μ_0 tuning as introduced in our method, as discussed in Section 4.4.

Delta RMS box plots summarize AF performance quantitatively. In general, boxes clustering near zero typically indicate minimal suppression or low artifact presence, while boxes and scatter points shifted notably toward positive values indicate more effective MA suppression. Conversely, negative outliers or scatter points prominently positioned in the negative region often signal instability, distortion, or problematic filter performance. It is important to note that delta RMS values strongly depend on the magnitude and intensity of the original MAs, influencing achievable suppression levels.

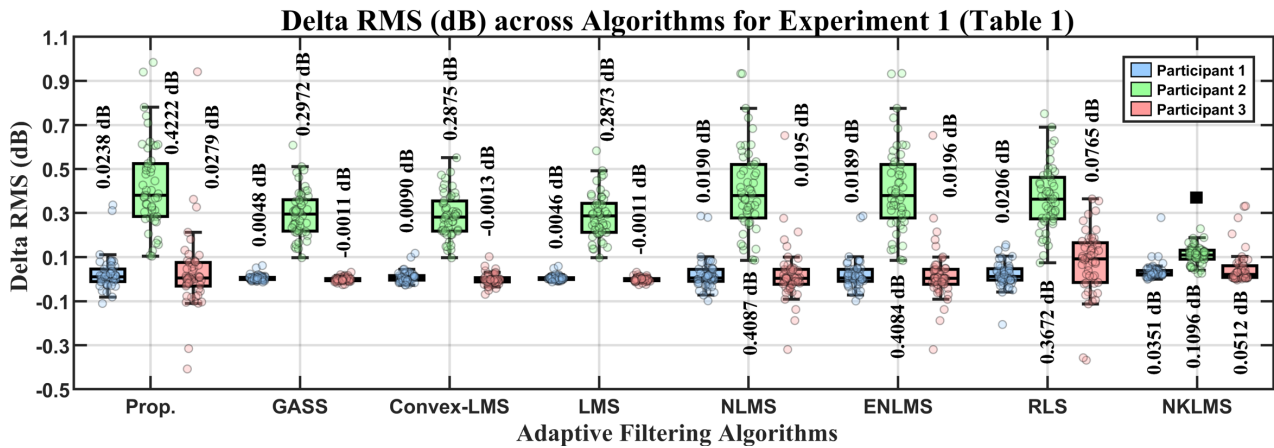


Figure 5-8. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 1 – Exp1).

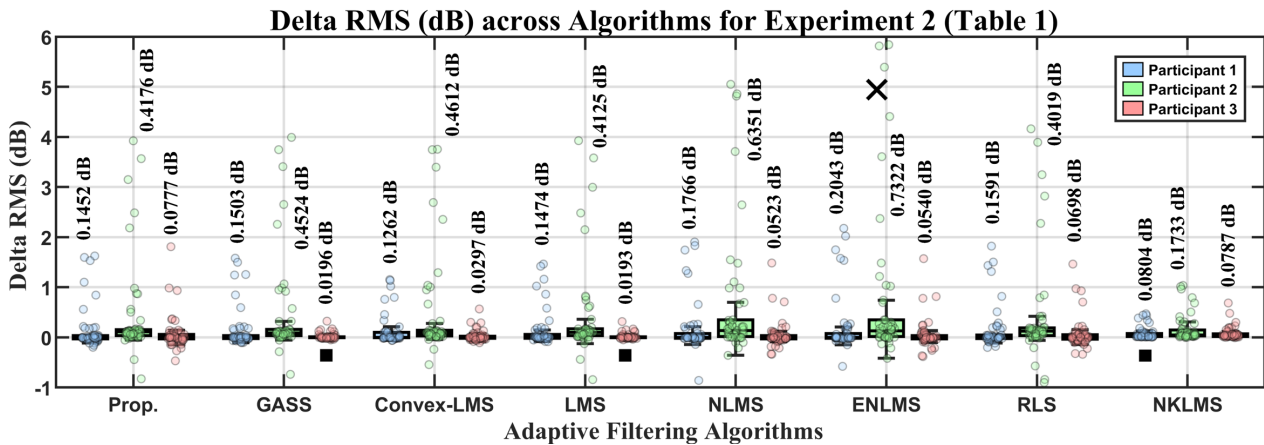


Figure 5-9. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 1 – Exp2).

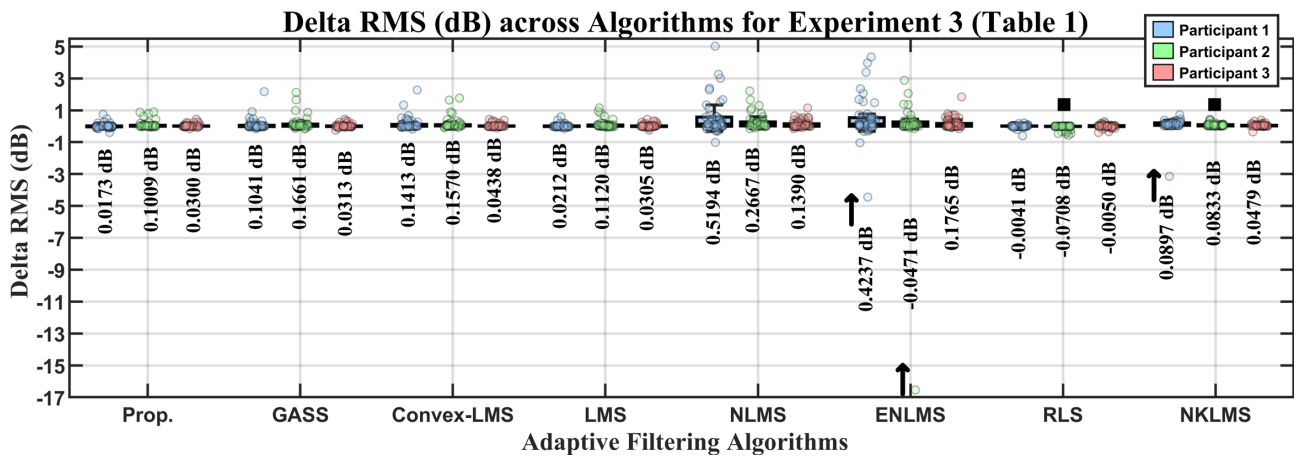


Figure 5-10. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 1 – Exp3).

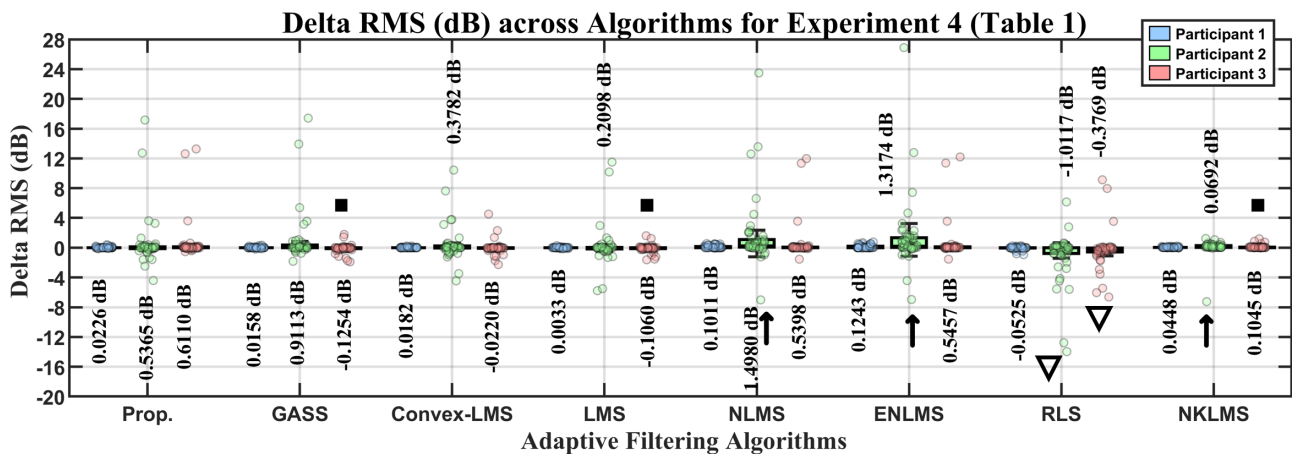


Figure 5-11. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 1 – Exp4).

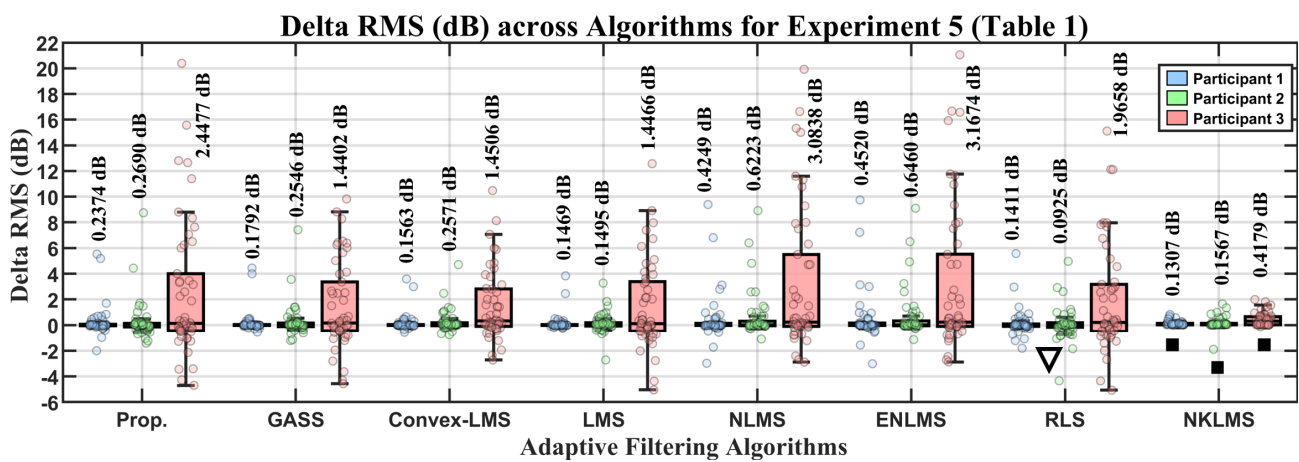


Figure 5-12. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 1 – Exp5).

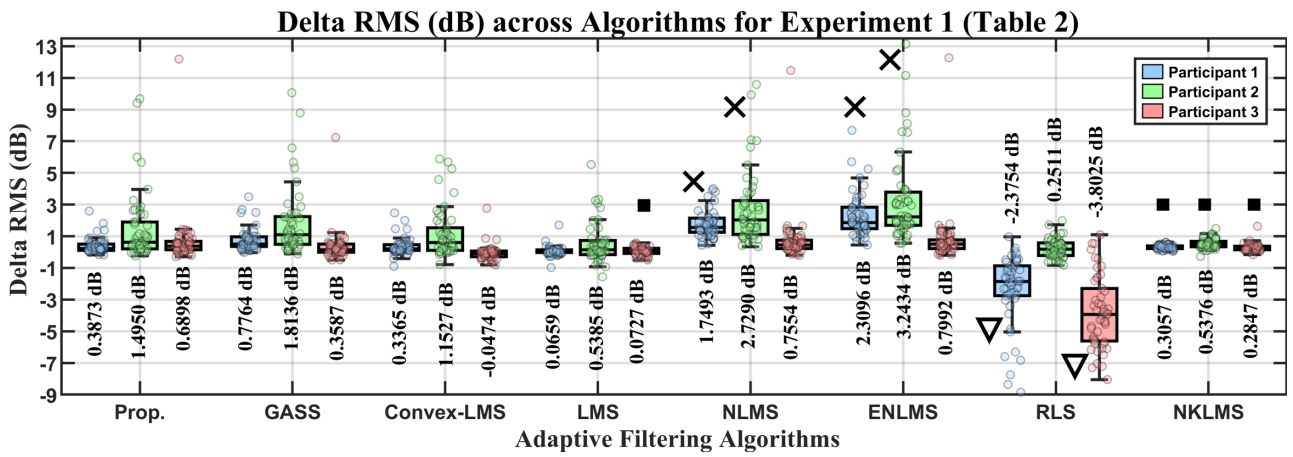


Figure 5-13. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 2 – Exp1).

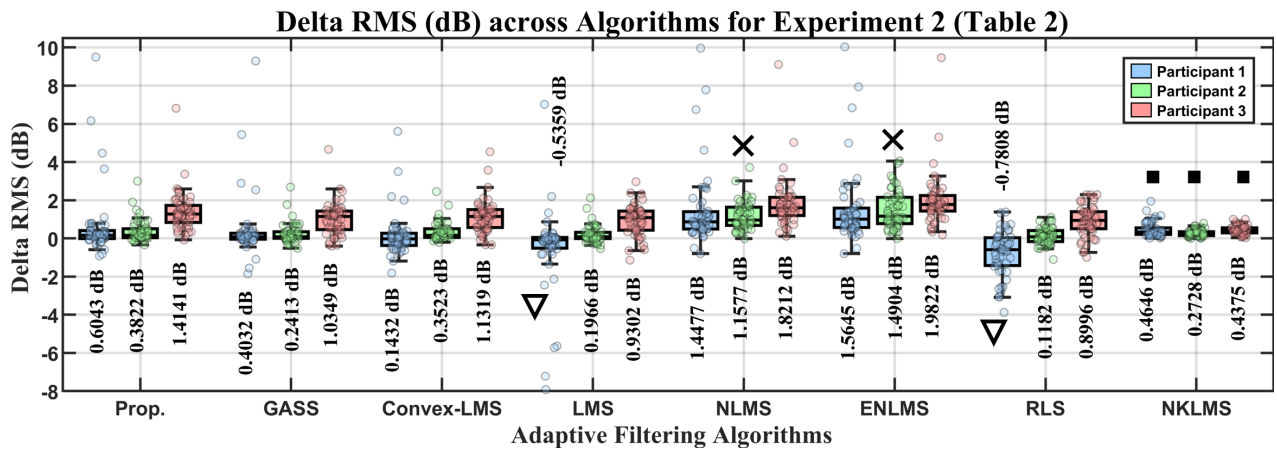


Figure 5-14. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 2 – Exp2).

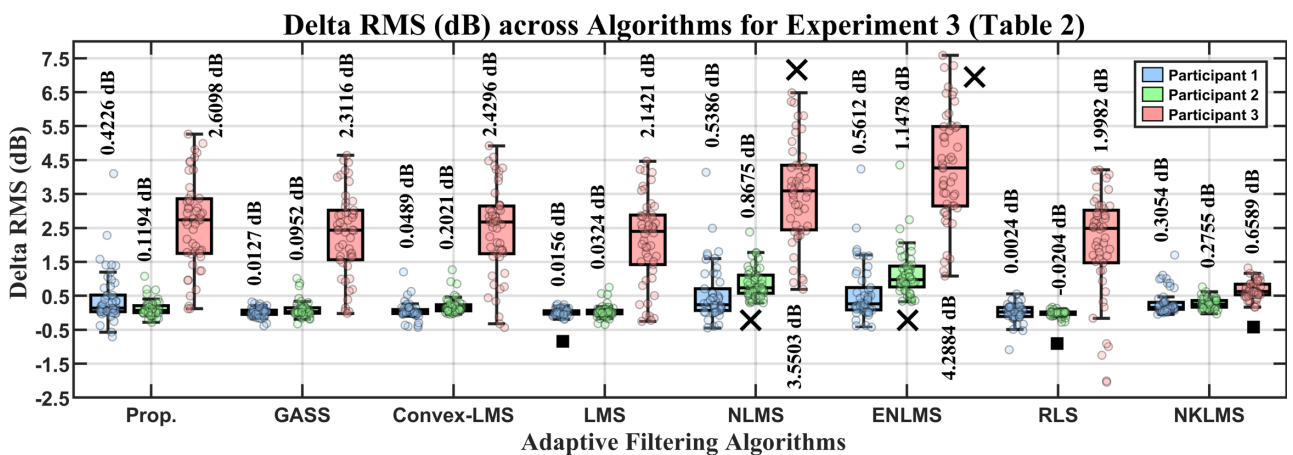


Figure 5-15. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 2 – Exp3).

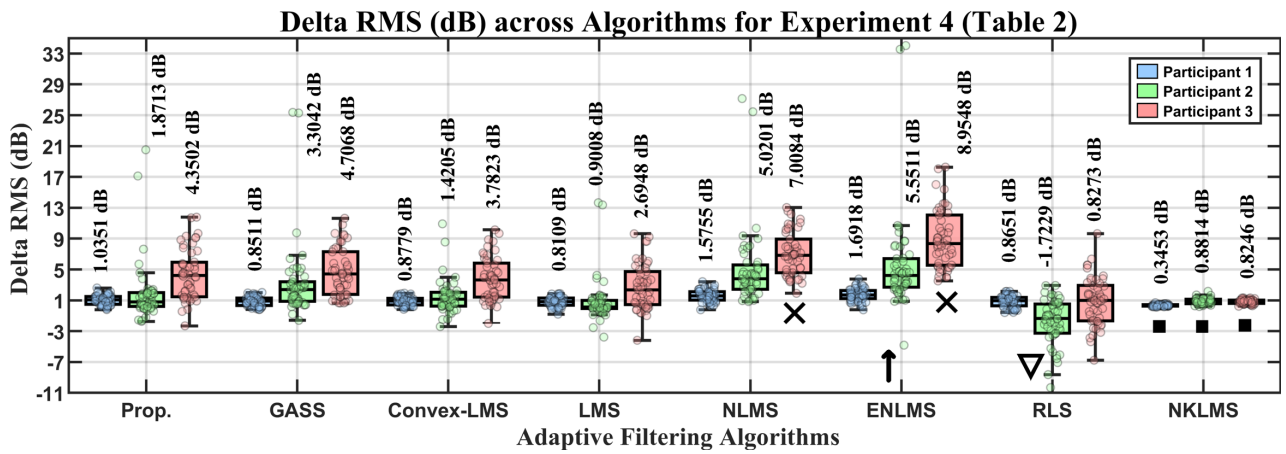


Figure 5-16. Delta RMS box plots comparing the proposed algorithm with seven AFs across participants (Table 2 – Exp4).

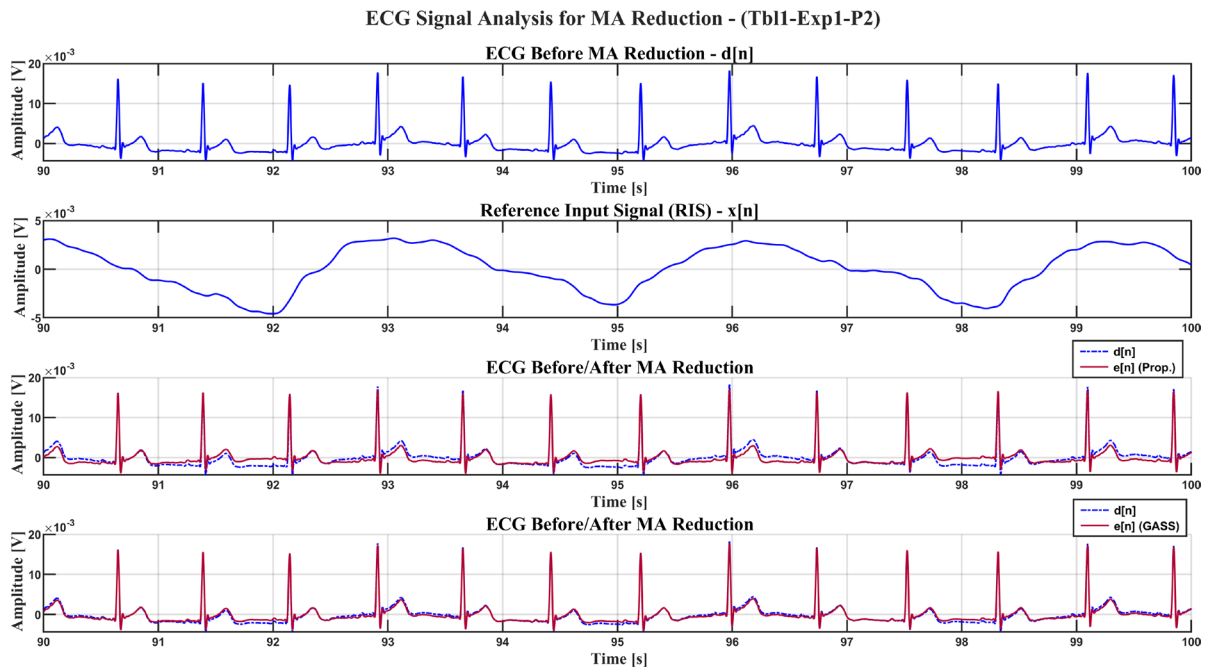


Figure 5-17. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and GASS filters (Tbl1-Exp 4-P2). RIS-MA correlation is observed. Stationary condition with low respiration-induced MA; the proposed AF shows better suppression.

ECG Signal Analysis for MA Reduction - (Tb11-Exp2-P2)

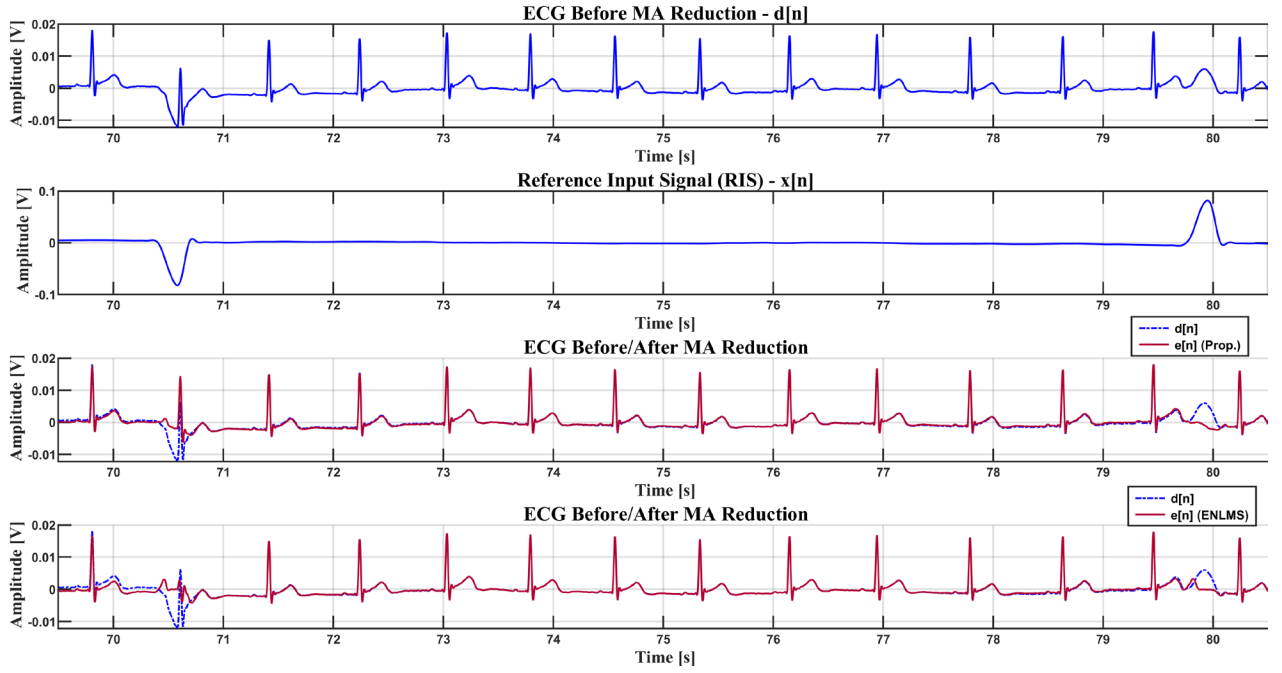


Figure 5-18. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and ENLMS filters (Tb11-Exp 2-P2). High RIS-MA correlation is observed. In the first MA segment, the R-peak is recovered by the proposed AF but lost with ENLMS; in the second, MA is more effectively suppressed by the proposed AF.

ECG Signal Analysis for MA Reduction - (Tb11-Exp3-P1)

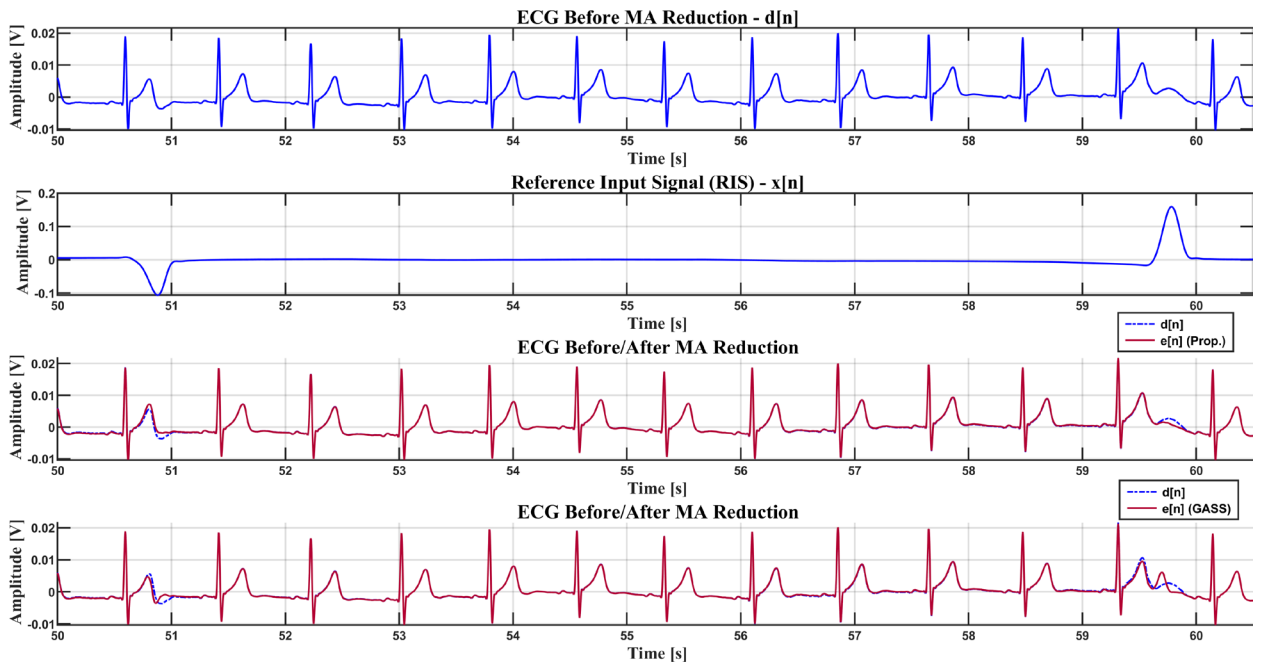


Figure 5-19. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and GASS filters (Tb11-Exp3-P1). High RIS-MA correlation is observed. Despite high RIS amplitude and minimal MA, the proposed AF preserved signal quality, while GASS introduced distortion.

ECG Signal Analysis for MA Reduction - (Tb11-Exp4-P3)

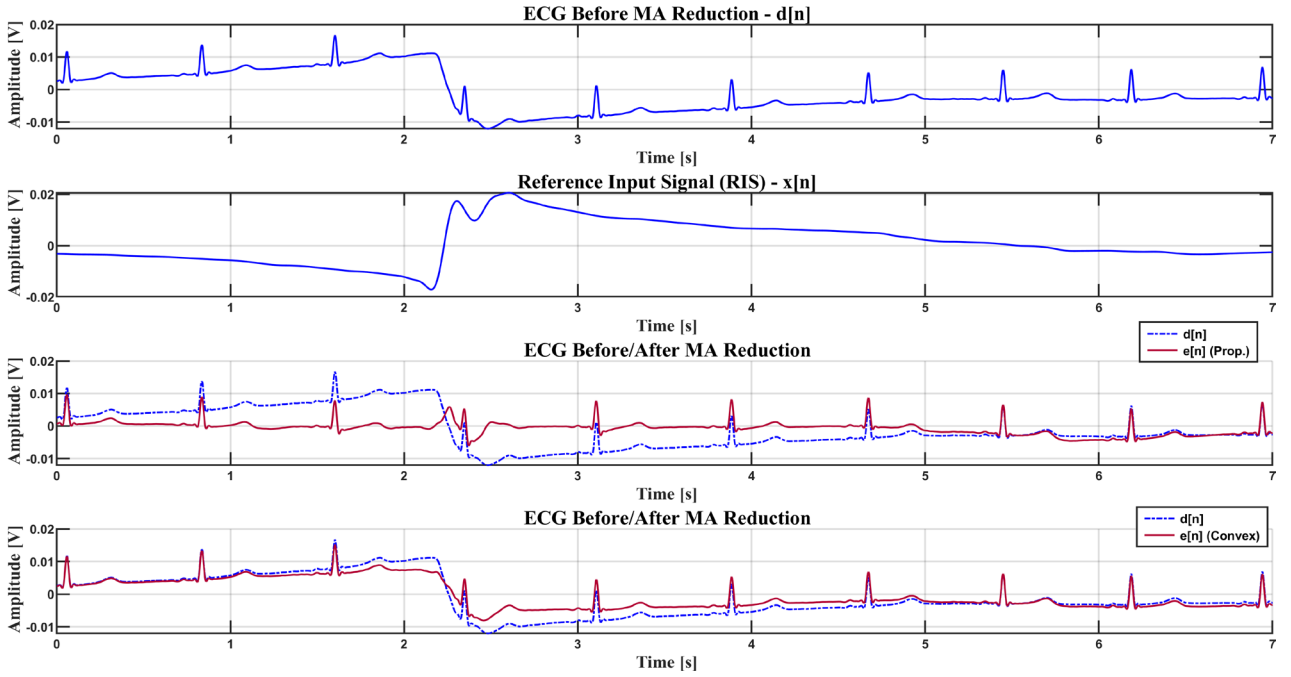


Figure 5-20. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and Convex filters (Tb11-Exp4-P3). High RIS-MA correlation is observed. Prop. High RIS-MA correlation is observed. The proposed AF outperformed Convex, with only minor residual MA remaining.

ECG Signal Analysis for MA Reduction - (Tb11-Exp5-P3)

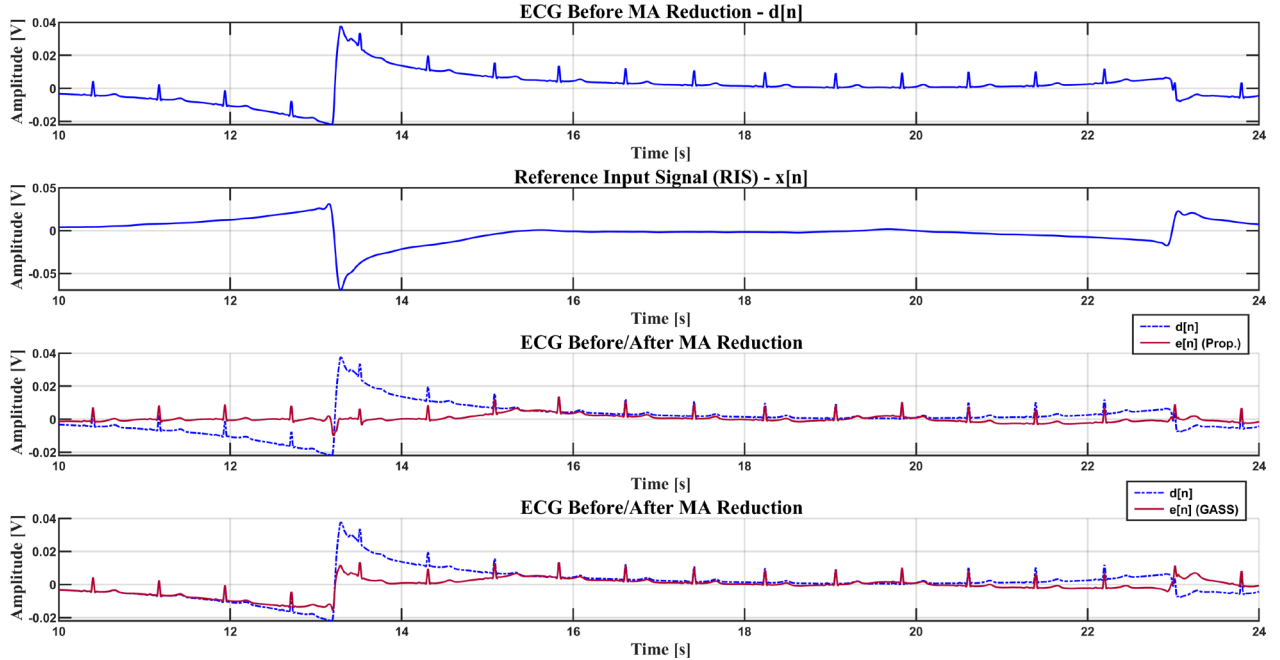


Figure 5-21. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and GASS filters (Tb11-Exp5-P3). High RIS-MA correlation is observed. The proposed AF performed better than GASS, with some residual MA remaining in both motion segments.

ECG Signal Analysis for MA Reduction - (Tb12-Exp1-P2)

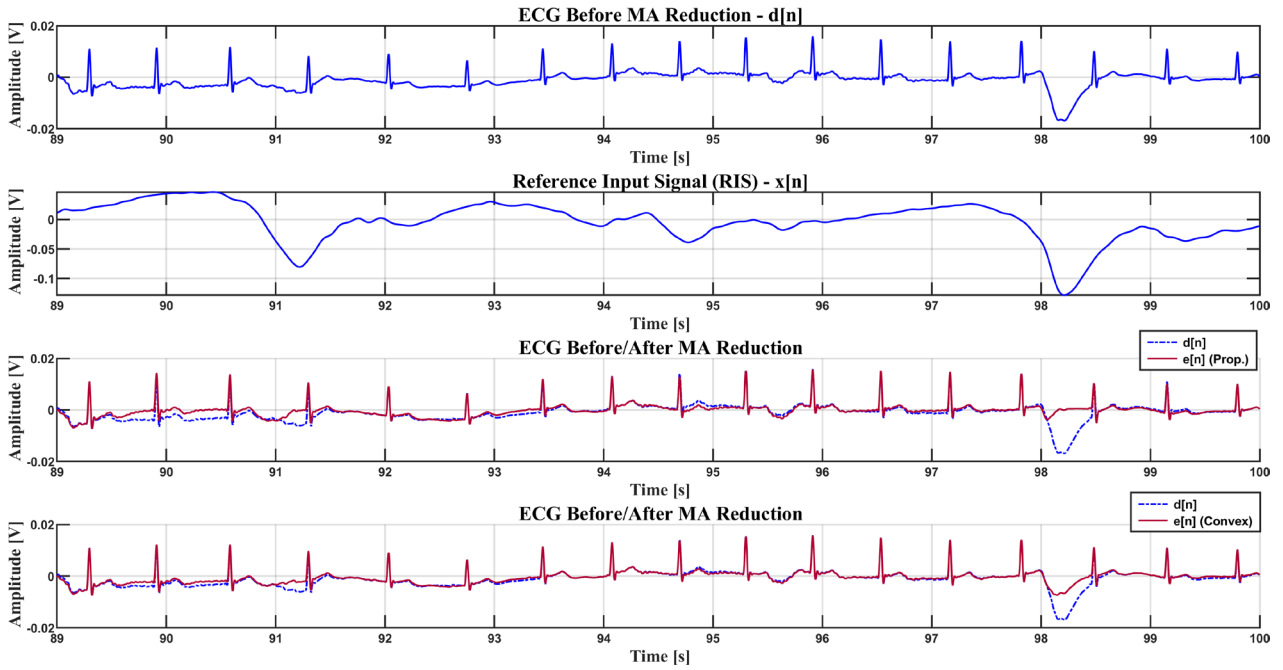


Figure 5-22. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and Convex filters (Tb12-Exp1-P2). RIS-MA correlation is observed. The proposed AF outperformed Convex, especially around seconds 98–99, with some residual MA remaining.

ECG Signal Analysis for MA Reduction - (Tb12-Exp2-P1)

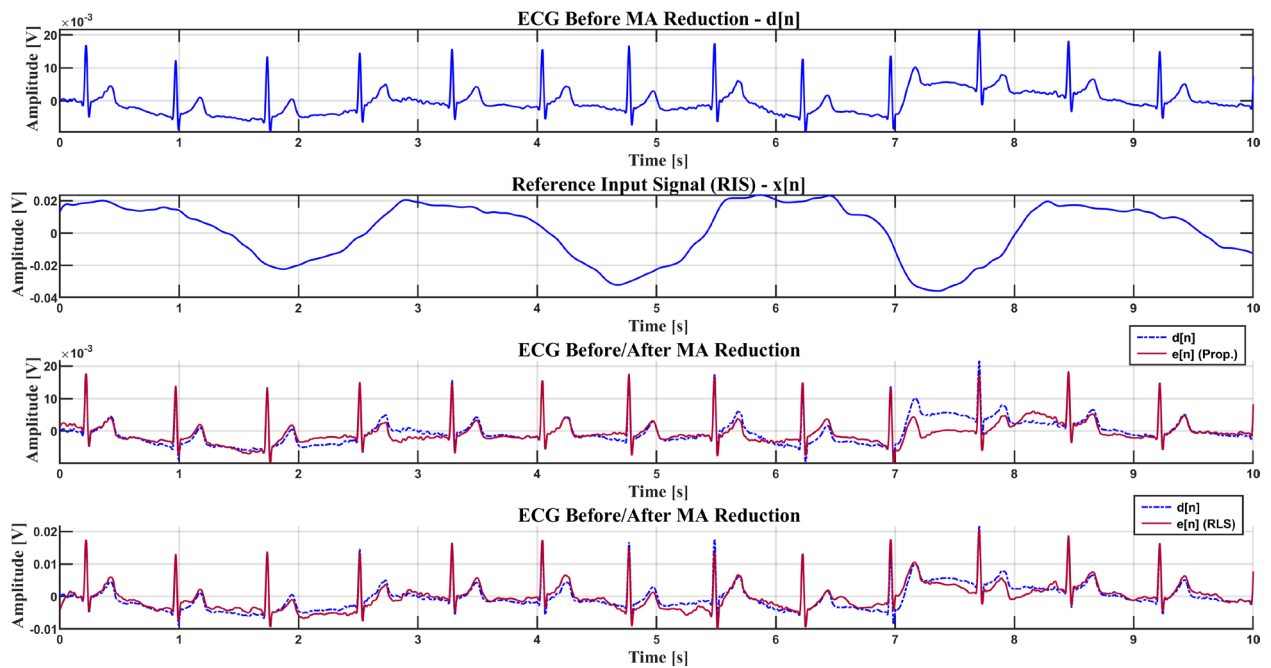


Figure 5-23. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and RLS filters (Tb12-Exp2-P1). RIS-MA correlation is observed. The proposed AF outperformed RLS, which showed stability fluctuations; minor residual MA remained with the proposed AF.

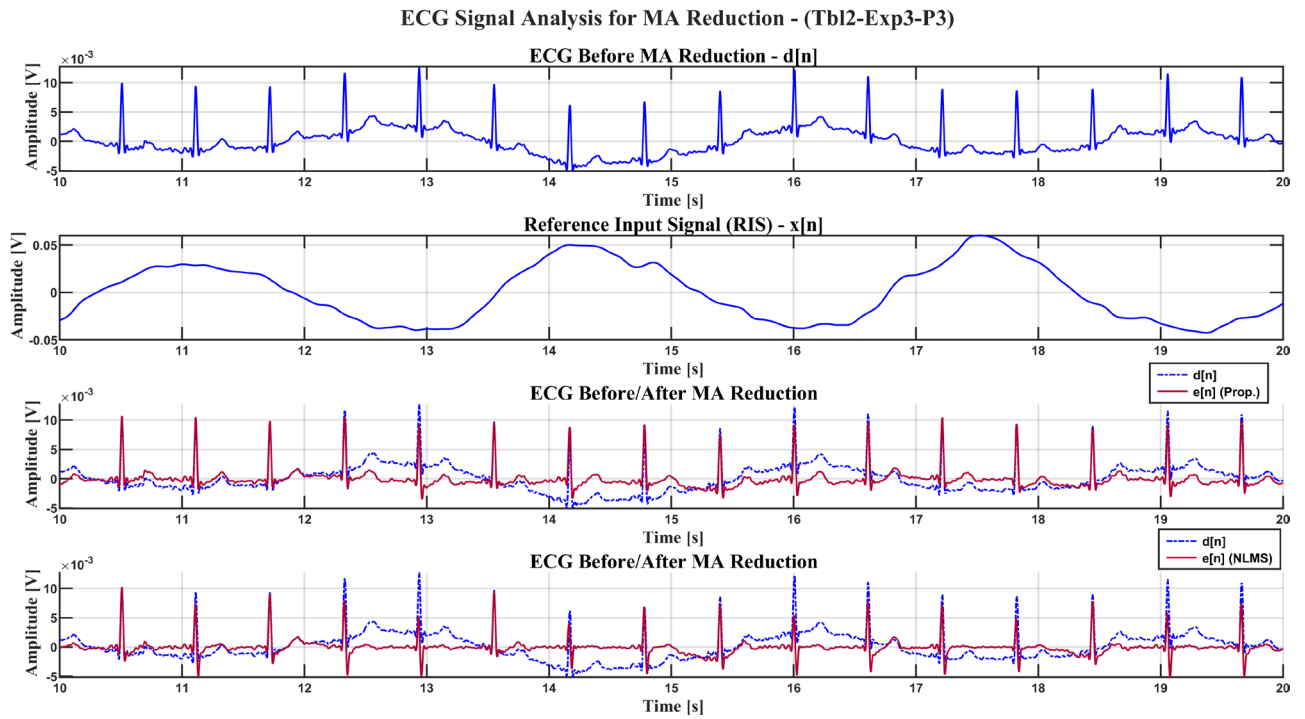


Figure 5-24. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and NLMS filters (Tbl2-Exp3-P3). High RIS-MA correlation is observed. The proposed AF outperformed NLMS, which caused distortion in P, T, and R wave morphology.

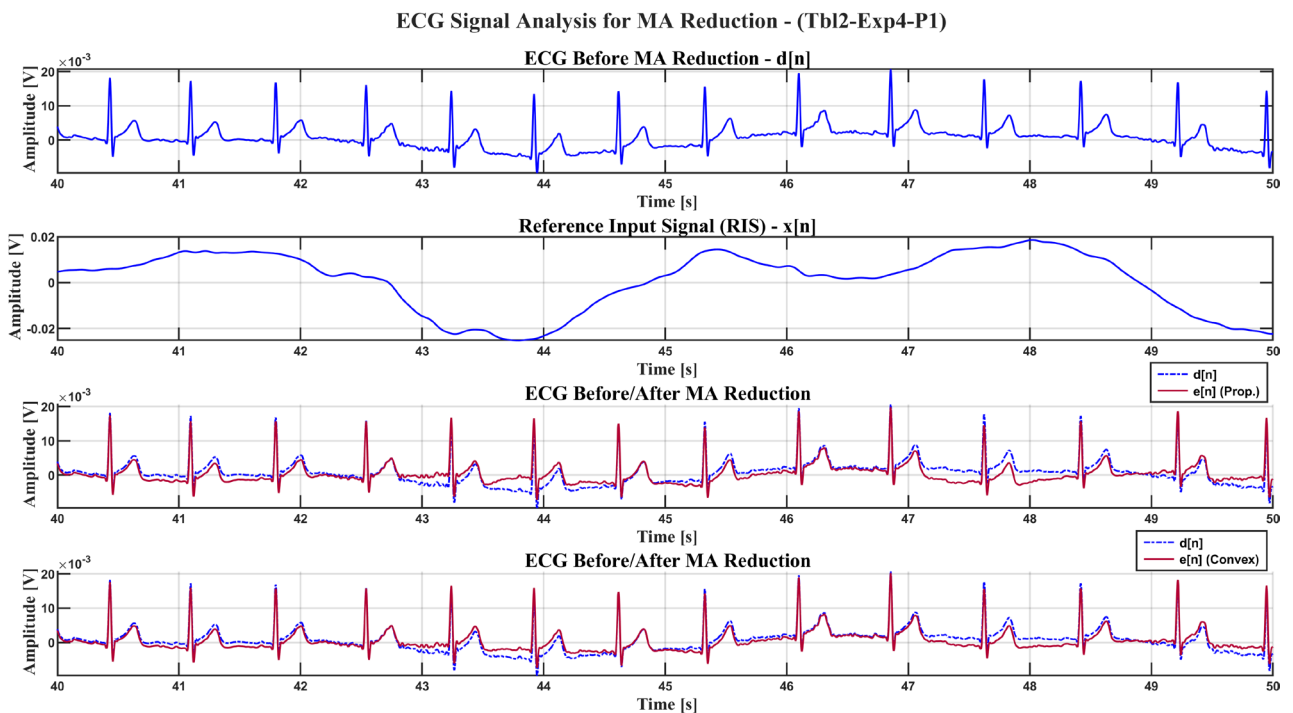


Figure 5-25. Selected signal plots showing $d[n]$, $x[n]$, and ECG before/after filtering with the proposed and Convex filters (Tbl2-Exp4-P1). RIS-MA correlation is observed. With minimal MA present, the proposed and Convex AFs performed similarly.

5.7 Discussion and Future Work

5.7.1 Performance Interpretation Based on Quantitative and Qualitative Results

Careful comparison of the delta RMS box plots (quantitative) and signal plots (qualitative) reveals essential insights. These are summarized below and provide context for evaluating the behavior of different AFs under various motion conditions.

Key Observations:

1. Minimal MA – Accurate Performance Differentiation

In low-artifact cases (e.g., Tbl1-Exp1-P1/3, Tbl1-Exp3-P1, Tbl1-Exp4-P1, Tbl2-Exp4-P1), delta RMS box plots show values clustering near zero for all filters, apparently implying negligible differences. However, slight but meaningful differences become apparent when examining the signal plots more closely. For instance, in Figure 5-19, despite clearly visible high RIS power, the MA was low and the proposed algorithm successfully preserves ECG integrity through correlation-based modulation; relying solely on power-based boosting would have distorted the signal. This is evident in the GASS algorithm, which introduces visible distortion. Conversely, in another situation showing low MA, Figure 5-25 demonstrates comparable performance between the proposed and Convex-LMS algorithms perform comparably well, confirming their robustness in minimal-artifact conditions.

To clarify specific issues in adaptive filter performance, symbols are introduced within the delta RMS box plots (Figure 5-8 to Figure 5-16):

2. Poor Performance Due to Ineffective Step-Size or Adaptation Strategy (marked with ■ in box plots)

In contrast to the previous condition, in this case only the AFs with ineffective step size or poorly tuned adaptation parameters exhibit inadequate MA suppression ($\text{delta RMS} \approx 0$), marked explicitly with ■, while the box plots of other AFs are noticeably shifted toward positive values, indicating meaningful RMS improvement. Notably, LMS, NKLMS, and occasionally RLS and GASS frequently fell into this category, as evident from the box plots. LMS suffers from fixed step-size limitations, NKLMS is sensitive to kernel width, and RLS critically depends on the forgetting factor γ . These misconfigurations severely restrict filtering efficacy.

3. Instability-Induced Fluctuations (marked with ▽ in box plots)

Instability appears as predominantly negative delta RMS scatter points, marked explicitly with ▽ in box plots. Instabilities differ in intensity and frequency, sometimes only affecting short signal segments. RLS, and

occasionally LMS, demonstrated such fluctuations. For example, Figure 5-23 vividly illustrates minor fluctuations occurring between 1–2 seconds, significantly reducing signal reliability. In contrast, the proposed algorithm consistently exhibits stable performance without such fluctuations.

4. Spike Artifacts Due to Instability (marked with ↑)

Spike artifacts, appearing as extreme negative delta RMS outliers and marked with ↑, were particularly prominent for ENLMS, NLMS, and NKLMS. Signal plots confirm these spike artifacts, clearly highlighting episodes of instability that compromise reliability.

5. Morphological Distortion Due to Over-Adaptation (marked with ×)

Over-adaptation leads to substantial delta RMS improvements at the expense of ECG waveform integrity, marked explicitly with × in the box plots. This phenomenon was especially prominent for ENLMS and NLMS. Signal plots (Figure 5-18 and Figure 5-24) explicitly demonstrate compromised ECG morphology (notably distorted P-wave, T-wave, and R-peaks), underscoring the need for balanced artifact suppression and signal fidelity. The proposed algorithm successfully maintains this balance, suppressing artifacts without compromising critical waveform features.

6. General Trends Across Remaining Cases

All specific patterns and behaviors observed in the plotted signals were thoroughly analyzed, and the remaining cases can be interpreted as follows. Other situations, where higher delta RMS can be used to compare the performance of different AFs, are evaluated by examining the box plots and their corresponding scatter points. Filters whose box distributions are more strongly shifted toward positive values, with greater point density in the positive region, generally exhibit superior performance, clearly indicating improved results without significant distortions or instability.

Summarizing the above observations clearly highlights the limitations and strengths of the investigated adaptive algorithms. LMS, NLMS, ENLMS, and NKLMS frequently struggled due to parameter rigidity or instability, manifesting as poor suppression, spikes, or waveform distortion depending on artifact intensity. RLS demonstrated theoretical strength but frequent instability in practical contexts. GASS and Convex-LMS performed overall better than other AFs but exhibited inconsistency across different experiments. To further highlight the advantages of the proposed algorithm over GASS and Convex-LMS, specific signal plots were selected to illustrate these differences more clearly. For instance, Figure 5-17 shows a stationary condition with respiration-induced MA, where the proposed algorithm preserved waveform integrity more effectively.

In Figure 5-20 to Figure 5-22, both Convex-LMS and GASS failed to adequately suppress MAs, whereas the proposed method achieved noticeably cleaner ECG signals. Overall, it is evident that the proposed VSS-LMS-CPB algorithm, employing Correlation-Power Boosting with automatic μ_0 adaptation, consistently demonstrated robust suppression across diverse MA intensities, effectively removing artifacts while preserving ECG waveform integrity, as clearly illustrated in both quantitative box plots and qualitative signal plots.

5.7.2 Comparison with Prior Work

Comparison with prior studies is constrained by differences in evaluation methodology, system design, development stages, and the nature of induced MAs. This work focused specifically on capacitive ECG systems, with a full-stack approach, from electrode development and simultaneous RIS/ECG acquisition to adaptive filtering.

Although we benchmarked the proposed AF against seven established adaptive algorithms, direct comparisons with prior work remain challenging. Many studies isolate algorithm development using benchmark datasets [158, 178], which support inter-study comparisons but ignore real-world hardware variability. Meanwhile, recent capacitive ECG studies often neglect MAs altogether [36, 179, 180]. To address this gap, we compared our system's key features against existing platforms (see Table 5-5). Most prior setups were tested under stationary conditions or limited MA scenarios, frequently with a single subject, and typically emphasized R-peak detection and RR interval calculation using metrics like per-peak SNR. In contrast, our two experimental sets covered nine scenarios, including both stationary postures and active MAs, across three participants. The proposed method preserved full ECG morphology, including P, QRS, and T waves, under most conditions.

5.7.3 Methodological Advantages and Future Directions

Overall, the VSS-LMS-CPB algorithm demonstrated superior robustness, adapting its step size dynamically to handle both high- and low-intensity MAs. It maintained stability, avoided spikes, preserved morphology, and consistently outperformed traditional filters.

Some limitations remain. In certain experiments, the RIS exhibited low correlation with MA, suggesting that integrating additional sensors (e.g., optical skin stretch sensors, 3-axis or 6-axis accelerometers) could enhance motion detection and RIS accuracy.

Additionally, remaining MAs in selected segments motivate further work on parameter optimization or AI-based strategies, such as reinforcement learning, neural-network-guided step-size modulation, or meta-learning frameworks, to improve adaptation in complex, nonstationary environments.

Table 5-5. Comparison of key features between the proposed system and existing capacitive ECG platforms.

Study	IEEE TBME'15 [41]	IEEE TBCAS'14 [66]	Sensors' 23 [128]	IEEE TIM' 22 [12]	IEEE TBME' 22 [100]	IEEE TIM' 19 [37]	Sensors' 19 [181]	Sensors' 16 [26]	This work
Electrode configuration	1 cECG ¹ chest sensor over clothing + 1 galvanic reference	Single-lead belt on chest (fabric n/s)	2 conductive-fabric electrode sets under cotton shirt (snap bandage)	Single capacitive electrode on phantom	3-lead Einthoven, bandaged over cotton shirt	Single-lead elastic belt on chest over cotton shirt	Single-lead II, non-contact seat + holding fabric electrode	2 sensors cECG ¹ (for ECG) + 2 cECG ¹ sensors (for RIS); chair/driver seat	Single-lead dry cECG ¹ electrodes (cotton-covered) on chest
MA-suppression alg.	ANC (Identification scheme)	ANC (LMS)	ANC (type n/s)	Mechanical actuator (AM modulation)	Discrete-wavelet denoising	ANC (NLMS)	EWT WT ² +	ANC(APA ³)	ANC (proposed VSS-LMS-CPB)
RIS acquisition	Injection voltage tracking	Injection current tracking	Extra electrode channel (novel structure)	—	—	Extracted from PLI	—	Adjacent cECGs ¹	Injection voltage tracking(new configuration)
Participants (n)	1	1	1	0	7 (M ⁴)	5 (M ⁴)	3	Indoor 4 (M ⁴); outdoor 6 (M ⁴)	3 (2 M ⁴ , 1 F ⁵)
Experiment types	Stationary	Push/pull; lateral	Stepping in place (1 m s ⁻¹)	Test bench/phantom	Stationary	Stationary; trunk ±15°	Static limbs; free-hand motion	Seated/random motion (indoor); driving (outdoor)	Electrode & skin MA; physical activity
Evaluation Metrics	Artifact-Reduction (dB), visual	RMS, STD; visual	ΔSNR; visual	P-P amplitude vs. WECG ⁶	CC ⁷ vs wet ECG; RR/QRS/P/ST; visual	SNR; compute cost; visual	Qualitative time/freq review	R-peak sensitivity & precision; combined (Se + P+)	CORR1/2; RMS vs 7 filters; visual

¹Capacitive ECG electrode

² Empirical Wavelet Transform and Wavelet Thresholding

³Affine Projection Algorithm

⁴Male

⁵Female

⁶Wet ECG electrode

⁷Correlation

5.8 Conclusion

This study proposed and validated a capacitive single-lead ECG measurement system capable of simultaneously acquiring ECG and a highly correlated RIS with MAs using a torso-worn chest strap. The RIS was carefully assessed across two experimental sets involving three participants, simulating realistic daily usage scenarios. CORR1 scatter plots revealed consistently strong RIS-MA correlations, frequently nearing 1.0, with the highest mean correlation observed as 0.866; however, correlation levels were lower in some low-motion or minimal-MA conditions.

Limitations of existing AFs were investigated, prompting the introduction of a novel adaptive algorithm, VSS-LMS-CPB, designed explicitly to address identified shortcomings. A comprehensive evaluation of the entire proposed system demonstrated its robustness across multiple participants and experiments. Moreover, detailed benchmarking against seven established AFs confirmed the superior performance of the proposed AF, combining Correlation-Power Boosting with automatic μ_0 adaptation, in dynamically adapting step size, maintaining consistency, effectively managing intra- and inter-experiment MA variability, adapting robustly to fluctuating RIS-MA correlations, maintaining stability without fluctuations, avoiding spike artifacts, preserving ECG morphology without over-adaptation distortion, and successfully tracking abrupt, high-amplitude MAs. The proposed system effectively suppressed MAs, notably achieving an RMS improvement of up to 11.12 dB and significantly reducing correlation from 0.866 to 0.107.

Nonetheless, some limitations remain. Lower RIS-MA correlation in certain scenarios suggests potential benefits from integrating additional sensing modalities to enhance RIS accuracy. Furthermore, residual MAs open opportunities for further enhancement via advanced parameter tuning or intelligent adaptive strategies. Future studies could beneficially explore artificial intelligence approaches to address these challenges.

Chapter 6 Discussion, Future Directions and Conclusions

6.1 Overview

This chapter reviews the research aims and objectives, summarizes the key findings, and outlines the contributions to knowledge. This is followed by a discussion of the implications of these findings. Finally, the chapter highlights the study's limitations and provides recommendations for future research.

6.2 The Fulfilment of the Research Objectives

The aim of this study was to reduce motion artifacts (MAs) in non-contact electrocardiogram (ECG) recording systems. Capacitive ECG (cECG) measurement systems have emerged as a promising alternative to traditional wet or dry electrodes, offering the benefits of non-invasiveness, improved long-term comfort, and integration into wearable or ambient health-monitoring devices. Beyond managing cardiovascular diseases, cECG systems are increasingly explored for applications in stress detection, mental health monitoring, and human-machine interaction, making them a versatile tool for both clinical and wellness-oriented contexts. These advantages make cECG systems highly suitable for out-of-hospital and continuous monitoring scenarios.

However, their sensitivity to MAs remains a major challenge. MAs have become a critical concern in capacitive ECG measurement due to the variable electrode-tissue impedance and the presence of various interference sources, which often degrade signal quality and limit clinical reliability. Therefore, reducing MAs is essential to fully realize the potential of capacitive ECG systems in real-world applications.

6.2.1 Objective 1: Demonstrating the Feasibility of Capacitive ECG Acquisition from Alternative Body Sites to Broaden Its Application Scope and Motivate Further Research

Chapter 2 reports the successful demonstration of using capacitive electrodes for ECG monitoring from the neck, highlighting its practical value in applications where chest-based monitoring is difficult or contraindicated, such as in patients with burns, post-surgical wounds, or injuries to the chest. Additionally, neck-based ECG acquisition enables integration into wearable systems for use in emergency care, and in environments requiring head-mounted devices, such as virtual reality systems, military helmets, or industrial safety gear.

A systematic evaluation of various head and neck locations identified the neck as the most promising site for capacitive ECG acquisition. This region provided a signal-to-noise ratio (SNR) of 14.25 dB and enabled the detection of multiple ECG waveform components beyond R-peaks. The ease of placing electrodes on the neck

also makes this approach particularly valuable for emergency and critical care scenarios, where quick deployment is essential.

Beyond its relevance for cardiovascular monitoring, neck-based capacitive ECG also holds potential for mental health assessments, expanding its diagnostic value. Furthermore, it presents a practical solution for patients with chest injuries, post-surgical recovery, or burns, where traditional electrode placement on the chest is either difficult or contraindicated.

Integrating capacitive ECG into wearable formats, such as neckbands or necklace-style devices, may allow seamless long-term monitoring in daily life. This work broadens the application scope of capacitive electrodes and emphasizes the need for continued research and address remaining challenges, such as MAs.

6.2.2 Objective 2: Comprehensive Understanding and Analysis of Motion Artifacts in Capacitive ECG Systems

Chapter 3 presents a structured investigation of MAs within cECG measurement systems. While cECG is recognized as a promising non-intrusive alternative to traditional contact-based methods, enabling long-term and wearable monitoring, its reliability remains hindered by motion-induced signal degradation. Maintaining diagnostic accuracy comparable to clinical-grade systems remains a major challenge due to the dynamic and often unpredictable nature of the body-electrode interface.

MAs arise primarily from variations in electrode-tissue impedance (ETI) and the influence of external interferences. However, despite being widely acknowledged, the definitions, mechanisms, and origins of MAs have often lacked consistency across the literature. To address this knowledge gap, Chapter 3 presented a structured and comprehensive review of existing models of MAs, offering insight into their underlying causes and classifications.

Additionally, the chapter critically examined current MA mitigation strategies across three major domains: analog circuitry, electrode fabrication, and digital signal processing (DSP). Special emphasis was placed on adaptive filtering approaches utilizing ETI-based Reference Input Signals (RIS), which have gained increasing attention in recent research.

By combining insights from existing models and mitigation strategies, Chapter 3 established a theoretical foundation for the development of improved capacitive ECG systems. It also identified the limitations of current approaches in finding a RIS that is highly correlated with MAs, as well as challenges in designing the adaptive filter itself, and emphasized the need for advancements in these areas to effectively reduce MAs.

6.2.3 Objective 3: Developing an Optimized Method for Extracting an ETI-Based Reference Input Signal Highly Correlated with the Characterized MAs

Chapter 4 describes the development and validation of a capacitive single-lead ECG measurement system integrated into a chest strap, alongside a MA reduction strategy customized to its design. The system's performance was first validated under stationary conditions by comparing the acquired ECG signals to those obtained using a buffered reference electrode configuration placed on two regions of the torso. The proposed system demonstrated excellent signal quality, with clearly visible ECG waveforms, a correlation coefficient exceeding 0.947, and a mean squared error (MSE) below 0.104, indicating negligible motion interference.

To address MAs in dynamic conditions, an MA-reduction algorithm was developed based on a detailed characterization of MA-generation mechanisms specific to the bipolar capacitive setup. The analysis revealed that increasing the coupling capacitance and selecting a higher bias resistor significantly improved ECG signal quality and enhanced the correlation between the RIS and the actual MA which is an essential requirement for adaptive filtering. A bias capacitor was further introduced to enhance the efficiency of high-frequency voltage injection through the bias resistor, thereby simplifying the analog front-end while preserving signal performance.

It was also demonstrated that injecting in-phase high-frequency signals into each electrode, and using the real part of the demodulated signal as the RIS, was critical for achieving effective MA suppression. The proposed approach was experimentally validated using three motion-induction protocols, including electrode pushing and pulling actions. In each case, the distorted ECG segments were effectively reconstructed. Comparisons with baseline signals and signals filtered using a 0.67 Hz high-pass filter highlighted the superiority of the adaptive approach.

Performance was evaluated using multiple metrics. The correlation between the raw ECG signal and the RIS (CORR1) remained consistently high across all experiments; the correlation between the raw ECG signal and the estimated MA (CORR2) closely tracked CORR1; and the correlation between the reconstructed ECG signal and the RIS (CORR3) confirmed the success of MA suppression. Quantitative improvements in RMS, standard deviation (STD), and per-peak SNR (17.9 dB / 650.2%, 4.24 dB / 36.8%, and 2.8 dB / 15%, respectively) provided additional validation of the method's effectiveness.

These results confirmed that the proposed system successfully met the study objectives of precise MA characterization, optimized RIS extraction, and comprehensive performance validation, thereby advancing the development of capacitive ECG systems capable of high-quality signal acquisition under motion conditions.

6.2.4 Objective 4: Designing a High-Performance Adaptive Filtering Algorithm with Consistent Intra- and Inter-Experiment Performance, and Validating the Overall System Across Diverse MA Scenarios Involving Multiple Participants

Chapter 5 presents the design, implementation, and validation of a capacitive single-lead ECG measurement system integrated into a torso-worn chest strap, capable of simultaneously acquiring ECG signals and a motion-correlated RIS. The RIS was thoroughly evaluated across two experimental sets involving three participants, each designed to simulate realistic daily chest-strap usage. Correlation between raw ECG signal and the RIS (CORR1) demonstrated consistently strong RIS-MA correlations, with mean values frequently approaching one and reaching a maximum average correlation of 0.866. Nonetheless, some experiments exhibited lower correlation values, reflecting the variability of MA behavior across different scenarios and underscoring the challenges of maintaining consistent performance in real-world conditions.

To address the limitations observed in existing adaptive filters (AFs), a novel algorithm, Variable Step-Size Least Mean Square with Correlation-Power Boosting (VSS-LMS-CPB), was developed. This filter was specifically designed to overcome common shortcomings in conventional AFs. These include the fixed step-size constraint in algorithms like LMS and NLMS, which often leads to a trade-off between convergence speed and steady-state error; the limited generalization capability of filters such as LMS based filters across different motion types or participants; and the instability seen in filters like RLS when the correlation between the reference signal and MAs varies over time.

A comprehensive evaluation of the complete system, including both hardware and algorithmic components, confirmed its robustness across diverse motion conditions and participant variability. Comparative benchmarking against seven state-of-the-art adaptive filters established the superior performance of VSS-LMS-CPB. Notably, the proposed algorithm dynamically adapted its step size based on real-time correlation and power trends, preserved ECG morphology without over-adaptation or distortion, suppressed spike artifacts, and consistently tracked abrupt, high-amplitude MAs.

The system achieved substantial artifact suppression, with RMS improvement reaching up to 11.12 dB, and correlation between the contaminated ECG and RIS reduced from 0.866 to 0.107, indicating effective MA

removal. These results validated both the high intra- and inter-experimental consistency of the system and the effectiveness of the proposed adaptive filter in realistic, multi-user applications.

6.3 Research Contributions Summary

This PhD research delivers several significant contributions that collectively advance the field of cECG monitoring and address the longstanding challenge of MAs:

1. **Demonstrated the feasibility of capacitive ECG acquisition from unconventional body regions**, specifically the head and neck, thereby broadening the application scope of cECG systems and providing viable alternatives to traditional chest-based configurations. While most prior studies investigating ECG monitoring from the head and neck have focused primarily on R-peak detection and evaluated performance using R-peak-specific metrics such as Peak Sensitivity (PSNS), Peak Accuracy (PACC), and Positive Predictive Peak Value (PPPV) [46–48, 51, 52], this study extends the analysis beyond R-peaks to demonstrate the potential for capturing additional ECG features, including the P and T waves.
2. **Performed a structured review of MAs in capacitive ECG systems**, analyzing their origins, modeling approaches, and mitigation techniques across analog circuitry, electrode design, and digital signal processing (DSP), with a focused assessment of ETI-based reference strategies. A notable gap in the literature is the lack of a unified source that consolidates the diverse definitions, modeling perspectives, and mitigation strategies for MAs into a comparative framework [23, 28, 32, 62]. To address this, we presented a detailed and integrative review of MAs, covering their origins, their specific effects on ECG signal morphology, and the contributing factors reported in previous studies, thereby advancing the foundational understanding needed for effective artifact mitigation.
3. **Designed and implemented a wearable single-lead capacitive ECG system capable of simultaneously acquiring ECG and ETI-based RIS highly correlated with MAs, suitable for realistic ambulatory use.**

While MAs are widely recognized as a major limitation in capacitive biopotential measurement systems, prior studies have often overlooked or underestimated this interference. For example, Wang et al. [64] identified high body-electrode impedance as the primary issue and proposed a negative impedance circuit to compensate for it. Zompanti et al. [98] attributed interference solely to electromagnetic-induced common-mode signals and addressed this through driven right leg (DRL) circuits and filtering. Moving forward, Serteyn et al. [41] modeled MAs in their simplified single-electrode configuration while avoiding

a single-lead design, such as the one proposed in this PhD study. Moreover, they selected a small formed coupling capacitor between the body and the electrode based on their configuration. In contrast, our measurements showed significantly higher coupling capacitance, which, when combined with a high bias resistor, enabled a simplified MA model and finally the extraction of a highly correlated RIS with the MA. To address output attenuation caused by voltage injection, we introduced a bias capacitor. Unlike Serteyn et al., this component improved output voltage stability, eliminated frequency dependency at higher frequencies, and enabled us to avoid the complexity of using current sources, as required in the method by Torfs et al. [66]. Moreover, Torfs et al. employed a 180° out-of-phase sine wave injection in a differential system to extract an ETI-based signal. However, we demonstrated that in-phase injection is necessary to obtain an RIS directly proportional to the MA. Torfs et al. did not explicitly model MAs, which led to poor and inconsistent correlation in their extracted signal.

Xu et al. [37], building on Serteyn's model, used 50 Hz demodulation to extract an RIS reflecting variations in coupling capacitance. However, due to insufficient preprocessing of the RIS and the lack of an explicit link to the modeled MA, their approach captured not only MA-related changes but also unrelated variations in power-line interference amplitude, which limited its accuracy. Other studies, such as those by Lee et al. [147] and Pholpoke et al. [38], used dry electrodes with slightly different equivalent circuit models and did not address the phase shift of the demodulated signal. These are critical aspects that we specifically targeted in our approach.

Moreover, most prior systems aimed at mitigating MAs in capacitive ECG setups were evaluated under stationary conditions or in limited motion scenarios, often involving a single participant. These studies typically focused on R-peak detection or RR interval analysis and relied on metrics such as per-peak SNR to assess performance [12, 26, 37, 41, 66, 100, 128, 181]. In contrast, our two experimental sets covered nine distinct motion scenarios, encompassing both static postures and dynamic MAs, and were conducted across three participants.

In summary, this study:

- Introduced an efficient voltage-injection technique for RIS extraction.
- Theoretically modeled and practically extracted an ETI-based RIS within a single-lead capacitive ECG measurement configuration, showing strong correlation with actual MAs.
- Validated the extracted RIS across diverse motion scenarios and multiple participants.

4. **Proposed and validated a novel adaptive filtering algorithm, Variable Step-Size LMS with Correlation-Power Boosting (VSS-LMS-CPB).** This filter was specifically developed to address key limitations of conventional AFs. These include the rigidity of fixed step-size configurations, limited generalizability across varying experimental conditions, and instability problems.

The algorithm is designed with the following key features:

- Dynamic step-size adaptation
- Correlation-power-based step-size boosting
- Automatic baseline step-size adjustment
- Preservation of ECG morphology
- Stability and spike artifact avoidance
- Superior tracking of abrupt MAs

Together, these contributions strengthen the technical foundation and clinical relevance of capacitive ECG technology, bringing it closer to robust deployment in real-world, wearable, and out-of-hospital health monitoring applications.

6.4 Research Limitations and Recommendations for Future Research

Chapter 2 explored the feasibility of capacitive ECG acquisition from the head and neck regions, demonstrating promising signal quality and practical advantages in seated, resting conditions. However, this setup did not allow for the observation or analysis of MAs, which are common in real-world scenarios involving activities such as head movement, jaw clenching, and swallowing. These types of motion can significantly affect signal integrity, especially when electrodes are positioned on dynamic anatomical regions. Therefore, before this configuration can be optimized for clinical or daily-life applications, further investigation involving a wider range of experiments is required to characterize MAs under diverse head and neck activities and postures. Another key limitation for Chapter 2 was the small sample size, as data were collected from only one participant, limiting the generalizability of findings. Future work should involve a broader and more diverse participant pool to evaluate inter-subject variability in signal morphology, noise characteristics, and electrode-tissue coupling. Such studies will help refine placement strategies, increase robustness across users, and support the development of general-purpose systems.

To facilitate a more application-oriented approach and reflect common practice in wearable health monitoring, the research was redirected to focus on chest-strap configurations, which are more widely adopted and better suited for continuous ambulatory monitoring. Chapters 4 and 5 therefore focused on capacitive single-lead ECG measurement systems integrated into a chest strap. These chapters adopted a full-stack approach, spanning electrode development, simultaneous ECG and RIS acquisition, and adaptive filtering.

Despite the proven effectiveness of the proposed system in suppressing MAs, limitations remain. In certain trials, the extracted RIS exhibited low correlation with the actual MAs. This suggests that relying solely on ETI-based reference signals may not always be sufficient, particularly during complex, multi-segment body movements or in the presence of slow baseline drift. To address this, future research should explore multi-modal sensing by integrating complementary sources, such as 3-axis or 6-axis inertial measurement units (IMUs), optical skin-stretch sensors, or accelerometers, to improve the RIS-MA correlation. Combining multiple modalities could provide a more comprehensive motion signature, enabling more accurate artifact tracking and suppression.

Additionally, although the proposed adaptive filter maintained high stability, effectively suppressed MAs, and outperformed seven established alternatives, residual artifacts were still observed in some segments in Chapter 5. This highlights the need for further enhancements to improve adaptability in non-stationary environments, enable real-time parameter tuning, and increase generalization across different participants and motion types. To address these challenges, future work could explore intelligent, data-driven frameworks, such as reinforcement learning for real-time adaptation, meta-learning to facilitate cross-subject generalization, or neural network-guided strategies for dynamic step-size modulation.

6.5 Conclusion

This PhD research demonstrated the feasibility and effectiveness of capacitive ECG systems for both conventional and alternative body sites, addressing the persistent challenge of MAs through systematic hardware and algorithmic innovations. Across four research objectives, a complete system was developed capable of acquiring high-quality ECG and motion-correlated RIS and effectively suppressing MAs using a novel adaptive filtering algorithm.

Although the proposed adaptive filter was benchmarked against seven established algorithms and outperformed them across multiple metrics, direct comparisons with prior studies remain limited. Many previous works either relied on simulated datasets or neglected real-world motion variability, often testing

under stationary conditions with a single participant and focusing only on R-peak detection. In contrast, this study covered nine realistic experimental scenarios across three participants, preserved full ECG morphology, and validated performance across multiple signal quality metrics.

These findings not only validate the practicality of capacitive ECG sensing for chest-based configurations but also lay the groundwork for deploying such systems in unconventional regions, such as the head and neck. This enables future designs of wearable form factors, e.g., VR headsets, smart helmets, or cervical collars, that can monitor cardiac signals non-invasively from previously inaccessible or impractical sites.

Moreover, this research contributes to the wider biomedical and health technology fields by enhancing the viability of capacitive ECG for continuous, long-term, and motion-resilient monitoring. Its potential applications extend beyond clinical use to sports performance tracking, remote patient care, eHealth solutions, and military or occupational settings where comfort, unobtrusiveness, and robustness are critical.

Overall, this work lays a strong foundation for the advancement of capacitive ECG systems, particularly in wearable and ambulatory health monitoring. Future research should expand participant diversity, enhance system robustness, and explore multi-modal sensing and AI-based adaptive filtering to further improve performance under complex, nonstationary conditions.

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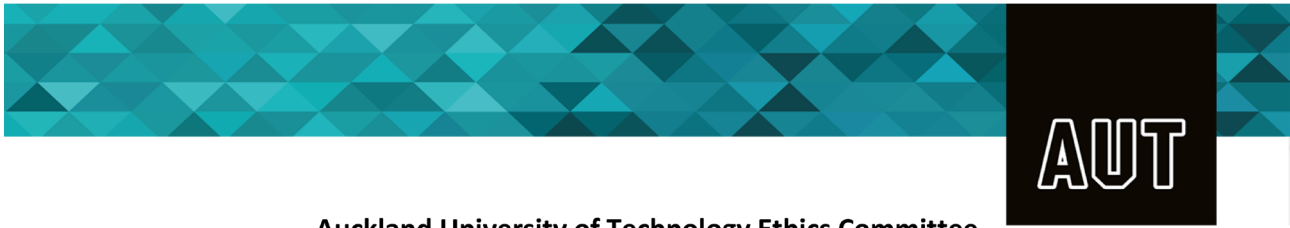
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Appendix A: Ethics Approval



Auckland University of Technology Ethics Committee (AUTEC)

17 July 2024

Andrew Lowe
Faculty of Design and Creative Technologies

Dear Andrew

Re Ethics Application: **24/81 Motion Artifact Reduction in Capacitive Electrodes for ECG Recording Systems**

Thank you for your responses to AUTEC's conditions.

Your ethics application has been approved for three years until 17 July 2027.

Non-Standard Conditions of Approval

1. Please proof read the Information Sheet for spelling and readability.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the [Auckland University of Technology Code of Conduct for Research](#) and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online <http://www.aut.ac.nz/research/researchethics>

For any enquiries, please contact ethics@aut.ac.nz

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat

Auckland University of Technology Ethics Committee

Cc: Matin.khalili@autuni.ac.nz; Hamid.Gholam.Hosseini@aut.ac.nz; matthew.kuo@aut.ac.nz

Appendix B: Tools

a) Participant Information Sheet



Participant Information Sheet

Date Information Sheet Produced:

Version 3: 15 July 2024

Project Title

Motion Artifact Reduction in Capacitive Electrodes for ECG Recording Systems

An Invitation

I am Matin Khalili, currently pursuing a Doctor of Philosophy degree at Auckland University of Technology through IBTec (AUT's Institute of Biomedical Technology). My research focuses on non-contact electrodes for electrocardiogram (ECG) monitoring. I invite you to participate in testing electrocardiogram measurements using a capacitive electrode chest strap device. As a participant, you will wear this device and engage in two sets of experiments. The first set involves applying motion artifacts to the capacitors, such as pulling or pushing electrodes. In the second set, you will perform routine exercises, such as upper body run motion (arms swinging), to simulate everyday movements. This research constitutes a significant aspect of my work and will contribute to my qualification. Your participation is invaluable in advancing our understanding of non-contact electrode technology and its application in ECG monitoring.

What is the purpose of this research?

This research aims to evaluate the performance of the proposed motion artifact reduction technique for use in capacitive ECG recording systems while motion artifact is present.

In cases where the ECG needs to be monitored for a long time, conventional wet/gel electrodes are used, providing accurate measurement. However, this electrode type can lead to skin irritation, require skin preparation, and is designed for disposable one-off application.

Non-contact electrodes, also known as capacitive electrodes or insulated electrodes, offer a solution for long-term ECG monitoring as they do not require skin preparation, do not have a galvanic connection with the skin, and can even be used over fabric clothing. Despite these benefits, non-contact electrodes have the disadvantage of being prone to measurement performance deterioration when the person wearing them is not in a resting or standstill state. This performance deterioration results from motion artifact. Motion artifacts originate from different sources, such as the variation in the position of the electrode relative to the body being monitored. In this case, the variation in the interface gap between the electrode face and the human body modulates the ECG signal due to the variation in coupling capacitance, sometimes making the ECG signal undetectable.

One of the methods for mitigating motion artifacts involves injecting a high-frequency signal into each electrode. By demodulating this signal, a reference signal reflecting variations in the coupling capacitance can be extracted. This reference signal is used to estimate the motion artifacts and subtract them from the ECG signal.

The experiment conducted in the research study covers a range of motion in a controlled environment to collect ECG and the reference signal simultaneously and to mitigate these motion artifacts in the system. The output data from test results will be post-processed and analysed. The aim is to verify the correlation between the estimated reference signal and to evaluate the mitigation technique and enable the broad utilization of non-contact electrodes for long-term ECG monitoring.

The research will aim to answer the following questions:

1. How does the shape of motion artifacts change in different experiments?
2. What is the correlation between the estimated "reference signal" and the motion of artifacts in different experiments?
3. How does this correlation change in different experiments?
4. Based on the introduced performance metrics, how successful is the motion artifact mitigation technique using the estimated "reference signal" and advanced signal processing algorithms in different experiments?

Who is founding this research?

This research is funded by the Ministry of Business, Innovation, and Employment (MBIE), as the primary researcher (Matin Khalili) is the recipient of an MBIE scholarship.

How was I identified and why am I being invited to participate in this research?

The study was advertised via posters around the AUT City campus, providing contact information for the primary researcher, along with a brief description and key details about the research. Interested individuals were invited to voluntarily get in touch. Upon contacting the primary researcher to express your interest in participating, you received this complete information sheet via email.

This information sheet includes the inclusion and exclusion criteria, as well as study procedures, which you need to read carefully. If you are still interested in taking part, please email the primary researcher. The researcher will then contact you to confirm your availability and schedule a time. If you meet all the study criteria, you will be invited to participate.

Inclusion Criteria

- If you are 21-50 years old.

Exclusion Criteria

- If you have had an acute myocardial infarction (MI), a diagnosis of atrial fibrillation (AF), or any known or suspected cardiac dysrhythmias.
- If you are with a pacemaker or defibrillator.
- If you have any other medical condition that is known to be exacerbated, acutely or chronically, by exercise.
- If you state you are not able to use treadmills for any reason.
- If you state you do not feel comfortable wearing a chest strap for any reason.
- If you have open wounds or infected, irritated, or inflamed areas of skin on the chest area.
- If you have allergic skin or known sensitivity to medical adhesives, isopropyl alcohol, fitness-worn devices, or ECG electrodes.
- If you are family or friends of the research team.

How do I agree to participate in this research?

You will be provided with a Consent Form where the conditions to take part in the study will be presented and then, if you agree, you will sign the document. Your participation in this research is voluntary (it is your choice) and whether you choose to participate will neither advantage nor disadvantage you. You can withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible.

What will happen in this research?

You'll be required to visit AUT City IBTec's research area (IBTec research area (WZ618) - WZ Building Level 6, 6 St Paul St, Auckland 1010). Before the experiment starts, you will be provided with a Health Screening Form to assure that there is no impediment to taking part in the study.

During the experiments, you will be wearing two different types of electrode sets: capacitive electrodes in a chest strap, as depicted in Figure 1, and gel electrodes, as illustrated in Figure 2.

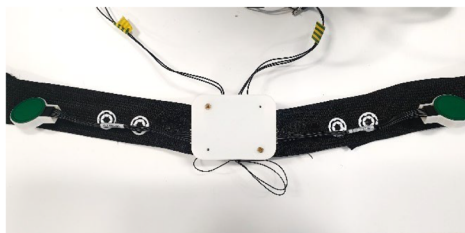


Figure 1 – Non-contact capacitive chest strap.



Figure 2 – Example of gel/wet electrode.

There are two sets of short tests, each distinct from the other and best performed on separate days to avoid your fatigue.

There are two sets of short tests, each distinct from the other and best performed on separate days to avoid fatigue. The first set of tests, shown in Table 1, entails carefully controlled scenarios, allowing for the precise applying of specific motion artifacts on the electrodes. The second set of tests, shown in Table 2, simulates routine bodily motions encountered in daily life. The purpose of these activities is to simulate everyday movements, so they should be performed lightly and at a controlled speed, rather than with intensity.

Table 1. Controlled Motion Artifacts Application Scenarios

Number	MA created	Duration
1	Sitting on a chair with the subject's trunk straight	5 mins
2	Pushing electrodes	5 mins
3	Pulling electrodes	5 mins
4	Twisting electrodes	5 mins
5	Stretching skin around electrodes	5 mins
6	Random generation of artifacts 2-5	5 mins
7	Lateral MAs	5 mins

Table 2. Everyday Activities Simulating Real-World Conditions

Number	MA created	Exercise Instructions	Duration
1	Sitting on a chair with the subject's trunk straight	-	5 mins
2	Up and down arms wing motion	- Stand with your arms at your sides (initial position). - Start. - Wait for 5 seconds. - Raise both arms up and down in a wing-like motion. - Return to the initial position slowly. - Wait for 5 seconds. Repeat this sequence for 5 minutes.	5 mins
3	Upper body run motion (arms swinging)	- Stand with your arms at your sides, elbows bent as if preparing for a run (initial position). - Start. - Wait for 5 seconds. - Extend your right arm forward and your left arm back (mimicking the first movement of running), then return to the initial position slowly. - Wait for 5 seconds. - Extend your left arm forward and your right arm back (mimicking the second movement of running), then return to the initial position slowly. - Wait for 5 seconds. Repeat this sequence for 5 minutes.	5 mins
4	Straight punch motion	- Stand with your arms at your sides (initial position). - Start. - Wait for 5 seconds. - Raise your right arm and mimic punching with it, then return to the initial position slowly. - Wait for 5 seconds.	5 mins

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		6. Raise your left arm and mimic punching with it, then return to the initial position slowly. 7. Wait for 5 seconds. Repeat this sequence for 5 minutes.	
5	Upper body twist motion	1. Stand with your arms on your waist (initial position). 2. Start. 3. Wait for 5 seconds. 4. Turn just your upper body to the right, then return to the initial position slowly. 5. Wait for 5 seconds. 6. Turn just your upper body to the left, then return to the initial position slowly. 7. Wait for 5 seconds. Repeat this sequence for 5 minutes.	5 mins
6	Walking on a treadmill	Simply walk on the treadmill at a speed of 3.5 km/h to simulate normal walking.	5 mins

Before the experiment

- You should wear comfortable light clothes.
- It is suggested if you are a female to wear a sports bra. A T-shirt can be worn on top of the chest straps if it's more comfortable for you.
- Avoid having caffeine and drinking alcohol. You can eat normally.
- You will be provided with a Consent Form that needs to be signed by you before starting the experiment.

Experiment Sequence and Explanation

Electrode placement:

The placement of the capacitive and gel/wet electrodes, along with their reference electrodes, is specified in Figure 3.

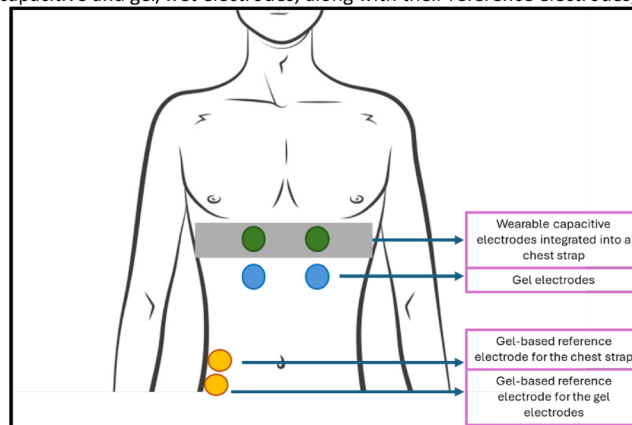


Figure 3 - The placement of the capacitive and gel/wet electrodes

Who places them:

The electrodes are easy to fit to the body. Therefore, you will receive support in fitting all electrode devices on your body, guided by the researcher.

- The primary researcher, Matin Khalili, will handle data recording, management, and participant interaction. Regarding assistance with fitting devices:
 - **If you are female:** The primary researcher (Matin Khalili) is also female, so there is no need for concern.
 - **If you are male:** If you are not comfortable being assisted by a female, please send an email to the researcher. A male researcher in the IBTec group, Usman Shaikh, will be available to assist you.
- **Capacitive electrodes:** Capacitive electrodes are attached to a chest strap that can be worn. The chest strap is shown in Figure 4.

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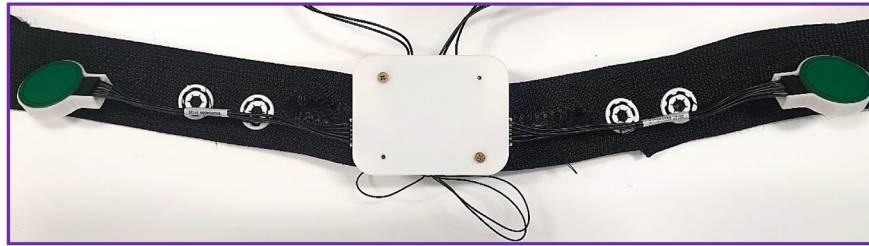


Figure 4 – Capacitive chest strap

- **Gel electrodes:**
The gel electrodes used in this study are shown in Figure 5 and can adhere to the body:



Figure 5 – Gel electrodes

Any skin pre required:

- **Capacitive electrodes:**
None required.
- **Gel electrodes:**
You will be asked to clean the area where the gel electrodes will be attached using alcohol swabs.

Who creates the motion artefact:

- **Capacitive electrodes:**

Since applying motion artifact is quite easy before each type of experiment, you will be instructed on what needs to be done and you apply it yourself.

- **Gel electrodes:**

No motion artifact is created with gel electrodes.

The researcher will explain you each step of the study and how to perform the experiments. Following this, signal recording for each day, based on the processes outlined in Figure 6, will commence. After conducting each test in the sequence, if you require rest, you may do so, and then we will continue.

Please note that the primary researcher has piloted the mentioned task protocols on herself to ensure their suitability for you.

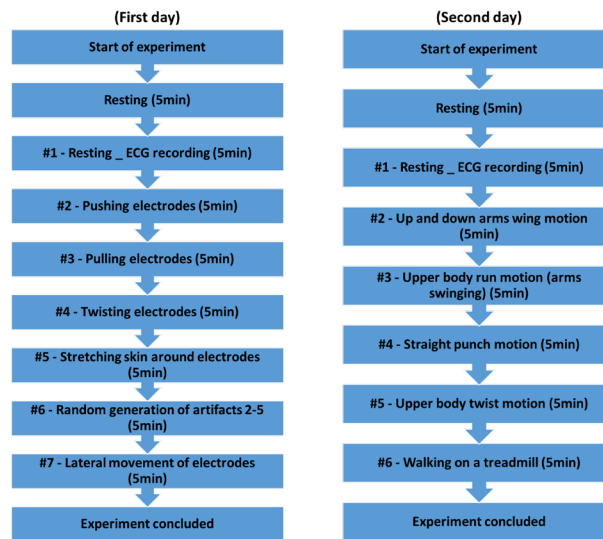


Figure 6 – Experiment sequences steps-by-step.

The researcher will keep track of the time and when the data recording should start or stop.

What process will be followed if any abnormalities are detected in the ECG that suggest a previously undiagnosed condition?

In this study, emphasis is placed on requiring ECG data from a small group of participants to evaluate techniques for mitigating interferences such as motion artifacts. Diagnosis of abnormalities or health problems among participants is not aimed for in this study. However, if any abnormalities are detected in your ECG, you will be informed and recommended to visit a doctor for further evaluation. A copy of the graphical ECG displaying any detected abnormalities is also offered to you if found helpful. If your data is unsuitable for the study, other participants are sought. Otherwise, a discussion is held with you regarding inclusion of your data in the study.

How will these discomforts and risks be alleviated?

The discomfort level is minimal as you will need to wear a chest strap, which is a conventional method for ECG monitoring. If you are female, the primary researcher, Matin Khalili, who is also female, will assist you with electrode placement and wearing the chest strap. If you are male and prefer assistance from a male, Usman Sheikh, a male researcher from the IBTec group, will help you prepare for the test.

The exclusion criteria state that if you have allergic skin, or known sensitivity to medical adhesives, isopropyl alcohol, fitness-worn devices or ECG electrodes should not be part of the study to minimize the risk of skin irritation.

What are the benefits?

You will benefit from this research by having experience with electrocardiogram electrode types that are still in the research stage and not widely available commercially. The researcher will benefit from having the researched non-contact capacitive electrode tested on human participants and achieving a PhD qualification. The wider community will benefit when the non-contact electrode advances to a well-defined robust solution, where more people will have access to a more comfortable and versatile long-term heart monitoring system.

A koha of \$40 gift card will be provided to you after completion of the experiment.

Who the research is of interest to and how the findings of the research will be disseminated to them?

The research findings are of interest to two main groups: researchers aiming to assess the effectiveness of this technique in mitigating motion artifacts in capacitive ECG electrodes for further study, and doctors and clinicians who rely on ECGs for patient diagnosis, seeking more comfortable and accurate measurement methods.

These findings will be disseminated through publication in journal papers and presentation at conferences, ensuring broad access and application among both research and clinical communities.

What compensation is available for injury or negligence?

In the unlikely event of a physical injury as a result of your participation in this study, rehabilitation and compensation for injury by accident may be available from the Accident Compensation Corporation, providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

The collected data will be securely stored. Paper documents will be physically stored in the IBTec archives locker. Digital data will be collected using the primary researcher's laptop and stored in her OneDrive. During data processing, it will remain on the primary researcher's OneDrive. After use, digital data will be removed from the primary researcher's OneDrive and archived with Prof. Andrew Lowe for 10 years. Passwords and restricted physical access will be implemented to protect the data in all environments.

After 10 years, digital data will be deleted from Prof. Andrew Lowe's OneDrive, and paper documents will be shredded and destroyed. Each participant will be assigned an identification number to ensure confidentiality. Age and gender will be included in data presentations as standard practice in research publications, such as stating, "This ECG waveform is from a 25-year-old female/male."

Furthermore, this research does not discriminate or show favouritism based on ethnicity, gender, culture, or religion.

What are the costs of participating in this research?

There is no cost of participating in this research other than your time.

You will be required to complete two sets of experiments over two separate days. Each experiment session will last approximately 1-1.5 hours. Therefore, you can expect your involvement in the research to span 2-3 weeks.

What opportunity do I have to consider this invitation?

After receiving this information sheet, you have 2-weeks (14 days) to reply confirming if you wish to be part of the research or not.

Will I receive feedback on the results of this research?

Yes, you will be provided with a summary of the results of this research.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Prof. Andrew Lowe, andrew.lowe@aut.ac.nz, and +6499219999 Ext.6303.

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTC, ethics@aut.ac.nz, (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:

Matin Khalili, matin.khalili@aut.ac.nz, AUT-WZ Building 5067706, IBTec, WZ903.

Phone number: +64 2041143226

Project Supervisor Contact Details:

Prof. Hamid GholamHosseini, hamid.gholmahosseini@aut.ac.nz, Dr. Matthew Kuo, matthew.kuo@aut.ac.nz, Prof. Andrew Lowe, andrew.lowe@aut.ac.nz

b) Consent Form



Consent Form

Project title: *Motion Artifact Reduction in Capacitive Electrodes for ECG Recording Systems*

Project Supervisor: *Prof. Hamid GholamHosseini, Dr. Matthew Kuo, Prof. Andrew Lowe.*

Researcher: *Matin Khalili*

- ☐ I have read and understood the information provided about this research project in the Information Sheet dated ___/___/202__.
- ☐ I have had an opportunity to ask questions and to have them answered.
- ☐ I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.
- ☐ I understand that if I withdraw from the study then I will be offered the choice between having any data or tissue that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, the removal of my data may not be possible.
- ☐ I have completed Health Screening Checklist.
- ☐ I understand that notes will be taken during the study.
- ☐ I understand that I will be assigned an identification number formatted as Participant_ID_Gender_Age, such as Participant_1_m_25, to ensure confidentiality.
- ☐ I understand that my gender and age may be used in data presentations.
- ☐ I understand that the data collected may be used for future academic publications, with the assurance that only my age and gender will be disclosed to ensure confidentiality, such as in the statement: 'These signals are measured from a 25-year-old male/female.'
- ☐ I give permission to use information or research for research purposes such as conference presentations and publications.
- ☐ I agree to take part in this research.
- ☐ I wish to receive a copy of my individual results (please tick one): Yes ☐ No ☐

Participant's name:

Participant's Contact Details (if appropriate):

.....
.....

For researcher use only.

Participant ID:

Participant's signature:

Date: ___/___/____. (dd/mm/yyyy)

Approved by the Auckland University of Technology Ethics Committee on *type the date on which the final approval was granted* AUTEK Reference number *type the AUTEK reference number*

Note: The Participant should retain a copy of this form.

c) Health Screening Checklist



Health Screening Checklist

This checklist is to identify any condition that may affect the study protocol and participation in the research. It will not be communicated to any party other than the research team and will be stored under Data Management Plan Guidelines.

Instructions: Fill in the checkbox ☐ to answer Yes or No for each of the statements below.

Item		Yes	No
1.	I have had an acute myocardial infarction (MI).	☐	☐
2.	I have had a diagnosis of atrial fibrillation (AF).	☐	☐
3.	I have a known or suspected cardiac dysrhythmia.	☐	☐
4.	I have a pacemaker or defibrillator	☐	☐
5.	I have a medical condition that is known to be exacerbated, acutely or chronically, by exercise.	☐	☐
6.	I am not able to use treadmills for any reason.	☐	☐
7.	I do not feel comfortable wearing a chest strap for any reason.	☐	☐
8.	I have open wounds or infected, irritated, or inflamed areas of skin on the chest area	☐	☐
9.	I have allergic skin or known sensitivity to medical adhesives, isopropyl alcohol, fitness-worn devices, or ECG electrodes.	☐	☐

Declared age:

Declared Gender:

Participant's signature:

Date: __/__/____. (dd/mm/yyyy)

For researcher use only.

Participant ID:

Appendix D: Publications From Thesis

- a)* **Manuscript 1:** Khalili M, GholamHosseini H, Lowe A (2026) Electrocardiogram Monitoring From the Neck Using Capacitive Electrodes. J Eng Sci Med Diagn Ther 9:011102. <https://doi.org/10.1115/1.4068149>.
- b)* **Manuscript 2:** Khalili M, GholamHosseini H, Lowe A, Kuo MMY (2024) Motion artifacts in capacitive ECG monitoring systems: a review of existing models and reduction techniques. Med Biol Eng Comput. <https://doi.org/10.1007/s11517-024-03165-1>



Electrocardiogram Monitoring From the Neck Using Capacitive Electrodes

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The monitoring of electrocardiogram (ECG) signals is crucial for both cardiac health and mental state assessment. Traditional ECG methods rely on chest electrodes; however, they pose challenges for individuals with chest injuries or burns and can cause discomfort over extended use. Capacitive electrodes offer a noncontact method, which is particularly beneficial for wearable applications, providing a comfortable and feasible alternative for long-term use. Findings suggest that neck-based monitoring can achieve effective ECG signal acquisition, reducing motion artifacts in certain configurations and potentially expanding the application of ECG for heart and mind monitoring. Additionally, using the neck area for diagnosing specific conditions could collect more information. This study explores the feasibility and advantages of using capacitive electrodes for ECG monitoring from the head and neck area. [DOI: 10.1115/1.4068149]

Keywords: electrocardiogram (ECG), noncontact ECG, long-term bio signal tracking, nonhospital ECG applications, neck-based ECG, patient comfort

1 Introduction

Electrocardiogram (ECG) monitoring is an essential tool in diagnosing and managing cardiac health, enabling the detection of arrhythmias, ischemia, and other heart-related issues [1]. Traditional ECG monitoring typically relies on wet electrodes placed on the chest, which allow for a direct electrical connection through conductive gel [2]. While effective, this approach has limitations, especially in cases where patients have, making contact-based electrodes uncomfortable or impractical. Additionally, conventional setups may not be ideal for continued monitoring due to the need for frequent reapplication of conductive gel, which can dry out, leading to inconsistent reading.

As the demand for remote and continuous cardiac monitoring grows, so does the need for alternative electrode technologies and placements that simplify monitoring and enhance patient comfort. Capacitive electrodes, which work without direct skin contact, address many limitations of traditional electrodes, particularly in wearable device applications. Locations, such as the head and neck areas, increasing their practical applications. For instance, in cases of serious injuries, like severe burns to the torso, accurate placement on the chest may be challenging or even impossible. Gard et al. [3] reported that at their regional burn center, which serves about 500 patients annually, chest burns accounted for 21% of admissions in both 2020 and 2021. In such cases, the head or neck areas offer viable alternatives for ECG monitoring.

Furthermore, early detection of cardiac events could be possible by continuously monitoring changes in cardiac activity patterns, providing a potential warning system before a heart attack occurs.

For nonhospital settings, a wearable device that combines clinical accuracy with a discreet design—especially one worn around the head or neck and connected to the cloud via smartphone—is ideal [4]. Such a device could also be integrated into furniture, like bed accessories, for nighttime monitoring [5].

Recent advancements in wearable technology have enabled continuous monitoring of biopotentials across various activities. In sports like cycling and motor racing, as well as in military applications, helmets with embedded sensors can conveniently monitor vital biosignals [6].

Beyond cardiac health, ECG monitoring from these areas holds potential for stress assessment. For stress assessment, several methods exist. Common approaches include self-reported questionnaires, biomarker analysis (such as adrenaline and cortisol levels), behavioral patterns, and physiological metrics like heart rate and skin conductivity [7]. Stress, an inherent aspect of daily life, can induce a hyperarousal state, resulting in subconscious neuroendocrine responses that alter respiration, muscle tone, and heart rate [8]. Like health monitoring, stress assessment benefits from long-term biosignal tracking outside of clinical environments. In this context, the head and neck areas show promise for stress monitoring.

Recent studies have highlighted the importance of measuring ECG from nontraditional locations, such as the neck and head, for improving cardiac monitoring accessibility and reliability. The Necklace-ECG device has demonstrated high sensitivity and specificity in detecting atrial fibrillation using a single-lead wearable ECG sensor positioned between the palm and chest, providing an alternative to traditional chest-based ECG measurements [9]. Another study explored neck-based ECG monitoring, emphasizing its advantages in detecting arrhythmias and palpitations, particularly in response to stress, exercise, and medication. The posterior neck region benefits from increased neural activity and enhanced electrode conformability, making it suitable for high-quality ECG signal acquisition [10]. Additionally, ear-based ECG monitoring has

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been investigated for seamless integration into wearable devices, showing strong agreement with traditional lead I ECG measurements and demonstrating feasibility for real-world applications, such as cardiac monitoring during driving tasks [11]. These studies collectively highlight how measuring ECG from the neck and head can enhance wearable cardiac monitoring by enabling continuous, comfortable, and effective ECG acquisition in various real-life scenarios.

While capacitive electrodes and nontraditional ECG placements have been independently studied, their integration remains under-explored. Existing research on capacitive electrodes has primarily focused on chest-based applications, while neck-based ECG studies have predominantly used wet or dry electrodes, which require firm skin contact. The combination of capacitive electrodes with head and neck ECG monitoring could bridge this gap, offering a noninvasive, comfortable, and effective alternative for both cardiac and stress monitoring, which is rarely found in the literature.

This study aims to explore the feasibility and effectiveness of capacitive electrodes for ECG acquisition from the head and neck, assessing their signal quality and practical applications in an initial stage.

2 Capacitive Electrodes as a Novel Approach

Long-term ECG monitoring plays a crucial role in diagnosing and managing chronic cardiovascular diseases, as well as in assessing mental health states through heart rate variability [12,13]. Capacitive electrodes represent a noncontact alternative to traditional ECG electrodes, measuring electric fields rather than relying on direct electrical conduction [14]. By detecting the displacement currents generated by heart activity, capacitive electrodes allow for indirect ECG signal acquisition. The noncontact nature of capacitive electrodes makes them highly suitable for integration into wearable devices, which can be embedded into clothing, accessories, or even furniture [15].

The advantages of wearable technology are particularly significant in patient-centered healthcare, as it reduces the need for frequent hospital visits and enhances healthcare management [16]. The ability to use capacitive electrodes in nontraditional locations, such as the neck, further enhances their practicality, as the neck can provide stable signal acquisition points while avoiding the challenges associated with chest-based monitoring for ambulatory ECG measurements.

3 The Potential of the Head and Neck Area for Electrocardiogram Monitoring

The head and neck areas are more easily accessible than the chest, especially in emergency or critical care situations where quick

electrode placement is essential. This reduces setup time and improves patient comfort. Placement in these areas can also be more comfortable for long-term monitoring, particularly for patients who find chest-based electrodes unpleasant.

Traditional chest-based ECG setups are often affected by motion artifacts (MAs) due to chest movements, especially during physical activities. Figure 1 demonstrates the influence of body movement on the recorded ECG signal using a capacitive chest-strap. The first part exhibits baseline wander, which can be filtered out using a high pass filter to obtain a clean signal. In the second part, the QRS complex is completely masked by MAs, but it can potentially be restored using state-of-the-art MA removal techniques. However, in the saturation region, the amplifier becomes saturated, resulting in a signal that is entirely lost and cannot be reconstructed. In contrast, neck-based monitoring can result in reduced MAs since neck movements tend to be less disruptive to electrode positioning. This makes neck-based

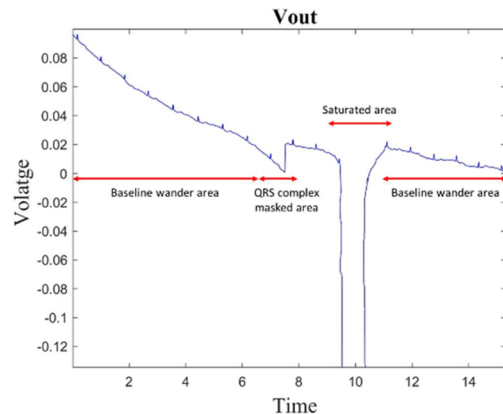


Fig. 1 Electrocardiogram signal captured from a capacitive measurement system using a chest strap during body movements

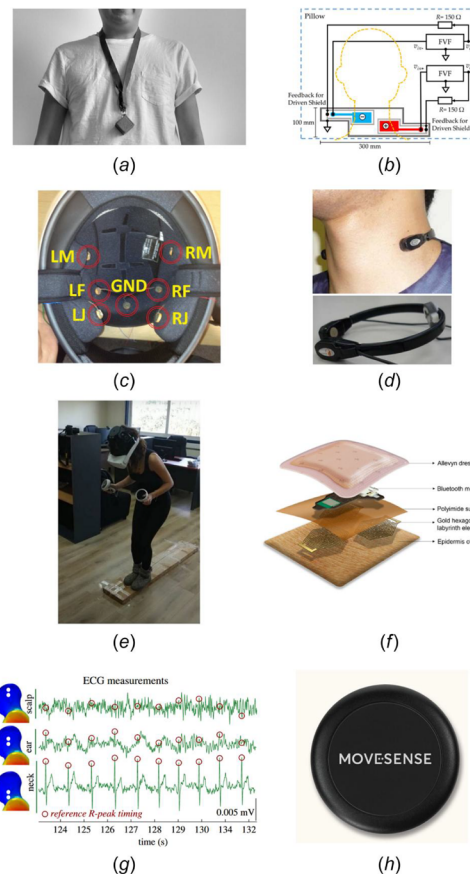


Fig. 2 (a) Necklace developed for continuous ECG monitoring [4], (b) smart pillow designed to detect both cough-associated electromyogram and ECG [5], (c) smart helmet capable of measuring biopotentials such as EEG and ECG [6], (d) neckband designed for ECG monitoring to assist in stress and anxiety management [13], (e) using virtual reality headsets while measuring biopotentials [8], (f) schematic of the wearable and wireless dry electrode ECG device attached onto the skin [10], (g) recorded ECG traces from the scalp-, ear-, and neck-ECG channels from a single subject [11], and (h) Movesense medical (MD) sensor [19]

monitoring particularly suitable for physically active individuals, as it offers a more stable baseline signal.

Moreover, for individuals recovering from surgeries, burns, or other medical conditions affecting the chest, ECG measurement presents several challenges, including chest palpation, lead adherence and removal, and signal conduction. Each of these factors requires a modified approach based on the burn severity and healing stage [3,17]. In these cases, head or neck areas can serve as possible replacements for ECG measurement.

Monitoring ECG signals from the neck could significantly aid in diagnosing atrioventricular nodal reentrant tachycardia (AVNRT). A study involving 370 patients identified that clinical variables, particularly the sensation of neck palpitations, are crucial indicators for AVNRT diagnosis. Notably, this symptom was the only significant predictor of AVNRT when positive ECG findings were absent [18].

The integration of ECG sensors into head- and neck-worn devices, such as necklaces, collars, patches, helmets, and headsets has expanded its potential applications. Researchers have explored various designs, including:

- A wearable ECG necklace for continuous cardiac monitoring, capable of detecting early cardiac abnormalities (Fig. 2(a)) [4].
- A smart pillow that simultaneously monitors cough-associated electromyogram and ECG during sleep, assisting in the

diagnosis of asthma and chronic obstructive pulmonary disease (Fig. 2(b)) [5].

- A smart helmet designed for biopotential measurement (ECG and electroencephalogram (EEG)) in applications such as sports, motor racing, and military use (Fig. 2(c)) [6].
- A neckband with dry electrodes developed for stress and anxiety detection, which identifies R-peaks in ECG signals (Fig. 2(d)) [13].
- Virtual reality headsets that integrate ECG and EEG monitoring for real-time stress assessment, allowing experimental simulations that would be impractical or unsafe in real life (Fig. 2(e)) [8].

Additionally, several emerging wearable ECG technologies further highlight the feasibility of head- and neck-based monitoring:

- Elango et al. developed a three-electrode wearable ECG sensor with dry hexagonal labyrinth electrodes, enabling continuous chest and neck monitoring. The design enhances skin contact and signal acquisition, making it effective for detecting arrhythmias and palpitations caused by stress, exercise, or medication. It is wireless, lightweight, and suitable for integration into wearable fabrics, demonstrating comparable performance to a 12-lead Welch Allyn ECG monitor (Fig. 2(f)) [10].

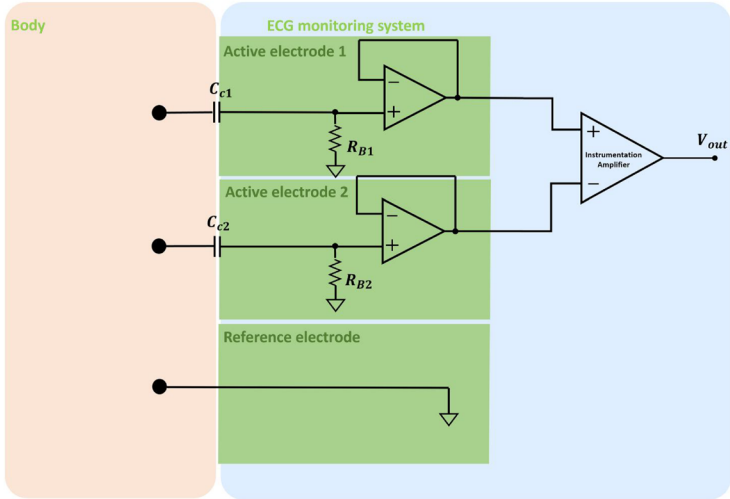


Fig. 3 Capacitive ECG measurement system

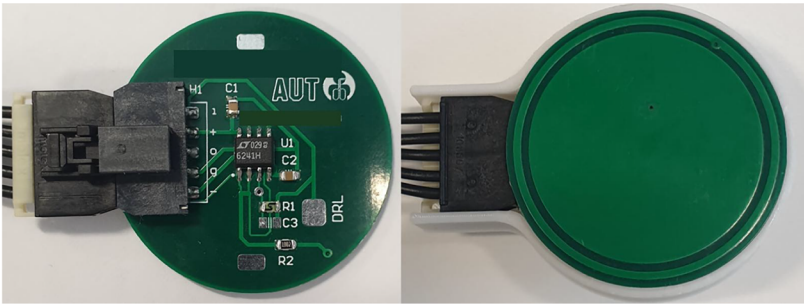


Fig. 4 Active capacitive electrode

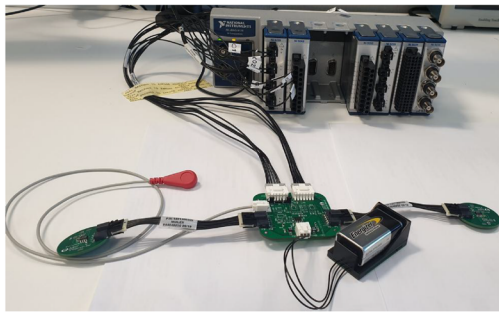


Fig. 5 Electrocardiogram measuring setup

- Ear-based ECG monitoring leverages wearable devices to track cardiac rhythms with high correlation to standard Lead I ECG, showing minimal amplitude and timing deviations. Tested in long-duration driving simulations, it proves feasible for real-time cardiac monitoring in everyday activities (Fig. 2(g)) [11].
- The Movesense medical (MD) sensor is a wearable, single-lead ECG device designed for remote cardiac monitoring and arrhythmia detection. It captures ECG and movement data, transmitting it via Bluetooth to a smartphone or PC for analysis. With a configurable sampling rate (125–512 Hz) and high sensitivity and specificity for atrial fibrillation, it meets ISO 13485 standards as a Class IIa medical device, making it ideal for both clinical and home use Fig. 2(h) [19].

4 Methodology

The methodology of this article includes the design and configuration of the capacitive ECG system, the specific placement of electrodes on the head and neck, and the procedures followed to

assess signal quality and feasibility. Finally, the results obtained from these trials will be analyzed and discussed.

4.1 Experimental Setup. In this study, a capacitive ECG monitoring system is developed. The setup utilizes two active capacitive electrodes, each forming a coupling capacitor (C_c) between the electrode and the body. The output of each electrode is connected to a main board containing an AD620 instrumentation amplifier, which is configured to enhance signal clarity and minimize noise, with a gain set at 10. A galvanic electrode is also used as the reference electrode, as shown in Fig. 3.

Each active electrode circuit, shown in Fig. 4, is designed using a voltage follower/amplifier configuration. This noninverting amplifier setup is often preferred for front-end stages due to its relatively high input impedance, which reduces signal attenuation compared to a charge amplifier [20]. The circuit incorporated an LTC6240 operational amplifier in the voltage follower/amplifier configuration.

Each electrode has a diameter of 36 mm. To estimate C_c , we used a Zurich Instruments Impedance Analyzer. Since measuring the capacitance requires a conductive plate forming a capacitor with the electrode, we placed a copper sheet on the opposite side of the electrode. The measured coupling capacitance (C_c) ranged from 450 pF to 550 pF, depending on the applied pressure of the electrode against the copper sheet.

Additionally, a 10 G Ω bias resistor (R_B) is used to provide a bias current path, as bias current cannot flow through the human body. This prevents charge buildup at the front-end input [20]. To mitigate the effects of stray parasitic capacitance, we implemented a technique known as “guarding.” This involves creating a guard layer around the input channel, maintained at the same potential as the input itself, along with a guard ring to effectively minimize parasitic and noise effects.

The complete setup, shown in Fig. 5, consists of two active electrodes and a galvanic reference electrode, all connected to the main board. Data acquisition is performed using a National Instruments NI-9239 module, which is a 24-bit data acquisition system. The sampling frequency is set to 1.613 Hz (the minimum sampling frequency of the NI-9239).

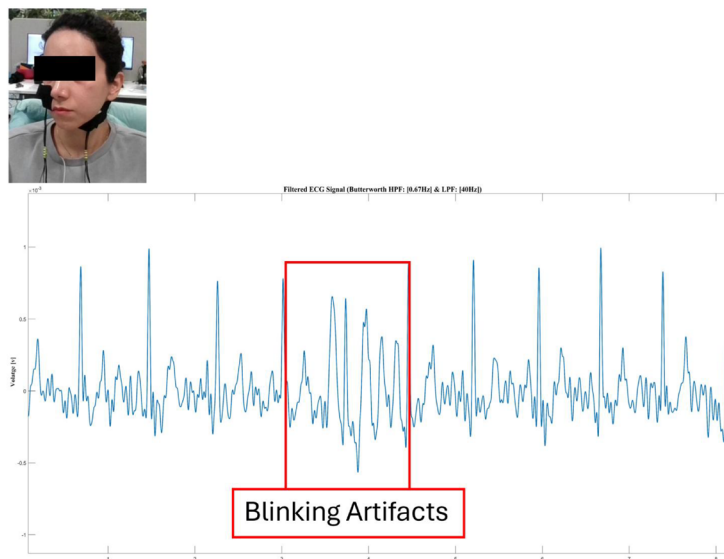


Fig. 6 Experiment 1: electrodes are positioned on the left side of the neck, the right cheek, and the right neck as the reference

No analog filters are applied; instead, digital filters are used. A fourth-order Butterworth low-pass filter with a 40 Hz cutoff and a high-pass filter at 0.67 Hz are implemented. These are specifically chosen for ambulatory ECG measurements to eliminate unwanted noise [21].

4.2 Electrode Placement Trials. The study involved multiple trials using capacitive electrodes positioned around the head and neck area, focusing on signal quality, clarity, and noise levels. These trials aimed to identify the optimal electrode placements that provided the highest signal quality with minimal interference. The following electrode placements are tested:

- (1) First experiment: Electrodes are placed on the left side of the neck, the right cheek, and the right neck as the reference.
- (2) Second experiment: Electrodes are positioned on the left side of the neck, near the right ear, with the right neck serving as the reference.

- (3) Third experiment: One electrode is held in the left hand, while the others are placed near the right ear and on the right neck as the reference.
- (4) Electrodes are positioned on the left side of the neck, the right side of the neck, and the right side of the neck as the reference.

For this study, only one subject is selected: a 35-year-old female with no known heart disease, including acute myocardial infarction, atrial fibrillation, or cardiac dysrhythmia.

4.3 Results. In the first experiment (results shown in Fig. 6), the signal quality is decent, and R peaks are clearly visible in most of the recording. However, the blinking noise is prominent, making this placement unsuitable. The blinking artifacts can be mistaken for R peaks, compromising accuracy. As a result, this trial is excluded from the experiment.

To compare the results of remaining experiments, a quantitative metric is needed. Various methods have been employed in the

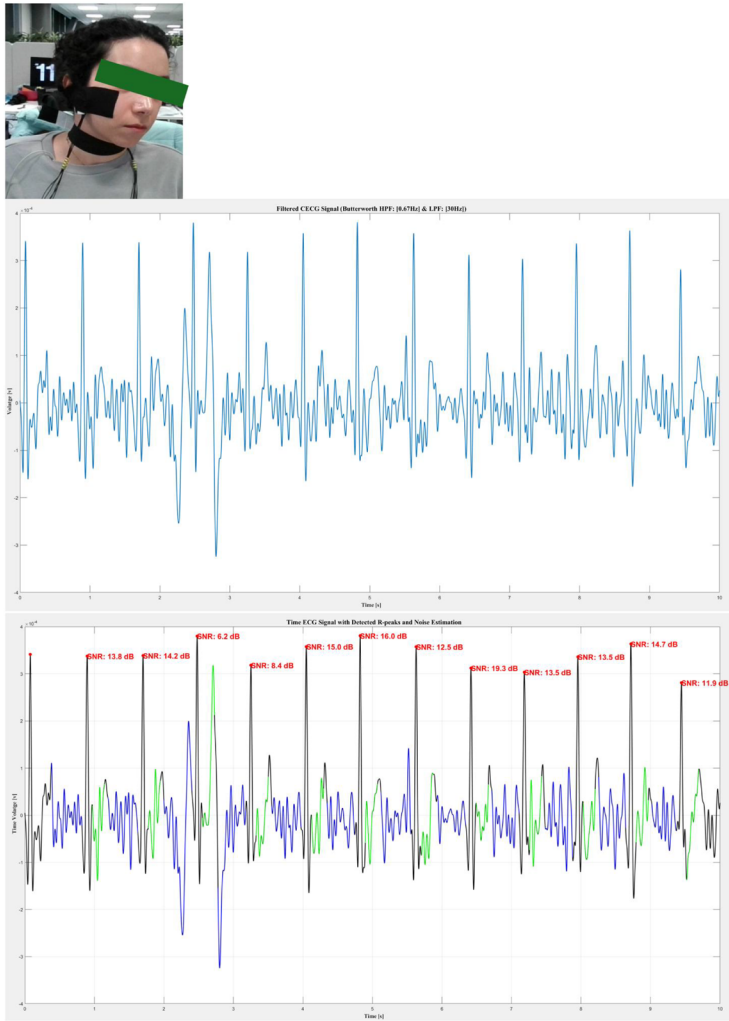


Fig. 7 Experiment 2: electrodes are positioned on the left side of the neck, near the right ear, with the right neck serving as the reference

literature to evaluate ECG signal quality, generally categorized into two main groups:

- (1) Subjective methods—These rely on expert assessment by cardiologists or other professionals.
- (2) Objective methods—These use mathematical equations to quantify signal quality.

Regarding objective methods, Since root mean square (RMS) and standard deviation are typically used when MA or baseline wandering are significant, they are not ideal for this study. Here, ECG is recorded while the subject is sitting still, as the main goal is to assess the feasibility of measuring ECG from the head and neck area using capacitive electrodes. Therefore, signal-to-noise ratio (SNR) is chosen as the evaluation metric. SNR is generally defined as

$$NR = 20 \cdot \log \frac{P_s}{P_n} \quad (1)$$

where P_s is the signal power and P_n is the noise power. However, in ECG analysis, signal power is proportional to heart rate, making this definition unreliable for R-peak detection, which is crucial for ambulatory monitoring. To address this, a modified SNR definition, proposed by Xu et al. [22], is adopted

$$SNR = 20 \cdot \log \frac{v_{pp}}{v_n} \quad (2)$$

where v_{pp} is the maximum value of each R peak, and v_n is the maximum noise value in two surrounding intervals. These intervals are defined as:

- $[t(i-1) + 300 \text{ ms}, t(i) - 75 \text{ ms}]$
- $[t(i) + 75 \text{ ms}, t(i) + 250 \text{ ms}]$

where $t(i-1)$ is the time of the previous R peak. These intervals ensure that the selected segment is free of QRS complexes, accommodating heart rates between 30 and 200 bpm.

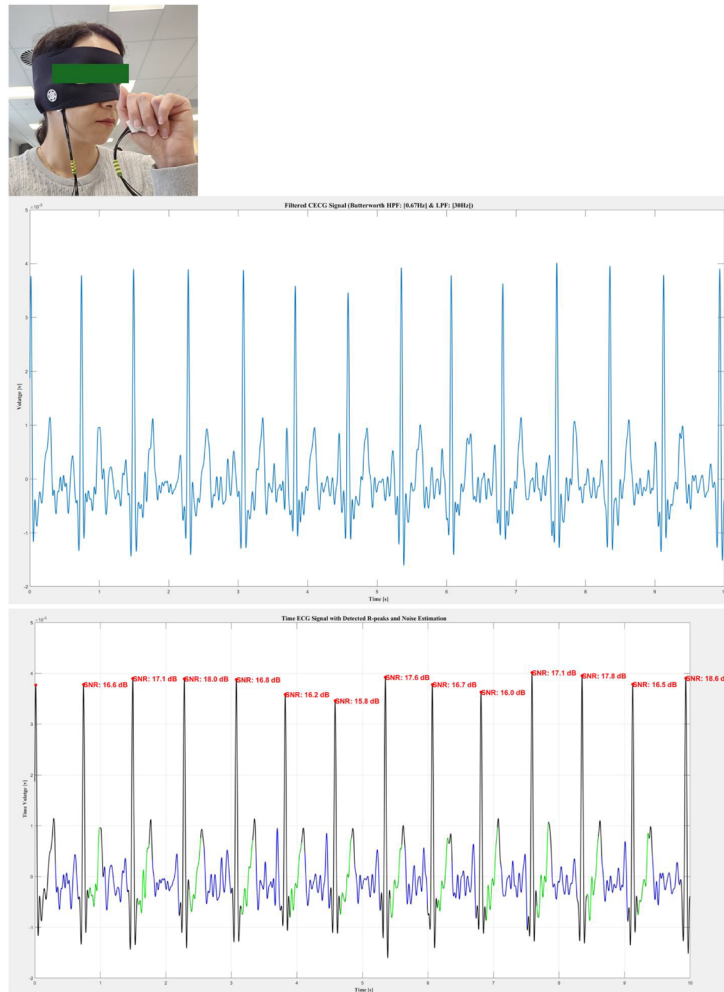


Fig. 8 Experiment 3: one electrode is held in the left hand, while the others are placed near the right ear and on the right neck as the reference

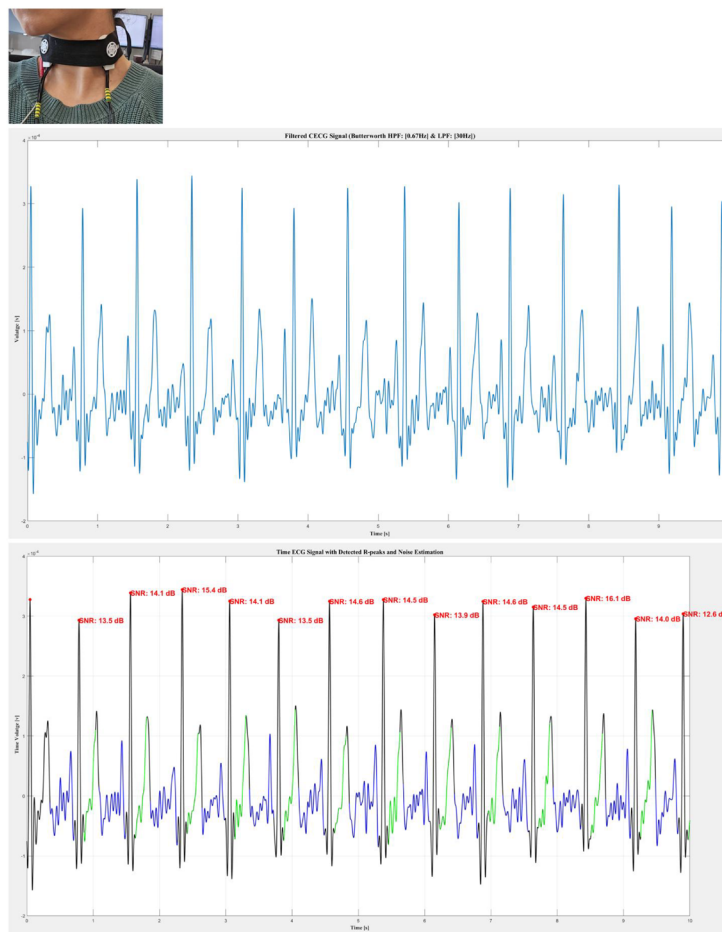


Fig. 9 Experiment 4: electrodes are positioned on the left side of the neck, the right side of the neck, and the right side of the neck as the reference

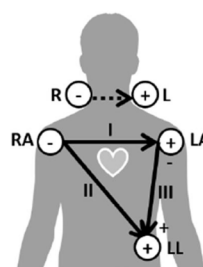


Fig. 10 Illustration of the Einthoven triangle with the electrode placement on the neck [4]

We further refined the SNR calculation by replacing v_n with its RMS value over the two surrounding intervals

$$\text{SNR} = 20 \cdot \log \frac{v_{pp}}{\text{RMS}(v_n)} \quad (3)$$

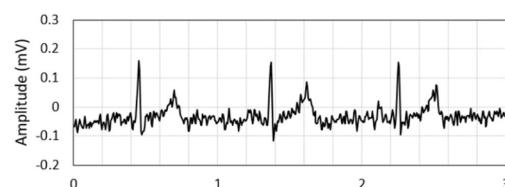


Fig. 11 Electrocardiogram signal from the backside of the neck [4]

This SNR is calculated for each R peak, and an average SNR is computed for comparison.

It is important to note that SNR alone is not sufficient for evaluating ECG quality. In some cases, a lower SNR may occur due to the loss of P and T waves, even if R-peak detection remains unaffected. Therefore, SNR should always be used alongside visual assessment for a comprehensive evaluation.

For consistency, 10-s segments from each ECG experiment are selected for comparison.

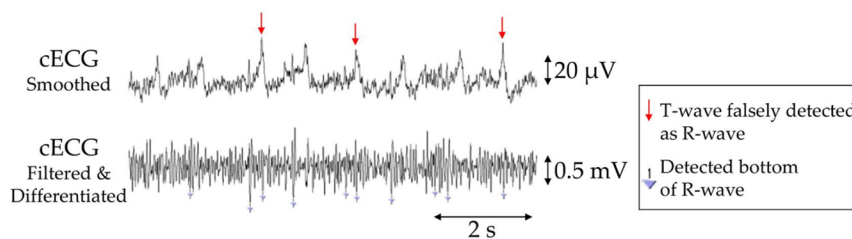


Fig. 12 Recordings of capacitive ECG and filtered and differentiated capacitive ECG [5]

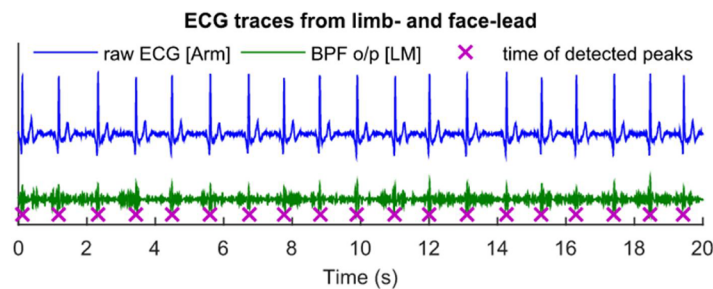


Fig. 13 Electrocardiogram recorded on left mastoid and its detected R-peaks compared to the reference from the arms [6]

Result of second experiment, illustrated in Fig. 7, this electrode arrangement provides good signal quality for detecting R peaks, and the increased distance from the eyes effectively removed blinking noise. The SNR of each R peak is calculated, with a maximum of 19.3 dB, a minimum of 6.2 dB, and an average of 13.24 dB. Based on subjective evaluation, QRS waves are clearly detected. However, detecting P waves is challenging due to noise in that segment, while T waves are more identifiable.

In the third experiment, depicted in Fig. 8, the signal quality improved compared to the previous placements. The SNR of each R peak is calculated, with a maximum of 18.6 dB, a minimum of 15.8 dB, and an average of 16.99 dB, which is 3.75 dB higher than the previous experiment. The signal appears less noisy, allowing for easier wave detection. Based on subjective evaluation, QRS waves are clearly detected. Due to the reduced noise, detecting P waves is easier compared to the previous setup, and T waves are easily distinguishable.

Finally, in the fourth experiment, shown in Fig. 9, the SNR of each R peak is calculated, with a maximum of 16.1 dB, a minimum of 12.6 dB, and an average of 14.25 dB, which is 2.74 dB lower than the third experiment. However, this does not necessarily indicate a lower quality signal. In this case, the T wave amplitude is higher than in the previous experiment due to electrode placement, leading to a lower SNR despite better wave detection. While P and T waves are more distinguishable in most cycles, the P wave is masked in the 12th cycle. This electrode placement also offers practical advantages for designing wearable ECG devices, such as collars and necklaces. Additionally, by relocating the electrodes from the arms to the neck, it remains possible to capture the Lead I vector from Einthoven's triangle, allowing the neck to reflect the same electrical activity as traditional limb leads [4], as demonstrated in Fig. 10.

5 Discussion

The primary goal of this study is not to compare the results with previous research but rather to assess the feasibility of ECG measurement using capacitive electrodes in the head and neck area and determine the practically optimal electrode placement.

Comparing our findings with other studies is inherently challenging, as each study has a different objective.

Most studies that have explored ECG measurement from the head and neck primarily focused on detecting R-peaks and evaluated performance using R-peak-specific metrics such as sensitivity (P_{SNS}), accuracy (P_{ACC}), and positive predictive value (P_{PPV}) values [4–6,11,13]. In contrast, our study goes beyond R-peak detection to assess the feasibility of identifying other ECG waves, such as P and T waves.

For instance, Iskandar et al. [4] primarily focused on R-peak detection using wet electrodes. A visual comparison of their results with ours (Fig. 11) suggests that our capacitive electrodes achieved better signal quality, despite the inherent challenges of capacitive sensing.

Similarly, Takano et al. [5] also utilized capacitive electrodes. While their study reported false detection of T-waves as R-peaks, our results (Fig. 12) demonstrate clear identification of R-peaks and other ECG waves, indicating improved signal fidelity.

In the study by Von Rosenberg et al. [6], R-peak detection was deemed sufficient, and their results (Fig. 13) compare ECG signals from the arm (upper signal) and face (lower signal). However, ECG signals measured from the neck using capacitive electrodes appear to be highly noisy, which may limit their reliability for clinical applications.

Mizuno et al. [13] presented ECG signals obtained using dry electrodes (Fig. 14, lower plot), which were sufficient for R-peak detection but did not provide clear visibility of other waves.

Elango et al. [10] used dry hexagonal labyrinth electrodes, but their study focused on evaluating electrode shape variations rather than ECG signal quality. Their results, which showed no observable signal, are not directly comparable to ours, as their primary objective was electrode design optimization.

Yarici et al. [11] explored the feasibility of ear-based ECG monitoring but also provided ECG measurements from the neck using gel electrodes. As they noted, additional gel was applied to reduce electrode-skin impedance. Their neck-based ECG results (Fig. 15) can be compared to ours, highlighting the differences in signal quality between gel and capacitive electrodes.

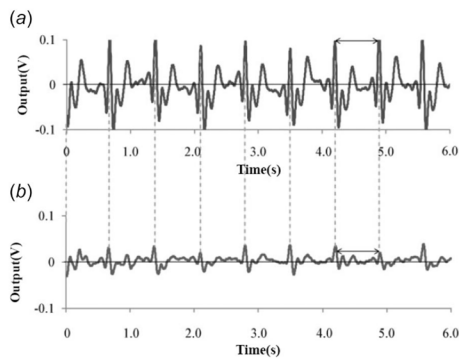


Fig. 14 Electrocardiogram measured by the neck band system ECG lead method and the conventional limb lead method during rest [13]

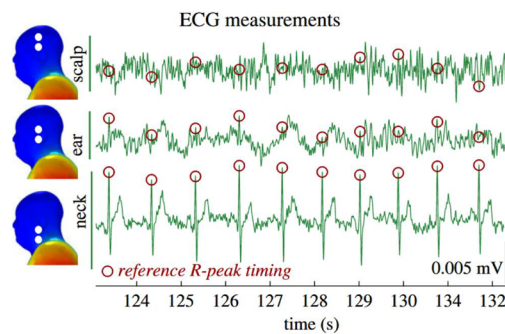


Fig. 15 Recorded ECG traces from the scalp-, ear-, and neck-ECG channels from a single subject [11]

Finally, the Movesense MD sensor [19] enables single-lead ECG detection from various body locations. However, as a commercial device, it is designed for sporadic ECG acquisition rather than continuous monitoring. This limitation makes it unsuitable for detecting transient cardiac dysfunctions such as arrhythmia [23]. Furthermore, detailed technical information about its sensor type and motion artifact removal methods is not publicly available, making direct comparisons with our study difficult.

6 Limitation and Future Directions

While this study demonstrates the feasibility of ECG measurement from the neck using capacitive electrodes, several limitations must be acknowledged. The signal amplitude is inherently lower than that recorded from the chest or arms due to the neck's greater distance from the heart and its smaller conductive surface area, which attenuates the heart's electrical signals.

Additionally, this study is conducted only in a seated, resting position, meaning MAs are not observed or analyzed. However, in real-world applications, head movements, jaw clenching, and swallowing are likely to introduce MAs that could degrade signal quality. Before optimizing the system, a thorough investigation of MAs under different activities and postures is necessary to understand the extent of the challenge. Once MAs are well-characterized, hardware design and signal processing techniques can be refined to mitigate their effects.

Another limitation is the small sample size, as only a single subject is examined. Future studies should include a larger and more

diverse group of participants to assess the variability in ECG signals across different users and improve the system's generalizability.

From a technical standpoint, further research should focus on hardware optimization, including electrode design and placement, to enhance signal acquisition and stability. Additionally, advancements in adaptive filtering techniques could improve noise suppression and artifact rejection. The integration of machine learning algorithms could also be explored to enhance robust ECG feature extraction and enable multimodal health monitoring by combining ECG with other wearable sensors.

Addressing these challenges will be crucial for developing a reliable, motion-resilient, and widely applicable neck-based ECG monitoring system.

7 Conclusion

This study demonstrates the feasibility of using capacitive electrodes for ECG monitoring from the neck, offering several advantages over traditional wet and dry electrodes. Unlike conventional electrodes, capacitive sensors do not require direct skin contact, making them well-suited for wearable and furniture-integrated ECG systems. They can operate effectively even when separated from the skin by a small gap due to hair, air, or fabric, increasing user comfort and long-term usability.

Through a systematic evaluation of different locations in the head and neck region, we identified the neck as the optimal site for capacitive ECG measurement. This location provided a SNR of 14.25 dB and enabled the detection of multiple ECG waveform components, not just R-peaks. Additionally, the convenience of electrode placement on the neck makes it particularly suitable for emergency and critical care applications, where rapid setup is essential.

Beyond cardiac health monitoring, neck-based capacitive ECG could also support mental health assessments, broadening its diagnostic applications. Moreover, this approach is especially beneficial for patients with chest injuries, postsurgical recovery, or burns, where traditional chest electrode placement may be impractical or uncomfortable. Wearable implementations, such as neckbands or necklace-style ECG devices, could integrate capacitive sensing into everyday life, making continuous heart monitoring more accessible.

Despite these advantages, challenges remain. MAs are not assessed in this study, as measurements are conducted only in a seated, resting position. Future research should systematically evaluate MAs under different movements and postures, followed by hardware and signal processing optimizations to enhance robustness against artifacts. Additionally, larger-scale studies with diverse subjects are necessary to validate signal consistency across different users.

By addressing these challenges, capacitive ECG monitoring from the neck can become a viable, user-friendly alternative to conventional ECG systems, contributing to the development of next-generation wearable health technologies for both medical and everyday applications.

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Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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Motion artifacts in capacitive ECG monitoring systems: a review of existing models and reduction techniques

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Abstract

Current research focuses on improving electrocardiogram (ECG) monitoring systems to enable real-time and long-term usage, with a specific focus on facilitating remote monitoring of ECG data. This advancement is crucial for improving cardiovascular health by facilitating early detection and management of cardiovascular disease (CVD). To efficiently meet these demands, user-friendly and comfortable ECG sensors that surpass wet electrodes are essential. This has led to increased interest in ECG capacitive electrodes, which facilitate signal detection without requiring gel preparation or direct conductive contact with the body. This feature makes them suitable for wearables or integrated measurement devices. However, ongoing research is essential as the signals they measure often lack sufficient clinical accuracy due to susceptibility to interferences, particularly Motion Artifacts (MAs). While our primary focus is on studying MAs, we also address other limitations crucial for designing a high Signal-to-Noise Ratio (SNR) circuit and effectively mitigating MAs. The literature on the origins and models of MAs in capacitive electrodes is insufficient, which we aim to address alongside discussing mitigation methods. We bring attention to digital signal processing approaches, especially those using reference signals like Electrode-Tissue Impedance (ETI), as highly promising. Finally, we discuss its challenges, proposed solutions, and offer insights into future research directions.

Keywords Adaptive filtering · Digital signal processing · ECG capacitive electrodes · Electrode-tissue impedance · Motion artifact

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1 Introduction

Cardiovascular diseases (CVDs) are a group of disorders affecting the heart and blood vessels. They are a leading cause of death worldwide, claiming more than 17.9 million lives annually [1]. Cardiac arrhythmia significantly contributes to almost 80% of CVD cases [2]. While some arrhythmias are not life-threatening, others, such as atrial fibrillation, premature ventricular contractions, and excessive supraventricular ectopic beats, can result in severe conditions like stroke, cardiac arrest, or heart failure [3]. The early detection of arrhythmias can prevent around 90% of CVDs [4]. To achieve this goal, physicians extensively employ electrocardiogram (ECG) technology to identify abnormal heart rhythms, investigate the origins of chest pains, and categorize CVDs in clinical settings. Typically, an ECG signal comprises P waves, QRS complexes, and T waves [5–7], with any variations in these parameters indicating potential abnormalities in heart function. The frequency range of ECG signals generally spans from 0.67 to 120 Hz [6], although the literature often reports deviations from this range depending

on the intended ECG application and the risk profile of the studied population [8, 9]. Additionally, real-time and long-term ECG monitoring has become important, serving two crucial purposes. Firstly, timely emergency care within the 'Golden Hour'—the first hour following the onset of cardiac symptoms—can significantly reduce mortality and improve the quality of life for patients with specific heart conditions, such as cardiac arrest [5, 10]. Secondly, continuous disease monitoring facilitates ongoing health management by effectively treating patients with certain types of CVDs. These conditions require extended monitoring periods to enhance disease diagnosis and prescribe the most effective treatment for the patients. However, the excessive cost of medical treatment poses a significant challenge, prompting a shift from hospital-centred to patient-centred healthcare [11]. This shift has led to the development of intelligent solutions and telemedicine applications [12]. This offers two distinct advantages: reducing patients' reliance on hospitals and lowering expenses. Moreover, telemedicine can improve public health, particularly in ageing societies in developed countries and in low- and middle-income areas. Presently, many studies are exploring the possibility of virtual care for people living in rural areas affected by CVDs [13]. After the COVID-19 pandemic, the importance of telemedicine has further grown. Notably, researchers such as Jiang et al. [14] have proposed wearable telehealth solutions for monitoring essential physiological parameters in COVID-19 patients, such as heart rate, blood oxygen saturation, and respiratory rate.

Telemedicine should provide patients with independent remote sensors, ensuring safety, comfort, precision, and real-time long-term monitoring capabilities without the need for specialized assistance. Traditional gel/wet ECG electrodes (Ag/AgCl), extensively used in clinical and research settings, are not useful in this field because these electrodes require direct skin contact through an electrolytic gel applied by technicians [12, 15–20]. They need multiple disposable electrodes, frequent need to be replaced, and there is significant potential for skin irritation. Consequently, they are not suitable for prolonged monitoring or use outside of a hospital setting [16, 17, 19, 21–25]. To address the limitations of conventional ECG measurement methods, capacitive electrodes were introduced as an innovative approach to measure skin surface potentials without necessitating direct conductive coupling to the skin, allowing measurement through materials such as hair, cloth, insulation layer, or air [26]. Their versatility has led to integration into numerous personal healthcare applications, including furniture, exercise aids, automotive devices, and wearable devices [17]. This innovation offers a cost-effective, long-term diagnostic solution for personal healthcare monitoring that avoids skin preparation and irritation [21, 27, 28]. Using these sensors can embed healthcare monitoring into patients' daily lives

and improve the health condition of people who have not yet developed a disease [29]. Moreover, they play a key role in monitoring heart activity beyond clinical settings in ambulatory ECG measurement systems. In contrast to traditional ECG systems that utilize ten electrodes, ambulatory ECG systems are characterized by their compactness, portability, and reliance, typically, on only 2–3 electrodes [25]. However, the design of electrodes involves finding a balance between comfort and reliable monitoring [21] and ensuring comparable quality to traditional medical instruments remains paramount. Despite the availability of heart rate monitoring sensors for consumers as standalone devices and integrated into smart technology, the challenge persists in achieving diagnostic precision comparable to hospital-grade 12-lead systems [30, 31]. Some of these challenges is because of some limitations in capacitive ECG electrode front-end. Moreover, there are several types of interference that can potentially contaminate the ECG signal in capacitive electrodes, including electromagnetic interference (EMI) and motion artifacts (MAs). EMI, particularly power-line interference (PLI), consistently introduces significant common-mode (CM) noise. PLI, with a frequency of 50 Hz in Europe and 60 Hz in the United States, is a major noise source in any ECG measurement system and is especially evident in capacitive ECG measurements. Generally, PLI is primarily caused by displacement currents coupling either into the measurement system or into the subject's body, and it appears in the final recordings due to unbalanced electrode impedance. However, it can be reduced to some extent by optimizing front-end electronics and system design [21, 32, 33]. On the other hand, the unidentified interference is commonly referred to as MA while its exact origin, cause, and definition remain unclear. MAs are commonly explained by the fluctuating high impedance between the body and the electrode because of body movements [21]. The variation of this impedance can modulate circuit leakage potentials and leads to MA. Another potential cause of MA is the triboelectric potential, which arises from the friction and separation between the electrode and the body. These interferences need to be mitigated to increase the SNR and ensure the reliability of the ECG signal for interpreting different types of cardiovascular diseases (CVDs) without misdiagnosis.

In many studies on capacitive ECG electrodes, MAs and their impact on the ECG signal are recognized as significant challenges, prompting numerous investigations to address these issues. Despite the proven adverse effects of MAs in ECG recording systems, their origins remain poorly understood and subject to varying interpretations across different research studies. However, these interpretations can vary due to differences in analog designs, electrode materials, and environmental conditions such as temperature and humidity, all of which uniquely influence system performance. A notable gap exists where

these varied definitions and interpretations have not been consolidated into a single source for comparative analysis. To address this gap, we provide a detailed overview of MAs, encompassing their origins, effects on ECG signals, and contributing factors based on existing literature, to enhance the understanding of MAs.

We proceed by reviewing the latest techniques for mitigating MAs, focusing particularly on Digital Signal Processing (DSP) methods. Specifically, we emphasize reference-assisted techniques using Electrode-Tissue Impedance (ETI) as a reference, as studies suggest that the variable high impedance between the body and electrodes during motion significantly contributes to MAs. While this method shows potential, there is a lack of thorough reviews in the existing literature, which we intend to address. To facilitate discussion, we present a comparative table summarizing previous works. However, comparing their efficiencies directly poses challenges due to variations in R&D statuses, design approaches, experimental methodologies, and selected performance metrics among others. Our primary objective is to explore methodologies used by each study, the challenges encountered, approaches taken to address them, and the success of their techniques. Finally, based on these reviews, we outline future research directions for those continuing work in this area.

However, addressing MAs is not the sole focus of our review. A complete understanding of capacitive ECG systems is crucial for identifying their causes and distinguishing them from other interferences. Therefore, optimizing signal quality by mitigating non-motion-related interferences precedes directly addressing MAs. To start, we discuss the fundamentals of capacitive ECG systems, which include discussing the limitations of capacitive electrodes and the impact of CM interferences on signal quality. Following this, we investigate strategies for enhancing front-end electronics and techniques aimed at improving the CMRR throughout the entire system.

Therefore, this article is structured as follows: Section 2 introduces the basics of capacitive ECG measurement systems. Section 3 addresses drawbacks in capacitive electrode circuitry and discusses solutions to improve the signal quality. Section 4 discusses the defined concept of MA in the literature, its origins, and its impact on the ECG signal. Current techniques for reducing MAs are addressed in Section 5. This part is divided into three key domains: analog circuits, electrode materials and fabrication, and DSP techniques. These domains must be addressed in parallel to achieve optimal results. Notably, this article emphasizes the DSP domain as a principal technique for effectively mitigating MAs. Section 6 engages in a discussion of the presented techniques and outlines potential directions for future research. Finally, Section 7 concludes the paper.

2 Capacitive ECG measurement systems

In capacitive ECG sensors, an interface between skin and electrode transfers the ionic current in human body into biopotentials that can be measured by a signal acquisition circuit [21]. Before exploring the specifics of capacitive ECG measurement systems, it's crucial to address the electrode-body interface for capacitive electrodes.

2.1 Electrode–body interface for capacitive electrodes

Biopotential sensing utilizes electrodes to acquire signals from the body. Often, these electrodes are not in direct contact with body fluids; instead, they reside on the surface of the skin, known as surface electrodes [21, 34]. The characteristics of the electrode–body interface for surface electrodes depend on the skin's electrical properties and the type of electrode [34]. In general, the coupling between the skin and electrode can be described as a layered conductive and/or capacitive structure, with series combinations of parallel R and/or C elements. The general layer stack and equivalent circuit model of capacitive electrodes coupled with the skin, based on various models found in the literature, result in structures depicted in Fig. 1a and b respectively.

The skin consists of three primary layers: the epidermis, dermis, and subcutaneous layer. The inner layers, dermis, and subcutaneous layer are highly conductive and are in direct contact with inner bodily fluids rich in ions, which is equivalent to the resistance R_d [34, 35]. In the epidermis layer, the Stratum Corneum, a high-resistance layer of the skin, is dominant, considered to have a resistance R_{sc} and capacitance C_{sc} in parallel [35–37]. The cloth layer is considered as a resistance R_{cl} in parallel with a capacitor C_{cl} , where R_{cl} is the resistance of the fabric surface and C_{cl} is the skin–electrode capacitance. This coupling impedance in the body–sensor interface is primarily influenced by the subject's clothing in this scenario [35, 38].

Since there is no electrode–electrolyte interface present, the circuit model of capacitive electrodes excludes impedances associated with this interface, as well as the electrode–electrolyte potential at equilibrium, referred to as the half-cell potential, V_{HC} , which is characteristic of wet electrodes. However, in numerous papers, the skin potential, V_{sc} , is considered for these electrodes [32, 34, 39]. The stratum corneum acts as a semipermeable membrane, effectively separating electrolytes, sweat, and body fluids of varying ionic concentrations. Consequently, this arrangement creates a potential difference across the stratum corneum, referred to as the skin potential [34]. It is worth noting, though, that in many papers, this potential is not accounted for in the context of capacitive electrodes.

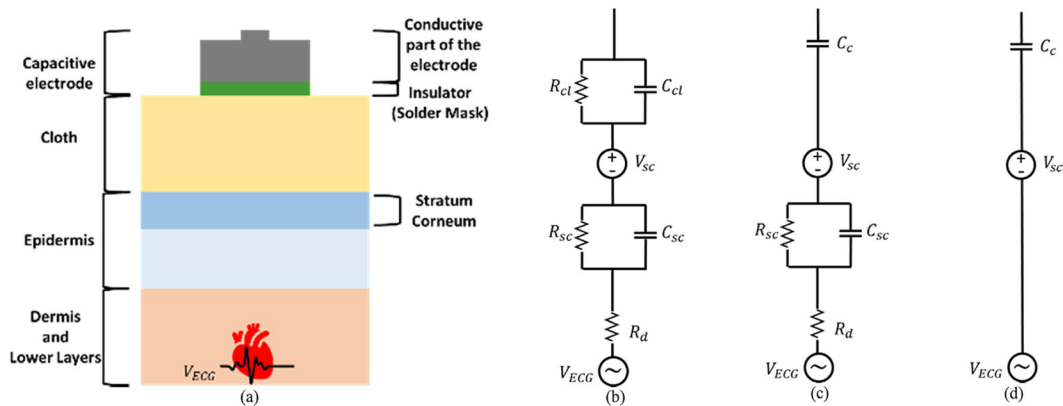


Fig. 1 Illustrations of the electrode–body interface for capacitive electrodes. **a** General layer stack. **b** General equivalent circuit model. **c** Equivalent circuit model without cloth (Representation of direct

contact between electrode and skin). **d** Simplified circuit model without considering cloth

Moreover, in some papers, the cloth layer is omitted, indicating that the capacitive electrode is directly connected to the skin, as shown in Fig. 1c. In this scenario, C_c is considered to model the insulation layer between the electrode and the skin surface, and no resistor is taken into account [34, 36, 37].

In numerous articles where the electrode directly interfaces with the body, there's an assumption that C_c represents the dominant layer in capacitive electrodes, thereby disregarding the impedance of other layers. This assumption stems from the fact that the value of this capacitor is typically lower compared to the other layers. Conversely, if the impedance of this layer is higher than that of the others, it leads to the equivalent model illustrated in Fig. 1d [17, 32, 39, 40].

2.2 Equivalent circuit of the capacitive measurement system

After introducing the electrode–body interface for capacitive electrodes, the equivalent circuit of the capacitive measurement system should be introduced. For simplicity, the capacitive electrode, along with the body surface, can be modelled by a coupling capacitor C_c , in series with the skin potential V_{sc} , as shown in Fig. 1d. In practice, C_c can be as small as a few pF, depending on factors like electrode size, dielectric material, and material thickness. Typically, an active electrode is used as an ECG acquisition system, with the front-end circuit including a buffer, usually an OpAmp with an ultra-high input resistor R_i and a low input capacitor C_i , along with active shielding. This setup enables transmission over long cables and mitigates sensitivity to PLI and cable movement.[21]. This can be achieved using a voltage

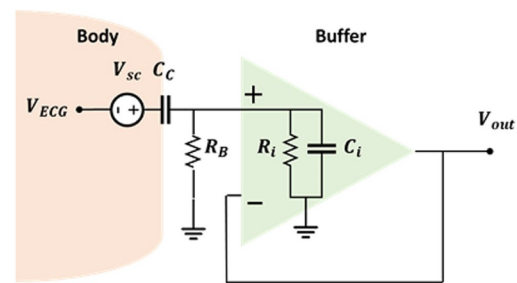


Fig. 2 Voltage follower schematic

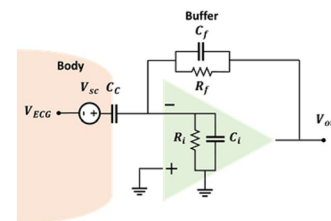


Fig. 3 Charge amplifier schematic

follower/amplifier (VA) or a charge amplifier (CA), depicted in Figs. 2 and 3, respectively. Other circuits like Instrumentation Amplifiers (INAs), bootstrap circuits, or application-specific integrated circuits (ASICs) with high input impedance [41] are also mentioned in the literature, designed for high input impedance. The VA, a noninverting amplifier, is preferred for the front-end in most cases due to its relatively

high input impedance, resulting in less signal attenuation compared to CA [21]. Conversely, CA is rarely employed for capacitive biopotential recording [42, 43] although some studies have reported successful ECG recordings using a CA [42]. Researchers like Peng et al. [44] have compared VA and CA designs in terms of their common mode rejection ratio (CMRR), noise performance, and frequency response. Xiao et al. [45] extended this comparison to their responses to artifacts caused by motion or interference. Their experiments indicated that the CA performs better under conditions of poor coupling (small capacitance, of the order of a few pF) due to its linear gain response and quicker recovery from triboelectricity artifacts. On the other hand, the VA performs better under good coupling conditions (hundreds of pF) due to its improved CMRR, stable gain, low noise, and reduced susceptibility to C_c variation artifacts. These two interferences are multiplicative in a VA, but remain independent in a CA. Consequently, a VA is preferred when triboelectricity artifacts are low and coupling capacitance is high whereas a CA is preferred when these artifacts are high, due to its faster recovery time [41, 44, 45]. However, overall, the VA is more widely adopted and accepted, and this paper exclusively focuses on investigating the VA.

3 Limitations in capacitive ECG measurement circuits

The electrical equivalent model shown in Fig. 2 is depicted in Fig. 4. It consists of the capacitor formed between the electrode's plate and the body (C_c), the skin potential source (V_{sc}), and the ECG signal represented as V_{ECG} . The front-end circuit includes the input resistor (R_i) and capacitor (C_i) of the OpAmp. Additionally, the bias resistor (R_B) is typically used with this configuration. In the subsequent

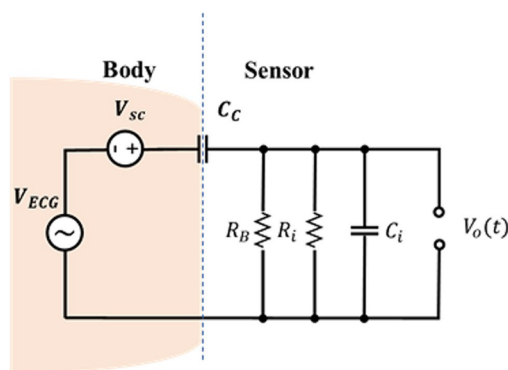


Fig. 4 Equivalent circuit model of the capacitive measurement system

discussion, we study the mentioned parameters and the difficulties encountered during the circuit design. However, it should be noted that due to the significant impact of V_{sc} on the circuit, it will be discussed later in Section 4.

3.1 Bias resistor

Ideally, op-amps would exhibit zero bias current. However, practically, bias current exists, and its magnitude varies depending on the type of op-amp. To address this issue, a bias current path can be used by connecting a resistor to the ground (refer to Fig. 4). This path is essential since bias current cannot flow through the human body and the charge will accumulate at the input front end [21, 28]. While a bias resistor is needed to discharge the input of the amplifier from its input bias current, it can introduce other problems. In this type of measurement, achieving a large input resistance is desirable, often by selecting an op-amp with a large input resistance, typically within the Tera Ohm range [21]. However, placing the bias resistor in parallel with the op-amp's input resistance can significantly reduce the overall input resistance. To overcome this, using a high-value resistor is a solution, although this can introduce issues related to drift and thermal noise. Moreover, it is difficult to fabricate tera-Ohm off-chip resistors. Additionally, using a bias resistor can cause an offset in the circuit. Though the induced offset voltage can be relatively high, it can be removed by filtering the dc component or by using negative feedback [46, 47]. Another consideration is the potential for op-amp saturation. In such cases, the maximum value of the resistor should be lower than $\frac{V_{sc}}{I_{Bias}}$ for rail-to-rail input stages [48]. Some researchers have tried including reset switches to manage saturation [45, 49, 50]. Moreover, Moreno-García et al. [17] found that the op-amp they employed, LMP7721, had a sufficiently low leakage current. In this case, they did not use a bias resistor in their design. They employed a passive RC high-pass filter to eliminate the generated offset. There are alternative approaches to establishing the bias path without relying solely on high-value resistor, for instance, the reverse leakage current of a low leakage silicon diode [36, 41], or bootstrap circuits [51–53]. However, implementing these circuits can cause more complexity and pose new challenges.

3.2 Frequency response of front-end circuit

A high-pass filter is formed in the front-end circuit due to the presence of C_c and the input impedance of the buffer. The input resistance of the circuit is determined by $R_i || R_B$. Since R_i (the input impedance of the op-amp) is significantly larger than R_B , the total input resistance can be approximated as R_B .

The frequency response of this filter is calculated using Eq. (1). The magnitude of the filter can be obtained from Eq. (2). By considering a very high bias resistor, this equation can be simplified to (3). The cut-off frequency of the filter can be obtained from Eq. (4).

$$H(j\omega) = \frac{R_B C_c \omega j}{1 + R_B \omega j (C_c + C_i)} \quad (1)$$

$$|H(j\omega)| = \frac{R_B C_c \omega}{\sqrt{1 + (R_B \omega j (C_c + C_i))^2}} \quad (2)$$

$$|H(j\omega)| = \frac{C_c}{C_i + C_c} \quad (3)$$

$$f_c = \frac{1}{2\pi R_B (C_c + C_i)} \quad (4)$$

It is important that the cut-off frequency of the formed high pass filter, f_c , be low enough to allow the lower ECG frequency components to pass through [28]. The question arises: how low should this cut-off frequency be? As previously mentioned regarding the ECG frequency range, the answer depends significantly on the intended application and the risk profile of the studied population. This underscores the importance of understanding the significant information gained or lost by selecting a specific frequency range. To address this concern, Young [9] published the proposed frequency requirements for the 80,601–2-86 committee draft in 2019, which can be found in Table 1, providing general guidance on selecting the ECG frequency range. Consequently, deviations can be observed in papers discussing capacitive measurement systems. For instance, Sun and Yu [21] proposed an ECG range starting from 0.05 Hz to preserve complete signal information, particularly emphasizing ST measurements shown in Table 1. In contrast, Torfs et al. [40] have suggested a cut-off frequency of 0.67 Hz for ambulatory ECG measurements, while, Asl et al. [28] recommend a cut-off frequency of 0.1 Hz, citing alignment with commonly used bandpass filters in ECG analysis.

After determining the value of f_c , the remaining parameters in Eq. (4) can be calculated. The value of C_c varies based on factors like sensor size, material, distance from the body, and insulator material. For instance, it may be as low as 0.1 pF when the signals are picked up through clothes and an air gap at a distance of > 100 mm. However, when the sensor is tightly attached to a cotton layer, the value be around 30 pF.

Furthermore, the input capacitance of op-amps, C_i , has remained relatively constant over the past decades, typically ranging from 3–10 pF [54]. As mentioned earlier, R_i is almost equal to R_B . Based on Table 1 for general usage and adopting $f_c = 0.67$, and $C_c = 30$ pF, using Eq. (4) allows us to deduce R_B , yielding a minimum value of 7 GΩ.

Ideally, the front-end circuit should act as a buffer with a flat frequency response. However, due to the voltage divider formed by C_c and C_i in Eq. (2), there may be some signal attenuation [17, 55]. The ECG signal voltage typically ranges from 1 to 5 mV. Therefore, even slight attenuation in the front end can decrease SNR, leading to a lower quality signal. Therefore, selecting an amplifier with a very small input capacitor is essential to minimize this attenuation. If C_i is sufficiently low, and the electrode, firmly attached to the body with a large area, results in a high C_c there should be no problem. But in situations where the distance between the body and the electrode increases, leading to a decrease in C_c , difficulties may arise. To address this issue,

techniques like power supply bootstrapping have been used over the years to reduce input capacitance [54, 56–58].

In capacitive ECG measurement, the electrodes are not fixed to the body, and even if they are tightly fastened, some movement remains. Additionally, the body's natural physiological vibrations can impact the coupling capacitance, even when no deliberate or unintended body movements occur [38]. These physiological vibrations include respiration and cardiac contraction, which can alter this coupling capacitance [59]. While many studies have overlooked this issue, Uguz et al. [38] studied the mechanical vibrations of the human body itself as a source of time-variant coupling capacitances. According to Eq. (5), changes in the front-end capacitor value are due to the varying distance between the electrode and the subject's body. However, the dielectric constant (ϵ_r) and the effective area of the electrode surface (A) remains constant.

Table 1 Summary of proposed frequency requirements in the 80,601–2-86 committee draft [9]

Intended use	Frequency response requirement
General use (rhythm interpretation)	0.67–40 Hz for all populations
ST measurement	Meets rectangular or triangle impulse response (0.05 Hz IIR or 0.67 Hz ZPD filter)
Diagnostic ECG (contour interpretation)	0.67–150 Hz for all populations and meets ST monitoring requirement

$$C_c(t) = \frac{\mathcal{E}_r A}{d(t)} \quad (5)$$

In this case, we are not dealing with a linear time-invariant (LTI) system due to the varying component $C_c(t)$. Even if we approximate the system as LTI within short intervals with a constant C_c , Eqs. (1) to (4) will remain time-variant due to this changing C_c . Consequently, both f_c and $|H(j\omega)|$ exhibit time-variant values.

For the specific values $R_B = 10\text{G}\Omega$, $C_i = 3\text{pF}$, along with seven different C_c values, Fig. 5 illustrates the Bode diagram of the circuit. Notably, when $C_c = 1\text{pF}$, $|H(j\omega)|$ is -12 dB, considerably lower than 0 dB. As C_c increases, $|H(j\omega)|$ approaches 0 dB. Simultaneously, the rise in C_c leads to a decrease in f_c , aligning with the desired outcome. Essentially, the system behaves like a dynamically changing high-pass filter for the ECG signal, $v_{ecg}(t)$ [39]. In simpler terms,

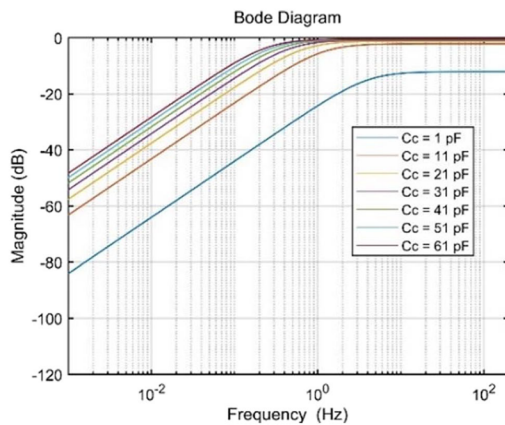


Fig. 5 Front-end circuit Frequency response for different values of C_c

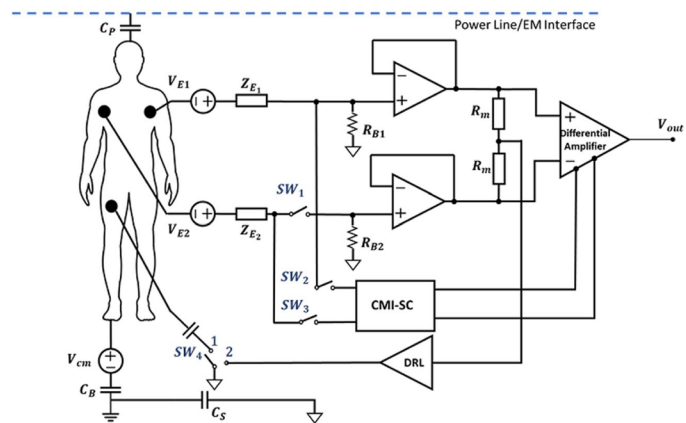
the time-varying coupling impedance causes multiplicative distortion of the ECG signal, resulting in a distorted version of $v_{ecg}(t)$.

3.3 Challenges of reduced CMRR and solutions

In this section, we introduce a comprehensive integrated electrical model for ECG capacitive recording systems, as depicted in Fig. 6. Within this model, there are non-common mode voltages denoted as V_{E1} and V_{E2} which are specific to each electrode and thus cannot be rejected using the differential measurement method and will be addressed later in the text. These individual voltages stem from various sources such as skin potential (V_{sc}), as discussed in Section 2.1, or other sources. The primary focus of this section is on CM noises, which are typically mitigated using the differential measurement technique in many applications.

In capacitive measurement systems, the body is electrically isolated, and this floating state makes it highly susceptible to external noises, thereby affecting the measurement system, particularly the CM noise [60]. The presence of CM noise sources, such as power lines, EMI, or wireless power transfer systems, can significantly disrupt the accurate detection of signals [15]. In an ECG system, considerable EMI can couple to the patient's body through the skin. Additionally, EMI may couple to the ECG system through coupling capacitors C_P and C_B , as illustrated in Fig. 6. Moreover, it can also be introduced to the system through the long ECG signal measuring cables and protection circuitry, typically located at the front of the ECG system. Furthermore, capacitance C_S is coupled between the AC ground and the ground of the ECG subsystem. The entire system's CMRR is dependent on the capacitance value of C_S [61]. The voltage source V_{cm} represents other CM voltages that are detectable throughout the body. The values of capacitors and V_{cm} are indicative and may vary depending on the measurement

Fig. 6 General integrated electrical model for ECG capacitive recording systems



methodology, environmental conditions, and parameters of the measuring device.

In general, the differential measurement method is highly effective in reducing CM noise due to its high input impedance and CMRR [62]. However, in capacitive ECG measurement systems, this method does not perform well because of the large asymmetry in the two signal paths. This asymmetry is caused by the difference in impedances between the two electrodes (Z_{E1} and Z_{E2} in Fig. 6). The capacitances between the body and the capacitive electrodes can differ due to body motion, leading to various amplitudes and phases of noise signals at the input of the differential amplifier. In this scenario, the external noise cannot be considered as the CM signal for the differential amplifier, as they are not the same in each path. Consequently, despite the high CMRR of an INA (around 120 dB), the amplifier's overall CMRR is decreased [52, 60, 63, 64]. Equation (6) shows the differential voltage resulting from the asymmetry in Z_E proportional to the CM potentials, V_{CM} . ΔZ_E stands for the difference of two electrode–skin impedances and Z_{in} represents the mean value of input impedances of the OpAmps (Z_{in1} and Z_{in2}) [52, 63, 64].

$$V_{diff} \approx V_{CM} \frac{\Delta Z_E}{Z_{in}} \quad (6)$$

Referring to Eq. (6), to enhance interference suppression, it is crucial to minimize the difference of impedance (ΔZ_E) or reduce the CM voltage (V_{CM}) as much as possible, or alternatively, increase the Z_{in} . In the literature, there are four known methods to improve the CMRR of the system. These methods are:

1. Active guarding
2. Isolation Capacitance
3. Driven-Right-Leg circuit (DRL)
4. Common-Mode Interference Suppression Blocks (CMI-SC).

By employing these techniques, the system's ability to reject CM interference can be significantly enhanced, resulting in better overall performance.

3.3.1 Active guarding

To mitigate the adverse impact of increased stray parasitic capacitance, a commonly employed technique is known as "guarding". This method involves creating a guarding layer that encircles the input channel and maintains the same potential as the input itself. The primary purpose of this guarding network is to minimize any voltage difference between the input wire and the guarding layer. It can effectively eliminate any parasitic capacitance that may exist

between them and safeguard high-impedance sensors from environmental EMI [65, 66].

3.3.2 Isolation capacitance

Improving the isolation between the device ground and the patient ground leads to a decrease in C_S , which, in turn, helps to enhance the system CMRR. This improvement is particularly noticeable in portable instruments that operate on batteries, where the CMRR tends to be exceptionally high [61, 67].

3.3.3 Driven-Right-Leg (DRL) circuit

In the DRL circuit, the reference electrode plays a crucial role by actively controlling the body's potential through a feedback mechanism. The primary objective is to maintain the body's potential close to a known bias point of the device, which is typically set to the desired CM level of the AFE. This feedback loop helps suppress the body's potential swing with respect to the AFE's ground, effectively reducing the CM input swing into the AFE. The DRL electrode is responsible for sensing the CM voltage on the body. By doing so, it can provide essential feedback to the patient's body, leading to a reduction in the V_{CM} as indicated in Eq. (6). Although the actual pathway of the current fed to the body is unknown, it is likely to be more controlled than the pathway taken by the measurement system itself. This process contributes to enhancing the overall performance and stability of the circuit, particularly by improving the CMRR.

3.3.4 Common-mode interference suppression blocks

In specific designs, the methods mentioned earlier are not employed. Instead, they rely solely on two sensing electrodes along with a CMI-SC Block in a feedback configuration to effectively reduce CM noises [68, 69]. However, in the absence of a third electrode, a two-electrode ECG AFE results in the grounding potential being virtually isolated from the CM potential on the body. This leads to a difference between the body's CM potential and the device's grounding, resulting in significant CM input. This significant CM input can saturate the differential amplifier, particularly when operating under low-voltage power supply conditions, rendering it unable to accurately reconstruct the ECG signal. Therefore, a critical aspect in preventing system saturation is to limit the CM input range. This is where the CMI-SC Block comes into play, as it detects the CM voltage from an internal node within the AFE and generates a proportional CM suppression signal. By implementing this mechanism, the circuit effectively reduces CM fluctuations at the AFE's input pads through a feedback loop.

By considering all the mentioned techniques, various systems and applications utilize different recording setups, such as single, two, or three electrodes, to measure ECG signals. The general setup is illustrated in Fig. 6, which can be modified using switches $SW_1 - SW_4$, as detailed in Table 2.

The first model employs a single electrode for ECG signal collection and another as a ground reference, as demonstrated by Serteyn et al. [39]. Their setup includes an active guard to eliminate CM noises effectively.

In the second model, two electrodes measure the biosignal without a reference electrode, a technique known as standard bipolar capacitive measurement [70]. In this configuration, a differential amplifier or INA is utilized to provide gain and convert the differential signal to a single-ended signal. In this configuration, the absence of any techniques aimed at enhancing the overall CMRR may result in a suboptimal signal quality. However, Yong et al. [71] devised an ECG measurement setup in a bathtub employing only two electrodes and made efforts to minimize PLI through the use of narrow-notch filters. In contrast, many other designs employing a two-electrode setup focus on integrating a CMI-SC circuit, representing the third model [68, 69, 72], to reduce CM noises and improve the SNR of the output signal.

However, many of these designs opt for a more conventional approach found in the literature, utilizing a three-electrode setup. This includes two active electrodes for sensing ECG and one passive electrode, forming the fourth model in Table 2. Alternatively, some designs employ a DRL active electrode as the reference, constituting the fifth model. This choice is made with the aim of enhancing the overall CMRR.

4 The source of Motion Artifacts (MAs) and their impact on the ECG signal

The primary concern of capacitive measurement systems is the presence of MAs. In numerous studies, any disturbance in the output signal caused by body movements is termed MA [30, 32, 33, 73, 74]. Such body movements involve respiratory or cardiac activity, as well as voluntary body motions. On the other hand, other studies interpret MAs as transient (but not step) random baseline wander resulting from either patient or electrode movement. These studies establish a separate category for baseline wander noise

caused by respiration and electromyography noise arising from muscular movements [24, 75]. Breathing-induced MAs lead to baseline wander appearing in the low-pass filtered signal, making R-peak detection challenging. However, the baseline wander resulting from body movement is significantly more substantial when compared to that caused by breathing alone [32]. Furthermore, MA extends the necessary dynamic range (DR) of input for recording devices, often requiring existing systems to employ low amplification gain in their signal amplification stages [74].

Figure 7 demonstrates the influence of body movement on the recorded ECG signal. The first part exhibits baseline wander, which can be filtered out using a High Pass Filter (HPF) to obtain a clean signal. In the second part, the QRS complex is entirely obscured by MAs, but it can potentially be restored using state-of-the-art MA removal techniques. However, in the saturated area, the amplifier is overwhelmed, resulting in a signal that is entirely lost and cannot be reconstructed. This issue can result in physicians facing challenges in diagnosing various CVDs accurately, and in critical situations, it may lead to the misdiagnosis of heart conditions. Recently, a phenomenon known as "toothbrush tachycardia" has gained significant attention, as depicted in Fig. 8. The illustration explains a scenario

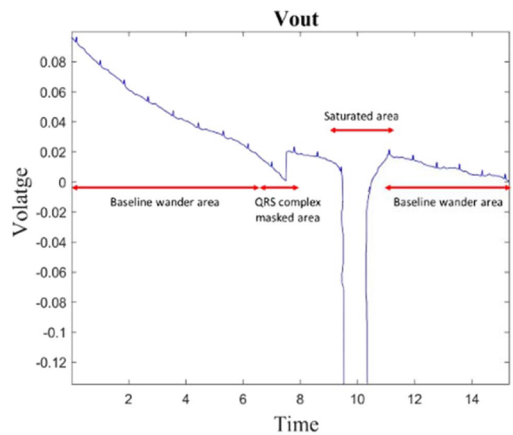
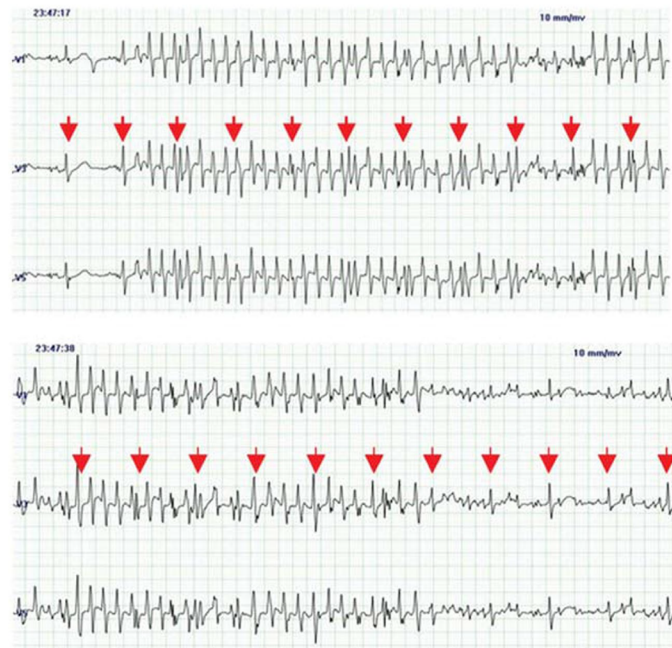


Fig. 7 Example of a capacitive ECG signal with body movements

Table 2 Various configurations of measurement systems

No	Type	SW_1	SW_2	SW_3	SW_4
1	One active electrode + One ground electrode as reference	Open	Open	Open	Connected to "1"
2	Two active electrodes	Close	Open	Open	Open
3	Two active electrodes + CMI-SC	Close	Close	Close	Open
4	Two active electrodes + One ground electrode as reference	Close	Open	Open	Connected to "1"
5	Two active electrodes + One DRL electrode as reference	Close	Open	Open	Connected to "2"

Fig. 8 A case of toothbrush tachycardia [76]



where a patient with paroxysmal atrial fibrillation, who had initiated flecainide treatment three weeks prior, underwent a Holter ECG examination. The recording indicated two brief episodes of rapid heart activity, occurring before bedtime and in the morning. Upon further inquiry, it was discovered that these episodes coincided with the patient's toothbrushing routine. Currently, the only reliable method to confirm or refute this observation is through cross-referencing with the patient's diary, a detail that physicians may not always have readily available.

While MA is widely recognized as a significant drawback in many studies, certain researchers, such as Wang et al. [35] identify the main challenge in capacitive measurement systems as the high impedance created between the body and the electrode. To mitigate this issue, they focused on reducing this impedance by designing a negative impedance in series with the formed impedance. In another study, Zompanti et al. [77] considered CM signals generated by EMI as the only interferences, and they attempted to eliminate them by implementing DRL circuits and filtering techniques.

In many studies investigating and modelling MAs in capacitive measurement systems, researchers have explored an electrical equivalent model for a single capacitive electrode, akin to the one shown in Fig. 9 [12, 32, 38, 39, 70, 78].

In this model, the ECG signal is represented as $V_{ecg}(t)$. The input resistor and capacitor of the buffer are modelled

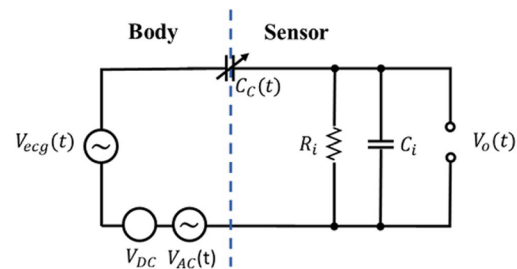


Fig. 9 Electrical model of a single capacitive electrode

as R_i and C_i . Furthermore, $C_C(t)$ symbolizes the variable capacitor created between the body and the capacitive electrode. The leakage potential between the body's virtual ground and the reference point of the measurement system is determined by the sum of V_{DC} and $V_{AC}(t)$. The voltage across the coupling capacitor can originate from various sources, leading to debates and disagreements about its origin. One contributing factor is triboelectricity [39], which results from the accumulation of static charges due to friction between the body and the electrode surface. The act of rubbing two materials together can produce significant voltages [12, 32, 39], although the exact underlying physics remains somewhat uncertain. A

potential explanation involves an enlarged contact area due to rubbing, facilitating electron transfer between the materials. In addition to the effects of electrical double layers, other mechanisms contribute to contact voltage, such as the removal of charged particles or mass transfer between the two objects [79]. This phenomenon is also observable in classical ECG sensors, but it poses a greater challenge in capacitive sensors. This challenge stems from the prolonged negative impact resulting from the delayed discharge caused by the high impedance between the body and these sensors [12, 38, 80]. Consequently, this situation can lead to the generation of more substantial electric fields than those produced by the actual ECG signal [12].

A significant aspect originates from the skin potential, often referred to as electrodermal voltage [32, 39]. This voltage stands as a major contributor to MAs within the ECG signal; however, it has received limited attention, particularly in the capacitive measurement field. Comprehensive information concerning the nature and magnitude of this voltage remains elusive. Current research on wet electrodes reveals the presence of an inherent voltage source across the epidermis. This voltage has been observed to change due to skin deformation caused by lateral stretching, rotational stretching, or vertical forces [81, 82]. Notably, variations in impedance do not influence this voltage. The design of the electrode's structure significantly affects the degree of interference [83]. Despite its significance, there have been no studies to date that explore the fluctuations in skin potential in response to pressure or the motion of capacitive sensors. This knowledge gap emphasizes the necessity for additional research in this specific area.

DC bias currents from amplifiers can also contribute to this phenomenon [39]. An additional source of leakage potential comes in the form of PLI potential. Moreover, it can be related to earthing, also known as grounding, occurs when the human body comes into direct contact with the Earth, allowing for the free transfer of ions between the two. Recent research has highlighted a prevalent belief suggesting that the human body tends to maintain a positive charge, a phenomenon that cannot be effectively balanced due to the prevalent insulation from the Earth in modern lifestyles. In the past, routine activities such as walking barefoot and sleeping on the ground provided continual grounding, but today, the use of insulated footwear and the insulation of buildings from the ground have become commonplace [84]. Since these potentials contain a combination of both DC and AC voltages, they are represented as $V_{DC} + V_{AC}(t)$ in the model.

In the illustrated model shown in Fig. 9, the expected output is $V_{ecg}(t)$. However, the calculation of the current flow through a variable capacitor is expressed by Eq. (7) and this equation changes the characteristics of leakage potentials [32, 38, 39, 80].

$$I_c = \frac{d(C(t)V(t))}{dt} = C(t)\frac{dV(t)}{dt} + V(t)\frac{dC(t)}{dt} \quad (7)$$

The equivalent circuit of the capacitive sensor shown in Fig. 9 can be mathematically described in the time domain by a differential equation according to Kirchhoff's Current Law (KCL) as

$$\frac{d[(C_c(t) + C_i) \cdot v_{out}(t)]}{dt} + \frac{v_{out}(t)}{R_i} = \frac{d[C_c(t) \cdot (v_{ecg}(t) + v_{DC} + v_{AC}(t))]}{dt} \quad (8)$$

As a linear system, the output signal $v_{out}(t)$ is expected to comprise the superimposition of four components, which are the output due to $v_{ecg}(t)$, $v_{AC}(t)$, and v_{DC} as shown in (9).

$$v_{out}(t) = v_{out_{ecg}} + v_{out_{DC}} + v_{out_{AC}} \quad (9)$$

By using standard techniques for differential equations with time-varying coefficients we can solve (8) and obtain

$$v_{out_{ecg}} = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{ecg}(u)]}{du} e^{-\int_u^t f(s)ds} du \quad (10)$$

$$v_{out_{DC}} = v_{DC} A(t) \int_0^t \frac{dC_c(u)}{du} e^{-\int_u^t f(s)ds} du, \quad (11)$$

$$v_{out_{AC}} = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{AC}(u)]}{du} e^{-\int_u^t f(s)ds} du, \quad (12)$$

with:

$$A(t) = \frac{1}{C_c(t) + C_i}, f(t) = \frac{1}{R_i[C_c(t) + C_i]} \quad (13)$$

Reveal that each component in v_{out} is a function of the coupling capacitance $C_c(t)$ and the corresponding source.

Equation (10) demonstrates the dynamic high-pass filter effect discussed in Section 3. It illustrates how the time-varying coupling impedance distorts the ECG signal [12]. This distortion converts $v_{ecg}(t)$ into $v_{out_{ecg}}(t)$, producing multiplicative noise [32], which is of lesser significance if the cut-off frequency of the high-pass filter in Eq. (4) is low enough.

The main challenge relates to Eqs. (11) and (12), where V_{DC} and V_{AC} undergo amplitude modulation due to $C_c(t)$. The changing coupling impedance transforms leakage voltages into an AC signal with an unknown frequency, producing additive noise [32] to $v_{out_{ecg}}$ which is shown in Eq. (9). Various studies have indicated that both intended and unintended body movements mostly occur within a frequency range below 10 Hz [32, 85, 86], although some have suggested a range from 0 to 20 Hz [38, 39, 59]. The chosen frequency range (0.1–20 Hz) covers breathing movements

(0.1–2 Hz), body motion (0–10 Hz), and ballistocardiograph vibrations (0–20 Hz), aligning with the changing $C_c(t)$ [39]. As this range overlaps with the ECG signal, basic frequency-based filtering may not adequately eliminate AC-transformed voltages.

Additionally, the leakage voltages across $C_c(t)$ can reach several hundred millivolts or even a few volts, primarily depending on the static charge on the body surface or textile layers at the body-electrode junction. In the worst-case scenario, this voltage could entirely mask the measured bio-potential and potentially cause system distortion. This transformation of mechanical vibrations into undesirable electrical signals is sometimes called microphonics [39], sharing similarities with signals resulting from membrane movements in microphones [36]. In summary, microphonics can modulate the amplitude of body surface potentials captured by capacitive electrodes, regardless of whether these potentials originate from bioelectric or triboelectric sources. This modulation reflects variations in the distance between electrode plates triggered by activities like breathing, heartbeats, and voluntary body motions [59]. In Eq. (14), $a(t)$ represents what is known as the MA (additive noise), regardless of the source of leakage voltages ($V_{DC} + V_{AC}$). The signal $s(t)$ represents the distorted version of the ECG signal in Eq. (15), contaminated with multiplicative noise. Consequently, $x(t)$ in Eq. (16) describe the recorded signal by the system.

$$a(t) = v_{out_{DC}} + v_{out_{tri}} \quad (14)$$

$$s(t) = v_{out_{ecg}} \quad (15)$$

$$x(t) = s(t) + a(t) \quad (16)$$

While these equations have been validated in numerous papers using the defined model, some studies suggest that the alteration in impedance may not be the sole cause of MA [87, 88]. Nevertheless, it is generally agreed that both electrode motion and changes in electrode–skin impedance contribute to MA [89].

In another existing category, MA is divided into two sectors: MA caused by transversal and lateral electrode movements. Transversal movement brings about changes in coupling distance, which alters coupling capacitance and gives rise to the microphonic effect. On the other hand, lateral movement creates friction at the interface between the body and the electrode, resulting in triboelectricity [30, 36, 70, 79]. Nevertheless, this explanation might not cover all aspects. Transversal movement, alongside lateral movement (sliding and friction), can also generate triboelectricity. This is especially true when using rigid PCBs as electrodes that may not align perfectly with the body's surface. In such cases, significant changes in the gap between the PCB and the body occur during motion [90]. Furthermore, when two surfaces previously

in contact separate from each other, there is charge accumulation and redistribution due to triboelectricity. This leads to a significant amount of noise being introduced and interfering with the desired signal. However, lateral motion produces even greater friction and triboelectricity. This phenomenon is like what happens in triboelectric nanogenerators (TENGs). In this model, the coupling between the electrode and skin consists of not only a capacitor ($C_c(t)$) but also includes a voltage source (V_{Tribo}), connected in a series, as illustrated in Fig. 10 [30, 91]. TENGs operate based on the triboelectric effect and displacement current principle, similar to capacitive electrodes. They have different operational modes with specific structures, among which the transversal contact-separation mode (Fig. 11. a) and lateral mode (Fig. 11. b) exhibit a triboelectric effect like that of capacitive electrodes.

A model explaining the triboelectric effect on capacitive electrodes can be derived from the V-Q-x relationship of TENGs, as shown in Eq. (17). Sirtoli et al. [30] formulated this model for situations involving contact-separation, as expressed in Eq. (20). The derivation of this equation involves calculating $C_c(y)$ using Eq. (18), where $y(t)$ signifies the time-variable distance between the electrode and the body surface. Additionally, the calculation of $V_{Tribo}(y)$ is carried out using Eq. (19). σ_d represents the surface charge density, $y(t)$ refers to the displacement at a given time (t), ϵ_{die} is the dielectric permittivity of the capacitive electrode, and ϵ_0 stands for the vacuum permittivity.

$$V_{tot} = -\frac{1}{C_c(y)}Q + V_{Tribo}(y) \quad (17)$$

$$C_c(y) = \frac{A\epsilon_0}{\frac{d_{die}}{\epsilon_{die}} + y(t)} \quad (18)$$

$$V_{Tribo} = \frac{\sigma_d y(t)}{\epsilon_0} \quad (19)$$

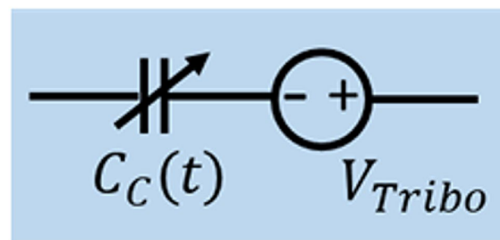
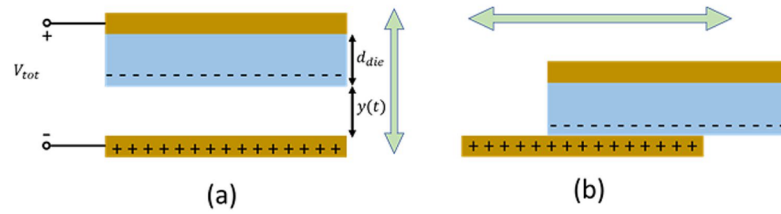


Fig. 10 Electrical coupling of skin–electrode interface for a capacitive electrode

Fig. 11 Fundamental modes of TENGs. **a** Transversal contact-separation mode. **b** Lateral mode



$$V_{tot} = -\frac{Q}{A\epsilon_0} \left[\frac{d_{die}}{\epsilon_{die}} + y(t) \right] + \frac{\sigma_d y(t)}{\epsilon_0} \quad (20)$$

5 The latest techniques for MAs reduction

To minimize the disturbance from MA, it's crucial to address three key areas: Analog circuits (dealing with electrical components), Materials and Fabrication (selecting suitable electrode materials, and optimizing fabrication) and DSP approaches. These elements must collaborate to efficiently reduce noise and improve the overall quality of the ECG signal.

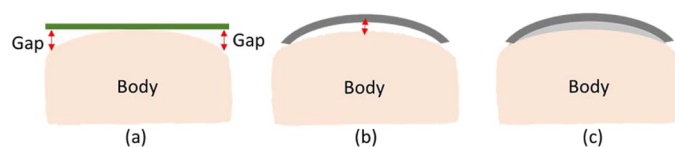
5.1 Analog circuits

The circuit design techniques in Section 3 can help reduce MA by mitigating leakage potentials. Therefore, addressing this section is highly necessary. However, when measuring ECG with two active electrodes, a challenge arises as these electrodes can move independently, causing varying MAs. Different frequency changes of $C_c(t)$ and leakage voltages ($V_{DC} + V_{AC}(t)$) for each electrode lead to different additive MA, $a(t)$ in Eq. (14)). Additionally, the triboelectric voltage from Eq. (20), varies due to the varying distance between the electrode and the body ($y(t)$). Consequently, the CMRR factor cancels out extra CM voltages, except for the portion transformed into a differential signal due to the skin–electrode impedance mismatch. This transformed portion is then amplified by the differential mode gain of the differential amplifier, degrading the output signal [64]. Enhancing CMRR through the mentioned techniques in Section 3 does not offer a solution to this issue.

5.2 Materials and fabrication

Research in another area examines the characteristics of capacitive electrodes—size, shape, and material—that affect system performance. Expanding the surface area is beneficial for increasing coupling capacitance. However, rigid materials have limitations in surface expansion, as shown in Fig. 12. (a), due to difficulties in full adherence to the body. Even with added layers of cotton or cloth, gaps persist, impacting impedance and signal quality [21]. To overcome this, researchers are investigating flexible electrodes that can conform to the chest's curvature, as depicted in Fig. 12. (b). This improves contact surface and, consequently, enhances coupling capacitance [21, 90]. Nevertheless, Lee et al. [92] suggested that when conventional flexible electrodes are used, air gaps can still exist due to the chest's uneven surface caused by ribs. To compensate for this, they propose the use of conductive foam, as depicted in Fig. 12. (c), to eliminate additional air gaps. Moreover, Asl et al. [28] proposed that by increasing capacitance with flexible electrodes, we can use a lower bias resistor to achieve a low enough f_c in Eq. (4), thereby minimizing voltage noise. Importantly, prior research [28] indicates that the electrode shape (circular, rectangular, etc.) has no effect on voltage noise. Additionally, High-spatial resolution ECG recordings provide valuable insights for diagnosing a wide array of cardiac abnormalities, including infarction and arrhythmia [93]. To enhance spatial resolution in ECG, researchers have developed body surface potential maps by expanding the standard 12-lead ECG to encompass a greater number of recording points across the body surface [94]. It is widely recognized that reducing the spacing between electrodes leads to higher spatial resolution [93]. Additionally, it is important to consider the impact of electrode size on spatial resolution. Studies have shown that enlarging the area of the plate electrode reduces spatial resolution [95]. While our discussion primarily focuses on capacitive electrodes with fewer leads, it is essential to consider

Fig. 12 **a** Rigid electrode. **b** flexible electrode. **c** flexible electrode with conductive foam



the trade-off between increasing the surface area to enhance capacitance for improving signal strength and preserving spatial resolution. This balance requires further exploration.

Numerous research studies have explored diverse dielectric materials and their influence on bioelectrode performance. A higher dielectric constant enhances capacitance, but the intended application must be carefully considered. Metal oxides, for example, provide a high dielectric constant suitable for capacitive biosensing; however, their reactivity with sweat may lead to more MAs [20]. Moreover, fabrics and polymers are typically characterized through chemical processes, making it essential to consider their reactivity with skin exudates [20]. Capacitive electrodes with insulated layers are designed to minimize skin reactions, ensure stable interfaces, and enhance overall patient comfort [21]. However, the selection of unsuitable materials can impede the achievement of these goals. For instance, using anodic aluminum oxide (Al_2O_3) as the dielectric can lead to interactions with sweat chloride ions, causing discomfort for patients [96]. Furthermore, as stated earlier, friction and the separation of dielectric surfaces can produce charges against the skin, ultimately leading to MA. In such scenarios, two fundamental principles are employed to assess the quantity of generated charge from a dielectric material on a surface, aiding in the selection of materials with reduced charge generation. The first principle is “charge affinity”, which classifies materials based on their inclination to exchange electrons through contact/friction. The second is TriboElectric Charge Density (TECD), a measure of the interaction between two materials influenced by factors such as humidity, surface roughness, temperature, stress, and other mechanical properties [30, 91].

5.3 DSP approaches

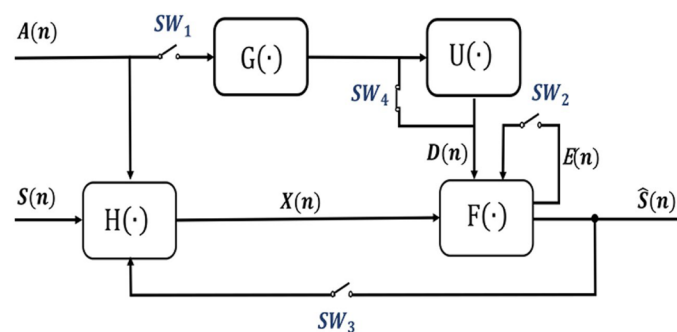
After addressing interference in the two previous sections, any remaining issues can be tackled within the DSP domain. DSP is an integral component of ECG monitoring systems. Figure 13 presents a general overview of the

multi-channel artifact suppression techniques discussed in this review, inspired by previous articles [21, 30, 97]. Three matrices — $S(n)$, $A(n)$, and $X(n)$ — comprise multiple column vectors of signals. Each rectangular block symbolizes a generalized transfer function, such as linear time-variant, nonlinear time-invariant functions, etc. The process involves combining two signals: $S(n)$ (uncontaminated ECG signal) and $A(n)$ (MAs), using a transfer function denoted as $H(\cdot)$. The outcome is the final recorded signal, $X(n)$, which contains both multiplicative and additive MAs. $X(n)$ represents Eq. (16) discussed in Section 4. Triboelectric potential outlined in Eq. (20) can also be integrated into this signal. This diagram can also incorporate future modifications to the MA model.

Various filtering methods can be conducted through the filtering subsystem, represented as operator $F(\cdot)$. Some studies employ high-pass or band-pass filters, represented by opening switches $SW_1 - SW_4$ in Fig. 13, to eliminate MA. However, these approaches are rudimentary and can introduce further signal distortion due to the overlap of MA frequencies with the ECG signal, as well as similarities in shape to P and T waves [74, 98]. By utilizing switches $SW_1 - SW_4$, optional paths and blocks can be employed. The configuration and positioning of these elements differ across various systems. Instead of selecting a straightforward filtration process, a different approach was taken by Ottenbacher and Heuer [70]. They investigated restoring the ECG signal by solving the inverse system function, $H^{-1}(\cdot)$, and utilizing it as $F(\cdot)$. However, their reconstruction technique demands knowing all model parameters, a challenge that is frequently hard to meet.

Consequently, many studies have turned to computationally intensive algorithms for suppressing MAs. These approaches can be categorized into two groups: self-referencing techniques that do not require additional signals, and therefore, do not necessitate the use of $G(\cdot)$ and $U(\cdot)$ (indicated by the open switches SW_1-SW_3), and those that necessitate supplementary signals for signal analysis (SW_1-SW_2 are closed, while SW_3-SW_4 are optional).

Fig. 13 A general framework for artifact removal in DSP methods



5.3.1 First category: self-referencing techniques

The first category exclusively relies on DSP techniques to filter out MA. More traditional methods, such as filter banks [99], use time averaging and frequency analysis, assuming the statistical independence of MA and the signal, which has not been verified and can distort the original ECG signal to some extent [100].

On the other hand, the wavelet transform is widely used as a denoising method due to its time–frequency localization and multi-resolution characteristics [101–104]. This method can effectively describe the non-stationary characteristics of the signals, such as ECG. This method has three steps: decomposition, denoising, and reconstruction. First, the original signal is decomposed into an approximate coefficient and several levels of detail coefficients using low-pass and high-pass decomposition filters. Then, all the decomposed coefficients are processed with a denoise algorithm, and the inverse discrete wavelet is applied to reconstruct a noise-free signal [78]. However, the choice of wavelet is important for denoising performance, and comparative studies have shown different conclusions mainly due to differences in the noise characteristics used. The wavelet transform is also computationally intensive and depends on specific MA and ECG signal characteristics and parameters, which may limit its effectiveness. Additionally, since MA is time-varying, wavelet transforms may not be effective in separating the artifact from the ECG signal [75].

Blind Source Separation (BSS) techniques assume that the sources of ECG and MA are uncorrelated and require input ECG signals to be linearly independent from each other [105, 106]. Although these methods are popular and widely used, they require many recording channels and high computational power due to their high algorithm complexity for good performance. Additionally, BSS methods are blind to the wider sensing situation and assume that all ECG channel signals are affected by the same source of noise, which is implausible due to the spatial distribution of skin impedance under the electrode sensors [98, 107].

According to the literature, these methods are not effective enough, and MA remains largely in the system output [75]. They are also unsuitable for wearable applications that require a low number of parallel channels, small size, and quick setup, while the available processing power is limited by power consumption constraints [107].

5.3.2 Second category: reference-assisted techniques

Figure 14 provides a more detailed illustration of the second category, derived from Fig. 13. In this representation, $H(\cdot)$ is simplified as a sum block. Consequently, the output signal, $\hat{x}(n)$, results from the summation of the signal of interest, $s(n)$, and the MA, $a(n)$. The operator $G(\cdot)$ denotes a

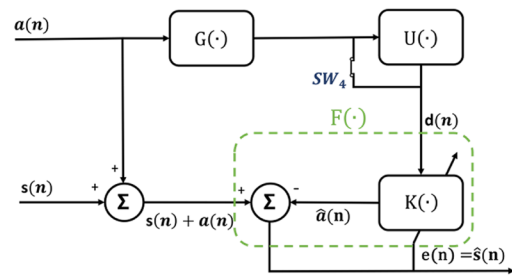


Fig. 14 A general framework for artifact removal for reference-assisted techniques

measurement subsystem generates a reference signal, $d(n)$ for the input of $K(\cdot)$. $K(\cdot)$ generates $\hat{a}(n)$, an estimation of the MA, $a(n)$. Subsequently, $\hat{a}(n)$ is subtracted from the recorded signal.

Several assumptions are associated with this method:

1. The MA is not correlated with the signal of interest, $s(n)$.
2. The reference signal is correlated with the MA, $a(n)$.
3. The reference signal is not correlated with the signal of interest, $s(n)$.

The difference between the main input signal, $x(n)$, and the output, $\hat{x}(n)$, of the noise reduction system can be utilized as the error output, represented as $e(n)$, as shown in Eq. (21):

$$e(n) = s(n) + a(n) - \hat{a}(n) \quad (21)$$

The mean square of $e(n)$ is given by Eq. (22):

$$E[e^2] = E[(s + a - \hat{a})^2] = E[s^2] + E[(a - \hat{a})^2] + 2E[s(a - \hat{a})] \quad (22)$$

If $s(n)$ is not correlated with $d(n)$, Eq. (22) simplifies to Eq. (23):

$$E[e^2] = E[s^2] + E[(a - \hat{a})^2] \quad (23)$$

As the difference between $a(n)$ and $\hat{a}(n)$ approaches zero, the error output $e(n)$ can be considered the best least-squares estimate of the ECG signal, as shown in Eq. (24). The effectiveness of noise reduction relies on the level of correlation between $d(n)$ and $a(n)$. Therefore, ensuring a high correlation between them is essential to suppress the noise [108].

$$e(n) \approx s(n) \quad (24)$$

This method can be categorized into two types. In the first type, there is an assumption that $K(\cdot)$ represents a known

transfer function for estimating MA. In the second type, an adaptive noise filtering approach is employed to estimate MA. In this scenario, the correlation between the reference signal and MA becomes crucial.

5.4 First type: $K(\cdot)$ is known

In the first type, the entire system is mathematically modeled, where $K(\cdot)$ represents a known transfer function containing certain unspecified parameters. Unspecified parameters in this method can be estimated using the reference signal and Block least-squares minimization. Equation (22) is then employed to mitigate MA. This technique is highly effective in eliminating MA if the model is accurately calculated; otherwise, it may not yield acceptable results. Serteyn et al. [39] utilized this method, demonstrating effectiveness in both simulation and lab setups. However, the proposed method does not completely eliminate the artifact under real-life conditions. Factors such as a simplified system model, thermal noise, and other artifacts like triboelectric effects and EMI induced by unaddressed motion may obscure R-peaks.

5.5 Second type: adaptive noise filtering

Active noise cancellation [109] or adaptive noise filtering [74] methods estimate the transfer function, $K(\cdot)$, between a reference signal and the MAs [32]. Essentially, by employing a reference signal that correlates with the MA present in the recorded ECG, the adaptive filter adjusts its coefficients to minimize the error signal, $e(n)$, as defined in Eq. (23). This adjustment aligns the reference signal with the MA [40]. The recorded signal is subtracted from the mapped reference signal, resulting in an output with cleaner ECG waveforms [74]. This approach shows promise in MA removal due to its low computational complexity.

The coefficients of this nonlinear filter frequently change based on predefined conditions [106]. In cases where the characteristics of MAs change over time due to movement, adaptive filtering proves to be more effective than other methods. Its ability to adapt parameters facilitates better capture of evolving signal characteristics. While adaptive filtering algorithms can be implemented with a single-channel input, achieving high filtering performance necessitates a reference signal that exhibits a strong correlation with the additive noise [32, 100, 105]. The limited correlation between the two signals often leads to more contamination of the desired ECG signal [74]. Moreover, alongside recording the ECG, simultaneous recording of a reference signal is essential [106].

The adaptive filter can be implemented using a variety of adaptive algorithms, with the most commonly employed ones being Least Mean Square (LMS), Normalized Least

Mean Square (NLMS), and Recursive Least Square (RLS) [32, 74, 75, 105]. Each of these approaches possesses its own set of advantages and disadvantages.

Many forms of reference signals, $d(n)$, have been employed for MA suppression, such as the measurement of skin stretching with optical sensors [110, 111], electrode motion using accelerometers [112, 113], deformation of electrodes [114], and the change in ETI [32, 39, 40, 74, 106, 109, 115, 116].

In a recent study, Ding et al. [108] introduced a novel reference signal using custom electrodes made of silver conductive fabric. Each electrode contained three layers: a rectangular layer of conductive material for acquiring ECG signals, a rectangular insulation layer above the previous layer, and a comb-tooth-shaped layer for acquiring the reference signal. This method showed good results; however, it adds one more signal acquisition channel. The main limitation of second category DSP methods is that they require additional sensors to measure a reference signal that correlates with motion and must be synchronized with the capacitive sensor [32, 39]. This solution may increase the complexity and power consumption of the recording system, and in some cases, their method is not automated [39], making it unsuitable for ambulatory monitoring, which is the primary goal of capacitive ECG measurements [32].

Among the mentioned reference signals, ETI seems a promising candidate. Although the first suggestion was to use an auxiliary capacitive sensor to track changes in the coupling impedance [117], other studies have shown better solutions that do not require additional sensors. ETI is a signal of significant interest since it exhibits a high correlation with MA, allowing for superior performance of beat detection algorithms compared to the use of other reference signals. Additionally, it is amenable to low-power circuit design since no additional sensor is required to produce ETI [74, 106]. The ETI signal can be recorded continuously and simultaneously with the ECG signal by sharing electrodes, injecting higher-frequency AC signals into the sensing electrodes, and amplifying the resulting voltage [40, 105]. Since the injected AC signals have spectral contents outside the ECG band, they do not corrupt the ECG's morphology [38, 74]. This technique is also utilized in traditional ECG measurement systems employing gel or dry electrodes, but it has also been recently suggested for use in ECG measurement systems employing capacitively coupled electrodes [106]. In recent studies on capacitive electrodes, an injection signal has been employed for tasks such as channel selection [118], respiration observation, artifact localization [59], and impedance measurement in static conditions [119]. However, its use for artifact reduction or ECG reconstruction had not been explored until Serteyn et al. [120] conducted the first test in this regard. Eilebrecht et al. [119] then measured the static value of the coupling capacitance for different textiles

and electrode designs. Buxi et al. [106] used an injection current at 20 kHz to monitor the ETI of wet and dry electrodes for different MAs. Torfs et al. [40] used a Howland current pump with very small current ranges to inject to the electrodes. In this measurement setup, the first indications of periodic MAs were seen, which could have been associated with heart activity. Current injection has been proposed for many wet and dry electrodes, too [105, 115, 116, 121]. Instead of injecting a current, another adaptive filtering approach injected voltage into capacitive electrodes to measure the ETI [39, 120, 122]. Demodulating the PLI allows for extracting a reference signal that reflects variations in coupling capacitance for adaptive MA removal, as proposed by Xu et al. [32]. They conclude that the reference signal obtained by this technique can include components that reflect variation in the PLI amplitude in addition to the variation in the coupling impedance. This can lead to an overestimation or underestimation of the MAs.

One important challenge is measuring the ETI signal without impacting the quality of biopotential signals and minimizing crosstalk [115, 123].

5.6 Challenges of MA reduction using adaptive filtering with ETI as the reference signal

Among the studied methods for reducing MA, the combination of adaptive filtering with an ETI reference signal has received significant attention. However, literature highlights that unlike the clear and direct relationship between the impedance signal and motion pattern, the correlation between MA and ETI signals is not often strong and straightforward. As a result, efficiently subtracting MA becomes challenging [82]. Buxi et al. [106] investigated the relationship between MA and ETI for different artifacts, types of electrodes, and impedance signals. Their goal was to understand when ETI could effectively assist in reducing MA through algorithms. Their findings indicated that among the chosen electrodes, local electrode artifacts (such as pushing and pulling the electrode) had the highest correlation with MA. This was followed by local skin artifacts (like stretching, twist, skin), and then global artifacts (including actions like walking, jogging, jumping). Therefore, it becomes essential to understand the cause or mechanism of MA in order to identify a reference signal that is strongly connected to MA [100]. The ETI signal is usually thought to be purely capacitive in capacitive ECG measurement. Even materials like cotton or solder masks, which insulate well, show resistance in the range of a few Giga ohms. This is significantly lower than the input impedance of a common operational amplifier. Moreover, these materials exhibit some resistive characteristics within specific ECG frequency ranges [124]. Apart from the fully capacitive model, there are other impedance models of the ETI. One proposed by Akabane et al.

[125], involves using a combination of a series resistor and a parallel arrangement of resistor and capacitor. Buxi et al. [106] studied the Bode-plot of the skin–electrode impedance. They introduced three different components (real part, imaginary part, and absolute impedance) to provide a comprehensive description of the impedance signal. Addressing the issue of limited correlation, Cömert and Hyttinen [82] focused on the frequencies used for impedance measurements. They noticed that impedance responses at various frequencies differed in the waveform when subjected to the same motion. In the realm of studying motion, higher-frequency impedance measurements displayed a stronger connection to motion compared to lower frequencies. At higher frequencies, impedance measurements turned out to be more sensitive to minor movements, thus delivering more accurate evaluations of applied motion across different motion levels. Additionally, these higher impedance frequencies could act as indicators of applied motion. They showcased that even though the correlation coefficients might be lower, higher frequencies exhibited stability in their relationship to the MA signal both in terms of time and frequency. They concluded that while impedance might not directly predict the shape of the MA signal over time, it could anticipate the key frequency components of the MA signal. Furthermore, it serves as an effective predictor of the actual applied motion.

To facilitate discussion of the remaining aspects, a comparative table is employed to offer a comprehensive overview of the previous works, as depicted in Table 3. Seriteyn et al. [39] applied the Block least-squares parameter estimation method to real-life data, achieving a reduction in artifact RMS amplitude by 9 dB. However, they noted instances of unclear visibility of R-peaks in certain sections. They suggested that remaining artifacts might stem from factors not addressed in their study or arise from the simplified electrical model they employed. In contrast, Torfs et al. [40] employed an LMS adaptive filter, resulting in an average reduction of 49% in the RMS content of the signal. They observed variations in the effectiveness of the capacitance impedance signal in correlation with different types of MAs. This finding highlights the importance of developing more sophisticated algorithms to fully take advantage of information from the capacitance impedance signal for effective MA reduction. In a similar study, Xu et al. [32] attempted to demodulate the PLI signal instead of injecting a signal to estimate ETI. They used an NLMS adaptive filter to mitigate MAs and claimed that their proposed method improved the system's SNR by an average of 1.2 dB, resulting in clearer visibility of R-peaks. However, they still observed high-amplitude MAs. They concluded that the reference signal obtained by this technique may encompass components reflecting variations in PLI amplitude, as well as variations in coupling impedance. This dual effect could potentially lead to an overestimation or underestimation of MAs. In the

Table 3 Comparison of previous works

Source	Methods for measuring ETI	Methods of MA mitigation	Type of experiments	Results
Serteayn et al. [39]	Voltage injection at a frequency of 1 kHz	• Reverse the transfer function • Block least-squares parameter estimation	• Simulation • Lab Data • Real-Life Data ○ Electrode Pushing	• Good results in simulation and lab experiments ○ Achieved clear visibility of R-peaks • Real-life data: ○ Reduced artifact RMS amplitude by 9 dB ○ Observed unclear visibility of R-peaks
Torfs et al. [40]	Current injection at a frequency of 10 kHz	• LMS adaptive filter	• Real-Life Data ○ Electrode pushing/pulling and lateral motion ○ Arm motion	• Acceptable results in push/pull motion • Not acceptable results in Arm motion • Reduced RMS content of the signal by an average of 49%
Xu et al. [32]	Demodulation of the PLI signal	• NLMS adaptive filter	• In-silico experiment • In-vivo experiment ○ Subject seated on a chair with their trunk straight ○ Subject seated on the chair, oscillating their trunk ± 15 degrees forward and backward	• Acceptable results in in-silico experiment • In-vivo experiment: ○ High-amplitude MAs observed ○ Achieved clear visibility of R-peaks ○ 1.1 dB improvement in SNR for the first test ○ 1.3 dB improvement in SNR for the second test
He and Min [100]	Current injection at a frequency of 5 kHz	• Improved LMS filter ○ Balances speed and accuracy	• Real-Life Data ○ Electrode pushing/relaxing	• 7~15 dB improvement on average (Performance metrics was not mentioned)
Pholpoke et al. [74]	Current injection at a frequency of 5 kHz	• Two stage MA mitigation ○ 1st-order lowpass filter ○ Sign-sign LMS adaptive filter	• Real-Life Data ○ Electrode pushing	• —
Kim et al. [126]	No information capable as they used database	• Two stage MA mitigation ○ LMS adaptive filter feedback to analog circuit ○ Adaptive step-size LMS adaptive filter	• Imec database	• Evaluated performance via heartbeat detection: ○ 9.8% improvement in sensitivity (Se) ○ 6.48% improvement in positive predictive value (+p)

following discussion of ETI as the reference signal, He and Min [100] suggested that the ETI signal may not exhibit the highest correlation with the MA. As a result, they generated a novel synthesized reference signal. This synthesized signal combines skin-induced impedance behavior, skin "slope," and recovery "time constant" to effectively mitigate MA. To address this, an additional processing step, denoted as the $U(\cdot)$ block in Fig. 14 was introduced. This step is designed specifically to enhance the correlation of the signal. In this scenario, the SW_4 component should be opened. Moreover, they addressed a key limitation of traditional LMS algorithms – the challenge of balancing convergence speed with convergence error. To overcome this trade-off, they introduced an enhanced LMS filter that incorporates both

fast tracking and low convergence error components. This modification successfully navigated the delicate balance between speed and accuracy, yielding promising outcomes and be able to 7~15 dB improvement on average in their system. But their experimental setup involved offline signal processing to adjust applied vertical forces to sensors, and they did not explore various artifact types in their study of MA. Recognizing the low correlation between MA and ETI, Pholpoke et al. [74] used an additional layer of digital algorithms, BSS, in the backend to effectively reduce MA. They also highlighted the need for recording devices with higher input dynamic ranges (DR) to handle MAs. This requirement necessitates existing systems to use low gain in their amplification chains to prevent output saturation.

To tackle this challenge, they implemented LMS filtering to generate a cancellation signal capable of nullifying MA near the system's input. For this design SW_3 in Fig. 13 needs to be closed. By effectively suppressing MA, the signal could then undergo additional amplification without encountering output range saturation. In the field of using a more efficient method to tackle with different types of MA, Kim et al. [126] proposed a MA removal method employing more efficient techniques to address various types of muscle artifacts (MAs). Their approach utilized a two-stage cascade LMS adaptive filter. In the first stage, an LMS algorithm with analog feedback was employed to prevent signal saturation, similar to the technique used by Pholpoke et al. [74]. This aids in reducing the input dynamic range. For the second stage, an adaptive step-size LMS algorithm was used. This adaptive step-size algorithm facilitates rapid convergence to track large, sudden MAs while preserving the integrity of the ECG component. The filtering performance was evaluated based on heartbeat detection, measured by sensitivity (Se) and positive predictive value (+p), resulting in an improvement of 9.8% and 6.48% respectively.

6 Discussion and future directions

In capacitive ECG data loggers, it is evident that suboptimal circuit designs can introduce signal distortion, often misidentified as MAs. To address this issue, it is essential to carefully examine electrode construction and circuit design aspects, often overlooked in current literature. Rectifying these shortcomings will pave the way for a more comprehensive understanding of the origins of MAs. Presently, the definition and sources of MAs remain unclear. While there have been discussions on the study of MAs involving wet electrodes by introducing various artifacts to establish improved models, research efforts have predominantly centered around capacitive electrodes, given their growing demand in wearable telehealth monitoring systems. Consequently, most published works explore MAs, examining their amplitude and frequency characteristics across various applied artifacts in diverse ECG experiments utilizing capacitive electrodes. The ultimate goal is to present a reliable model for MAs.

Another related domain necessitating attention is DSP for MA removal. Although adaptive filtering, often utilizing the ETI as a reference signal, holds promise in mitigating this issue, it has yet to yield sufficient outcomes. Therefore, a more in-depth exploration of ETI is imperative and could serve as a main point for future research. Beyond solely relying on the capacitive model for skin–electrode impedance, there is room for investigating alternative models. Moreover, the circuit used for estimating the ETI requires further examination.

The efficacy of MA estimation through adaptive filtering significantly depends on the availability of a highly correlated "reference signal". While ETI is a widely accepted candidate, enhancing its correlation through pre-processing algorithms holds the potential for generating a more efficient reference signal. This approach has been adopted in studies involving wet and dry electrodes but remains unexplored in the context of capacitive electrodes. Additionally, using supplementary reference signals, such as accelerometer data, may hold promise for improving the SNR, a direction that merits investigation.

Another promising path for further research lies in the design of adaptive filtering itself. While current literature primarily concentrates on identifying reference signals that exhibit high correlation with MAs, designing adaptive filters capable of effectively mitigating MAs has received limited attention and deserves more research. Lastly Moreover, there are instances where combining DSP techniques with analog designs can potentially prevent amplifier saturation and signal loss, presenting another attractive area for future research.

It should be noted that besides traditional denoising techniques, there are other emerging approaches, such as machine learning and deep learning techniques, which are not as commonly cited in academic works. While deep learning techniques share certain characteristics with adaptive filters in the domain of ECG signal processing, they have primarily been utilized for tasks such as feature extraction and noise detection rather than direct ECG signal reconstruction. Although less frequently mentioned in the literature compared to traditional denoising techniques, the relevance of machine learning and deep learning methods in ECG denoising may increase in the coming years, particularly as research in this area continues to develop.

7 Conclusion

This review highlighted the significance of capacitive ECG measurement systems as a promising alternative for ECG measurement, offering non-intrusive long-term monitoring. However, the challenge lies in maintaining diagnostic accuracy comparable to hospital-grade systems. MAs have emerged as a critical issue in capacitive ECG measurement due to the variable impedance between the body and the electrode, along with existing interference sources. Despite being commonly acknowledged; the exact origins and definitions of MAs remain unclear. Addressing this gap, we reviewed existing models. Furthermore, this article studied state-of-the-art MA mitigation techniques, spanning analog circuits, electrode fabrication, and DSP methods. Emphasis has been placed on adaptive filtering using ETI as a reference signal, consistent with the approach of many recent articles. While advancements have been made in this field, challenges persist, warranting further research in several

areas concurrently. These include synthesizing a reference signal more correlated with MAs using ETI or add other reference signals, optimizing mitigation methods for improved accuracy and speed, developing advanced techniques adaptable to various MAs, and enhancing the dynamic range of the system to enable higher gains, as evidenced in prior studies.

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Declarations

Ethics approval This paper does not contain any experiments with human participants or animals performed by any of the authors.

Conflict of interest The authors declare no competing interests.

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