Post-Operative Hip Fracture Rehabilitation Activity Movement Monitoring

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Abstract

Hip fracture incidence is a life-threatening event that increases with age and is common among the older population. It causes significant problems as there is an increased risk of mortality, restriction of movement and well-being, loss of independence, and other adverse health-related concerns for the injured. Following surgery, physiotherapy is essential for strengthening muscles, mobilizing joints, and fostering the return to regular physical activity. Ideally, appropriate rehabilitation with a set programme performed under a predefined supervised and unsupervised environment can play a significant role in recovering the person's physical mobility, boosting their quality of life, reducing adverse clinical outcomes, and shortening hospital stays. Tracking, recording, and continuous real-time monitoring of activity movements can significantly help in following up the correct implementation of a predefined programme. The ever-increasing technology such as the Internet of Things (IoT), which produces advancements in digital health revolutionizing industries and markets could be useful in advancing conventional rehabilitation care. This will also aid in enhancing backup intelligence used in the rehabilitation process, and will provide transparent coordination and information about activity movements among relevant parties.

This thesis provides a motivational background for the problem and a critical literary analysis of the key components involved in structuring an IoT-based rehabilitation care monitoring system. The thesis proposes and presents a post-operative hip fracture rehabilitation model from the existing rules and health programmes. The model reflects the key stages a patient undergoes straight after hospitalisation, and provides clarification for the involved rehabilitation process, its associated events, and the main physical movements of interest across all stages of care. Considering the model monitoring requirements, the thesis highlights the system modelling and development tools for testing the proof-of-concept and overall conceptual ideology. To support this model, the thesis proposes an IoT-enabled wearable movement monitoring system architecture. The architecture reflects the key operational functionalities required to monitor patients in real-time and throughout the rehabilitation process. The conceptual ideology was tested incrementally on ten young and healthy subjects, for factors relevant to the recognition and tracking of movements of interest. The analysis reflects the recognition of the hip fracture rehabilitation activity movements based on frequency-domain analysis and concerning sensor localisation. Research findings suggested that the amplitude parameter was suitable for the classification of the static state of a patient and ambulatory activities. Whereas, for the hip fracture related movements, both the frequency content and related amplitude of the acceleration signal play a significant role. From the analysis, the ankle is considered to be an appropriate sensor location that can categorise the majority of the activity movements thought to be important during the rehabilitation programme and data collection time of four seconds is considered to be the minimum time for recognising a particular activity movement without any loss of information or signal distortion. Furthermore, the thesis presents the importance of personalisation and one-minute history of data in improving recognition accuracy and monitoring real-time behaviour. This thesis also looks at the impact of edge computing at the gateway and a wearable sensor edge on system performance. The approach provides a solution for an architecture that balances system performance with remote monitoring functional requirements. Finally, this thesis offers a clearly-defined structured rehabilitation follow-up programme use case and conclusion with an indication of our future research work.

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This Thesis is dedicated to my

Grandfather

Din Dayal Gupta

Parents

Gokul Chand Gupta and Sangeeta Gupta

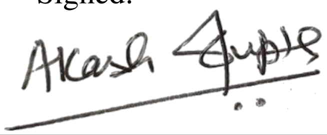
Younger brother

Aman Gupta

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), nor material which to a substantial extent has been accepted for the award of any other degree or diploma of a university or other institution of higher learning.”

Signed:



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List of Terms and Abbreviations

Acronyms

AAL Ambient Assisted Living.

ANN Artificial Neural Network.

BLSTM Bidirectional Long Short Term Memory.

CAS Cumulated Ambulatory Score.

Cf$_{MA}$ Corresponding Frequency Content of the Maximum Acceleration Amplitude.

CNN Convolutional Neural Network.

ECG Electrocardiogram.

FFT Fast Fourier Transform.

FS Frequency Scalar.

FW Fast Walking.

GPS Global Positioning System.

H3IoT Home Health Hub IoT.

HTTP Hypertext Transfer Protocol.

IMU Inertial Measurement Unit.

IoT Internet of Things.

LM Leg Movement.

LOB Lying On Back.

LOS Lying On Stomach.

LSTM Long Short Term Memory.

LTU Lifting Thigh Upwards.

MA Maximum Acceleration Amplitude.

MQTT MQ Telemetry Transport.

NMS New Mobility Score.

RAC Recognised Activity Code.

RFID Radio Frequency Identification.

RNN Recurrent Neural Network.

RPi Raspberry Pi.

SLTS Swinging Leg To A Side.

SW Slow Walking.

VRS Verbal Rating Scale.

Chapter 1

Introduction

The chapter principal objective is to highlight the motivation behind the emerging requirements of the long-term healthcare monitoring, with a special focus on post-operative hip fracture rehabilitation. The secondary objective is to provide an analysis of the hip fracture process and the significance of rehabilitation programmes for enhancing the recovery process. It reflects the current state-of-the-art of prevailing rehabilitation programmes for patients and addressing the relevant gaps that require immediate attention. The significance of how ever-increasing technology like IoT, enabled with wearables in healthcare, could be a potential solution in addressing the concern of the development of a long-term hip fracture rehabilitation activity movement monitoring system, is another objective that is discussed. Drawing from all the analysis, the final chapter objective is to present the study research question. This is followed by the research objectives, research scope and contribution involved in the overall study.

This chapter starts by providing the research motivation around hip fractures and rehabilitation in general. Section 1.2 presents an overview of hip fracture; how it is affected, what happens when the injury occurs and after surgical operation. Section 1.3 discusses how rehabilitation could play a significant role in the recovery of physical mobility, boosting the quality of life, reducing clinical outcomes and shortening hospital stays. Moreover, factual information from related work on the type of movement and the programme patients run on during the hip fracture rehabilitation programme is also highlighted. In Section 1.4, it examines how ever-growing technology like IoT, enabled with wearable and digital health, could be leveraged upon in playing a significant role towards the development of the smart rehabilitation care assistant movement monitoring system. It further provides a brief description of the IoT system used and its functionalities and limitations in the healthcare movement monitoring domain. The research question, objectives, scope and contribution are identified in Sections 1.5 to 1.7 respectively. Lastly, the thesis organisation is outlined in Section 1.8.

1.1 Research Motivation

According to the World Health Organization (WHO), it has been projected that the world's elderly population (aged 65 and above) is rapidly growing and is expected to increase from 900 million in 2015 to 2 billion by 2050 [4]. The current population of New Zealand is 5 million and is expected to rise to 7.9 million by 2068 [5]. Moreover, an 18% increase in the incidence of non-communicable diseases such as strokes, hip fractures and cancer has been observed in the last 10 years [6]. This is a big concern as the proportion of elderly people is increasing at a higher frequency compared to the entire population. As a result of the ageing population, given the increasing life expectancy, frailty level, poor postural or physical balance, chronic conditions, associated health concerns and fear of living independently, the healthcare system will be affected and costs are predicted to rise substantially from the so-called hip fracture epidemic. Without intervention, this will overburden the healthcare system and increase the demands for long-term care processes. Therefore, it is vital to find ways of improving patient outcomes.

Hip fractures are a global public health issue and a common event among the elderly population. It is a critical life-threatening injury that often leads to loss of independence with high morbidity and mortality rates [7] in the first year following the hip fracture despite continual patient follow-up, this is 20-24%. Contributing reasons include losing the ability to live independently and loss of physical function. 40% of patients are not able to walk independently, and 60% require assistance due to loss of confidence and motivation. As a result of these losses, 33% of these patients are completely dependent or reside in a nursing home upto a year following the hip fracture [8]. Therefore, there is a serious long-term devastating impact on the physical functionality of the elderly people, which causes substantial problems in their mobility, well-being, ability to live independently, and other health-related concerns [9]. Appropriate rehabilitation following the surgery has shown the ability to improve physical functionality, enhance the recovery process, aid patients in maintaining an independent daily life and shortening hospital stays. Ideally tracking, recording and monitoring daily movement activities can significantly help in correcting the implementation of a predefined rehabilitation programme.

1.2 Hip Fracture Background

Hip fracture is generally affected by hip anatomy, sheer forces applied to the hip joint and mechanical bone properties [10]. 90% of them occur from a fall (particularly in a sideways direction) [11] or due to medical conditions like osteoporosis, stress injuries, sedentary lifestyle, impaired nutrition and underlying bone diseases [12]. Therefore, it is anticipated to become the forefront in terms of demand for healthcare and social welfare services [13]. According to [14], most hip fractures can heal without surgery. However, healing would require 8-12 weeks on bed rest. Over the years, doctors realised that placing an ageing person on bed rest for long periods has a higher risk of developing critical complications, as compared to surgery. As a result, surgery is recommended for all patients with hip fractures. In New Zealand, around 3000-4000 incidence of hip fracture is estimated every year and 90% of hip fractures are repaired surgically [15]. However, on comparing it globally, around 1.6 million hip fractures occur every year and are expected to rise to 6.4 million by 2050 [8].

When a hip fracture injury occurs, the injury is most likely in the neck of the femur [9]. The fracture can be either in the head and neck of the femur or between/below the greater and lesser trochanters, as represented in Fig 1.1. After the doctor's examination, patients undergo a surgical operation. According to UK NICE guidelines, early surgery decreases pain prolongation and complications. Following surgery, patients are taken to a recovery unit where the rehabilitation process begins, within a day of the operation [9]. The purpose of rehabilitation is to restore pre-fracture physical functionality and mobility and enable independent living. Evidence indicates that rehabilitation is guaranteed to play a role in reducing pain, recovery time, boosting the quality of life, improving the physical functionality of patients in all stages of care and in achieving optimal rehab outcomes [9].

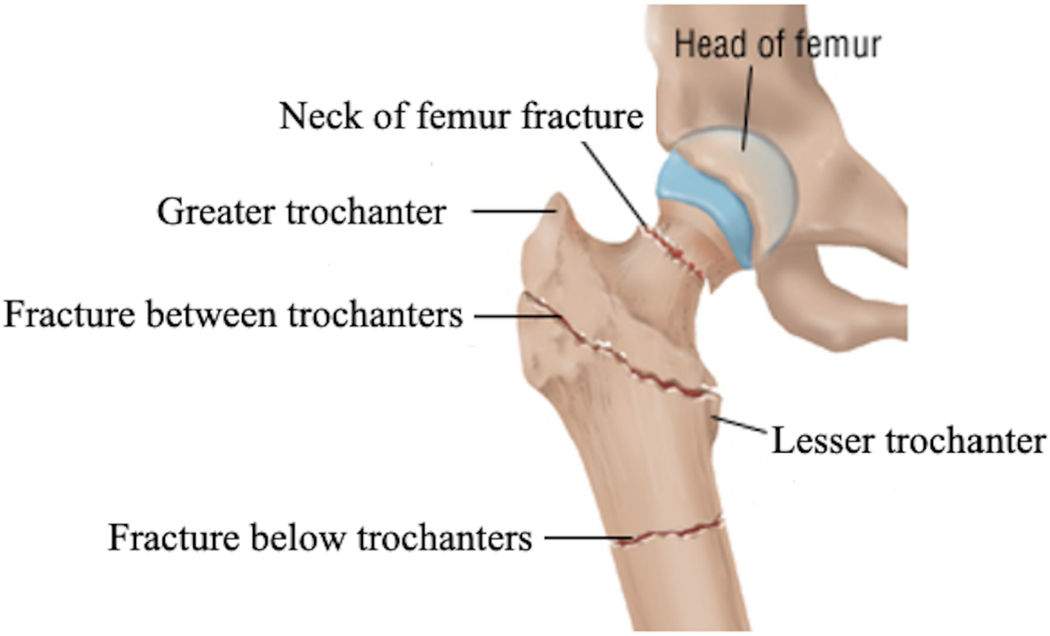


Figure 1.1: Hip fracture types [1]

1.3 Rehabilitation Programme

Rehabilitation plays a pivotal role in restoration of the pre-fracture functional mobility during the recovery process. However, rehabilitation protocols for hip fractures vary considerably from country to country. In some countries, inpatient rehabilitation is performed in the hospital, whereas in others it is conducted in nursing homes or rehabilitation centres. However, in NZ, it is more common to be discharged to home directly, usually between 3-10 days post-operation and mostly depends on the individual patient's functional mobility status, health and living environment. Mobilisation is the primary factor of post-operative rehabilitation, which aims in improving ambulation for posture maintenance and speed. In fact, it is recommended to start mobilising straight after the surgical treatment. During this period, emphasis is on bed exercises, muscle strength training, weight-bearing exercises and walking movements with the use of a walking aid. The rehabilitation ward normally comprises of a physiotherapist, physicians, an occupational therapist, nurses and they work closely together to provide an integrated approach to the treatment programme.

Many studies [16–19] have investigated the post-operative effect of physio-therapeutic exercises and mobility during the rehabilitation process in elderly patients who have undergone hip fractures, while [20–22] monitored the daily physical activity based on motion analysis and [23] analysed the effect of home-based exercise as portrayed in Table 1.1. One of the recent studies [24] investigated whether patients perform better at home or in an outpatient setting. In this study, discharge criteria from hospital to home is laid out and the rehabilitation programme is proposed. The discharge criteria includes that the patient should be able to ambulate independently 40-60 metres with a walking aid, have the ability to manage stairs, transfer and perform basic daily activities and able to demonstrate independence with a home-based programme. The rehabilitation programme proposed in this research includes activities like: (1) Ankle exercises; (2) isometric quadriceps contractions; (3) hip and knee bending; (4) Hip abduction; (5) bridging; (6) Hip extension and hip abduction while standing and (7) Hip extension and hip abduction while lying down. In this study, patients were instructed to perform these exercises three times daily, where each time, 5-10 repetitions are performed. Exercise (3)-(6) were continued after discharge from the hospital whereas exercise (7) were commenced after three months. From the findings, it is evident that the effect of late-stage rehabilitation requires further investigation.

In comparison to the aforementioned study, two other studies [25, 26] proposed a post hip fracture rehabilitation programme in their hip fracture guide that patients normally take on. In the first study [25], the programme was categorised into two phases. The activities involved during the first phase of the programme include; Hip abduction, swinging one leg to the side, hip extension and flexion and lifting the thigh upwards. The second phase includes exercises such as sitting down, bridging and standing up. However, in the second study [26], the movements include activities such as heel slides, ankle pumps, knee push-downs, buttock squeezes and ankle dorsiflexion-plantar flexibility, hip abduction, flexion and extension. All of these exercises were advised to be perform 2-3 times a day with 10-20 repetitions each time. From the above critical analysis, it is evident that there is no standardised rehabilitation programme that a patient normally implements during the recovery process. As a result, a more task-based structural rehabilitation programme, along with the continuous active monitoring system, is required to provide a personalised healthcare, catering to the needs of both the healthcare professionals and the patients in accelerating the return of physical functionality. Nevertheless, the effect of physical therapy has shown its potential to increase strength, range of motion, and mobility but some analysis reveals that there is considerable variability in response to rehabilitation.

Table 1.1: Physiotherapist, mobility exercises and daily physical activity movements

Mobility Exercises	**Daily Physical Activity**	**Physiotherapist exercises**
Gait speed in m/sec (4 meter acceleration, 3 meter deceleration)	Standing	Weight-bearing exercise
2,3,5 min walk test	Walking and Sleeping	Non-weight bearing
Timed up and go test	Lying on back and sides	One leg standing test
Step length, velocity test	Sit to stand and stand to sit	Balance test
Outdoor mobility	Postural transitions	
Public transportation	Lying on back and sides	

Several existing rehabilitation programmes are available [24, 26–31] that aid in the improvement and recovery of physical functional mobility. However, limited information is available that accurately describes the physical activities undertaken at key stages during the post-operative rehabilitation, particularly those stages that occur when the patient is at home. Moreover, the effectiveness of the programmes is still uncertain [3]. Appreciating the number of sets of different exercises and the time spent by the patient when sitting, standing, or walking during the course of the day is of significance as it has not been addressed sufficiently by other researchers. Therefore, the programme efficacy is ambiguous as rehabilitation mostly happens when the patient is living independently and unsupervised [9]. The instructions towards the implementation of exercises are either miscommunicated or wrongly implemented. This, in effect, results in prolonging the process and sometimes taking so long as to be fatal. It is clear that when the patient is in hospital, the exercises are supervised and have regular follow-ups by the healthcare staff.

However, the problem arises when the patient is discharged and lives independently at home, as exercises performed are unsupervised. Here, the transparency of what exercises the patient has performed are not precisely known to the healthcare personnel. As a result, there is a lack of transparency between the patient's implementation of the rehabilitation process and the health caretaker. In such cases, there are high chances of the patient neglecting the exercise programmes following the discharge and could lead to interruptions of rehabilitation instruction [3]. Therefore, it becomes challenging for healthcare professionals to keep track of the patient's daily activities/exercise and hence health progress. Furthermore, to avoid improperly exercising, continuous long-term monitoring of the activity movements by a physical therapist and rectifying it is essential [32].

Therefore, it renders a critical global challenge as the healthcare professionals lack the patient's short-term movement history data affecting the patient's ability to succeed in achieving their personalised recovery goals [3]. Moreover, understanding the recovery progression stages and the activities involved during the hip fracture rehabilitation process is essential for planning the wearable sensor-based monitoring system. At a time of such challenges, it urges for the development of a rehabilitation movement monitoring system that could provide a comprehensive rehabilitation care plan programme, recognise the activity movements in near real-time on a long-term basis, assist healthcare professionals in interacting with important events, assess their improvement levels, whether the activities are in supervised (in hospital and clinics) or unsupervised (at home or outside) environments, provide emergency care and have a timely follow-up [33].

The identification of human limb movements plays a significant part in distinguishing information about the human physiological state and daily physical changes [3]. The ever-increasing and unprecedented advancements in technologies like IoT enabled with wearable and digital health, could be leveraged upon in advancing and converting the existing conventional system to a smarter rehabilitation movement monitoring system [34]. The significance of each of these technologies within the healthcare rehabilitation domain is discussed in detail in the next section.

1.4 IoT Enabled Wearable Significance In Healthcare

IoT, also known as industrial internet or internet of everything, is an ever-growing technology paradigm, revolutionising industries and markets in essential ways [35, 36]. With unprecedented advancement in IoT, numerous services and prototypes have been developed and proposed [37]. Drastic transformations have taken place with the integration of the IoT into healthcare, due to the integration of heterogeneous types of physical hardware and software and using them to collect data, perform analyses, and facilitate services and various user interactions with the targeted process. Moreover, it can significantly boost their confidence and well-being, reduce costs and enrich a user's interaction experience. The development of fitness trackers, smartwatches and web-enabled glasses, wireless body-worn sensors have gained significant popularity in healthcare monitoring applications and medical use cases [38]. Findings show that IoT technology enabled with wearable can produce never-ending opportunities, especially for healthcare monitoring applications [38–43]. They play a central role in acquiring the patient's activity movement data, which are responsible for the recognition of the activity movements and controlling the overall movement monitoring process. In fact, wearable sensor-based activity monitoring has been considered quite effective for clinical applications in activity or movement measurement and classification [39].

It has been realized that IoT-enabled wearables [38] are becoming quite attractive in healthcare monitoring applications, as these make the healthcare system transparent and cost-effective as well as allowing personalisation, and improved outcomes and providing high-quality care, reducing diagnostic time, and enabling the effective utilization of the collected data which are accessible from anywhere and at any time. The use of wearable sensors supports patients to live an independent life safely. It also helps healthcare professionals in actively tracking a patient's activity levels on a regular basis, once discharged from the hospital [9]. The authors of [38–40] also indicate that wearables based on IoT technology would be realized when an integrated IoT system is available that has all of the needed functionalities, distributed at various levels.

A strong synergy exists between the unprecedented advancements made in the IoT and the emerging demands of healthcare applications. IoT could support the healthcare system, allowing people to reside and be supervised at home instead of being sent to clinics or hospitals. A recent article surveyed the significance of healthcare IoT from clinical perspectives by discussing its current trends, application demands, and challenges [44]. Moreover, many novel healthcare monitoring systems using machine learning techniques have been proposed and researched for advancing all healthcare applications [45]. The authors in [46] proposed a novel healthcare monitoring system framework based on ontologies and Bidirectional Long Short Term Memory (BLSTM), which can precisely analyse and store healthcare data and improve recognition accuracy. This approach is being applied to healthcare data related to blood pressure, diabetes, and mental health. The model is quite effective in improving the heterogeneous data handling and classification accuracy performance using various sources of patient data. A smart healthcare monitoring system using sensor fusion and deep learning techniques in heart disease prediction has been proposed and implemented by the authors in [47]. The experimental results show 98.5% of precision in terms of recognizing the disease, which is greater than that of existing state-of-the-art systems.

Another recent article [48] used the machine learning technique to predict circulatory failure in an intensive care unit. The proposed approach findings shows 82% of recognition two hours in advance. This shows that the implementation of machine learning techniques could make the system more seamless and precise in classification in managing the large amount of unstructured healthcare data. In addition, many scholars have proposed and implemented IoT-based architectural system solutions in applications including stroke and knee rehabilitation [49], bed egress [50], fall detection [27] as well as sleep [51], respiratory [52], cardiac [53], and glucose monitoring [54]. However, there has been less of a focus on other applications such as hip fracture rehabilitation [55]. Different multi-layered IoT-based architectures that involve wireless sensing, data processing, communication, edge computing and cloud computation have been proposed [2, 34]. Wearable IoT-based three-layered architectures for personalised [56], home-based healthcare services [57] have also been proposed.

The SPHERE project offered an architecture for the identification and administration of healthcare conditions and aimed to integrate different sensing modalities into an IoT solution for Ambient Assisted Living (AAL) [58]. Home Health Hub IoT (H3IoT) designed a simple layered architecture for monitoring the health of ageing occupants and could be extended and modified to suit clinical and emergency-based healthcare monitoring systems [59]. A wearable IoT architecture for home-based and personalised healthcare services is proposed by [56], based on edge computing. In their work, the system architecture component is composed of wearable human activity tracking devices comprising of many different sensors like 9-axis motion sensors, responsible for data collection, storage and processing. An edge computing device is used for storage, processing and for communicating information to the cloud. Cloud computing and other analytical services are used for real-time visualisation of subject data. Their architecture provides an explanation as to how each of these devices functions in formulating a complete system. However, the system lacks technical detailed explanations about the frequency of data acquisition, different types of storage available, data communication frames and protocols by providing examples. The paper has given examples of how their architecture could be suitable for clinical practices. However, there is no discussion on real-life testing on any of the applications to see what challenges the system can offer and how the researchers can benefit at each level while addressing application requirements.

In addition to the proposed design, the focus is now shifting from centralized to decentralized IoT architectural approaches. In the centralized approach, IoT devices directly forward data to the cloud before any decision making takes place. This means that all the computational resources are placed within the cloud. As a result, this could lead to challenges in handling the overhead on the used devices, as well as the latency and increased size of data traffic. In contrast, in the decentralized approach, the resources are utilized across all the three layers (i.e. IoT wearable devices, gateway/edge and cloud layers) [34]. In doing so, the computational and decision-making capabilities are distributed, reducing the data packet transmission size and communication delay time. This concept has not been applied to healthcare monitoring applications and could offer great potential if implemented as part of our proposed monitoring system architecture. However, some of the other promising challenges such as communication latency, wearable energy efficiency, activity recognition reliability, and solution scalability need to be discretely and collectively addressed, as further research efforts are required to address such concerns.

The consideration of the aforementioned factors could be of great interest while offering an overall IoT-enabled wearable system design for a long-term rehabilitation movement monitoring system architecture. In summary, despite all the progress attained in healthcare systems based on IoT and the potential to create an upsurge in different healthcare applications, there is limited focus on offering a wearable solution for the post-operative hip fracture rehabilitation process. This thesis attempts to reflect a healthcare remote support system development for a typical rehabilitation process, with an emphasis on the post-operative care of a hip fractured patient.

1.5 Research Question

“ Could activity movement monitoring through IoT enabled wearables help in accelerating the return of function to the post-operated hip fractured patient? ”

1.6 Research Objectives

The five key research objectives of this thesis are as follows:

1. Investigate the conceptual model for the process of post-operative hip fracture rehabilitation that clarifies the involved process key stages and associated events as well as main movements of interest a patient undergoes straight after hospitalisation.

2. Movement sensing and recognition analysis, which includes: Sensor selection, its placement covering a maximum number of activities and Fast Fourier Transform (FFT) based signal processing in recognising an activity precisely.

3. Investigate the significance of personalisation and one-minute history data in monitoring the core rehabilitation movements and offer an approach that improves movement recognition.

4. Investigate a generic IoT-enabled with a wearable-based test bed or environment for long-term monitoring of hip fracture rehabilitation-related activity movements that utilize the available computational resources at the wearable sensor edge, gateway edge and the cloud to support the overall system's performance.

5. Investigate the formulation of a rehabilitation alert system on the stages and related progression involved in the recovery process.

1.7 Research Scope and Contribution

After the operation for the hip fracture, it is vital to rehabilitate elderly patients with a combination of daily living activities and specific exercises which are usually prescribed by the physiotherapist. The focus of this research is on remote activity monitoring of elderly patients who have been through a hip-fracture operation. Both a quick recovery and the follow-up cost are targeted objectives here. The investigation will help with identifying the process requirements as well as the state-of-the-art technology that could address the solution at both system and components levels. The significance of the proposed approach can potentially improve upon the existing techniques by analysing the feasibility of monitoring daily activity and exercises in order to assess the vital changes/improvements or otherwise taking place in the months after the operation and by throwing light upon important aspects as a part of the architecture such as: Exercises, activities and related monitoring, sensing system and activity identification, local and remote communication, data handling and related services.

This thesis has four unique contributions. These are:

- **Firstly**, a conceptual model for the process of post-operative hip fracture rehabilitation is proposed and presented. This model reflects the key stages a patient undergoes straight after hospitalisation. This concept could support the development of an online activity movement monitoring system offering vital information to clinicians, related hospital people, and caregivers as well as patients themselves about their activity movements and improvement levels.

- **Secondly**, it proposes a frequency-based signal processing approach in recognition of the rehabilitation activity movements. This approach not only helps in validating the recognition accuracy, but also in identifying the optimal sensor placement covering most of the activities. The approach is further tested on the human subjects, analysed and improved by looking into the significance of personalisation and one-minute history of data in monitoring the real-time movement behaviour.

- **Thirdly**, it proposes an IoT-enabled with wearable movement monitoring architectural system design. The architectural design reflects the key operational functionalities implementation at three different levels (wireless sensing; IoT edge; and cloud level) required to monitor patients in real time and throughout the rehabilitation process.

- **Finally**, it utilises the available computational resources at the wearable sensor edge, gateway edge and the cloud to support the system's overall performance. The possible scenarios of architectural implementation, the available network functions, information transparency, and the wireless sensor's lifetime are taken into consideration. The approach provides a solution for an architecture that balances system performance with remote monitoring functional requirements.

1.8 Thesis Outline

The structure of the thesis is organised as follows:

- **Chapter 1** begins with providing the research motivation. It provides an overview of the hip fracture injury and the role of the rehabilitation process towards the recovery of the patient's physical functionality. Keeping the rehabilitation process in mind, it further discusses how with the help of ever-growing technologies like IoT-enabled with wearable and digital health, it could support the development of an online activity movement monitoring system. The systems could track the vital changes or ongoing improvements taking place in a patient's well-being as they go through the rehabilitation programme. The research question, objectives, research scope and contributions are also discussed.

- **Chapter 2** outlines a critical literature analysis to the key components involved in constructing a post-operative rehabilitation activity movement monitoring system. The key components discussion involved relation to the variant types of activities and exercise involved during rehabilitation, the hip fracture treatment pathway and its rehabilitation process, wearable sensing devices, sensor placement, activity recognition techniques and the involvement of IoT-enabled with wearable within the field of healthcare applications.

- **Chapter 3** elucidates the modelling and implementation tools used for testing the conceptual ideology. It provides detailed insights into the different available tools and their competence to investigate the overall concept of IoT-enabled post-operative hip fracture rehabilitation activity movement monitoring system.

- **Chapter 4** introduces the proposed " post-operative hip fracture rehabilitation model illustrating the significance of involved activity movements across different stages of hospitalization, indoor living, and outdoor activities". To support this model, this chapter presents the overall ideology towards the development of the IoT-enabled with the wearable post-operative hip fracture rehabilitation activity movement monitoring systems. The system reflects the key operational functionalities required to monitor patients in real time and throughout the rehabilitation process, involved within the proposed design.

- **Chapter 5** begins by testing and data analysis of core rehabilitation movements under its associated test conditions. The analysis is followed by identifying the optimal sensor placement that can cover maximum coverage of rehabilitation movements and sensing capability. Furthermore, it offer an approach that improves the recognition process and reflects the significance of personalisation and the significance of a one-minute history of data in monitoring the real-time behaviour. It then presents the conceptual modelling and implementation of the overall post-operative hip fracture rehabilitation activity movement monitoring architectural system design. Lastly, it discusses the system performance in possible scenarios of architectural implementation while taking into consideration the available network functions, information transparency, and the wireless sensor's lifetime.
- **Chapter 6** suggested a generic model for monitoring the hip-fractured patient. It reflects the possible usage of the IoT solution, illustrating a clearly defined rehabilitation follow-up programme.
- **Chapter 7** concludes this thesis with suggestions for future research work.

Chapter 2

Literature Review

2.1 Introduction

The chapter principal objective is to illustrate and provide a comprehensive critical literary analysis of the key components involved in constructing a post-operative hip fracture rehabilitation activity movement monitoring system. I will draw from the analysis, highlighting the ongoing current trends, comparative analysis and addressing the advantages, limitations and challenges that could aid in the development of a more robust system.

This chapter will start by highlighting the key components involved in formulating a rehabilitation activity movement monitoring system. Section 2.3 discusses the varying types of activities and exercises involved in human activity recognition research studies. Section 2.4 provides a critical analytical review of the hip fracture recovery process. It highlights the risk factors associated with hip fracture and how rehabilitation plays a significant role in addressing such concerns. The physiological interrelation between the activity movements performed during rehabilitation and related muscles is also shown. It further provides a critical review of the research study done in this area and the monitoring programmes and methods that are currently in use and implemented by researchers and clinicians. The associated challenges in enhancing the overall recovery process are also discussed. A detailed analysis of the sensor placement, highlighting the role of different on-body locations in activity movement recognition is presented in Section 2.5. It further provides an overview of the favourable body location for recognition of a particular type of activity movement. Section 2.6 highlights the role and significance of sensing devices that exist and are currently in use for healthcare monitoring. It also provides a comparative analysis of the different types of sensing devices used by researchers in movement recognition and which sensor is the most suitable for a particular movement recognition. Section 2.7 illustrates the different activity recognition features of extraction, machine and deep learning techniques used widely for classification of different human activities. It also provides a critical detailed analysis of these techniques in relation to the type of activity monitored along with their accuracy level achieved while monitoring. Section 2.8 portrays the significance of the ever-growing technology, such as IoT in the healthcare field. This is explained by providing a comprehensive analysis of the current trend in the medical and clinical domains. It also discusses the different types of architectures currently in use and proposed by researchers in healthcare monitoring. Moreover, the challenges associated at each level that could be useful and taken into consideration while designing an overall healthcare monitoring system are also discussed. Lastly, the chapter conclusion is outlined in Section 2.9.

2.2 Movement Monitoring System Components

In order to develop a continuous, accurate and robust post-operative rehabilitation activity movement monitoring system, five influential factors as represented in Fig.2.1. have been considered and are critically reviewed in this chapter. They formulate the key components in the equation of activity movement monitoring during the recovery process. In the following sections, the involvement of each component is critically addressed.

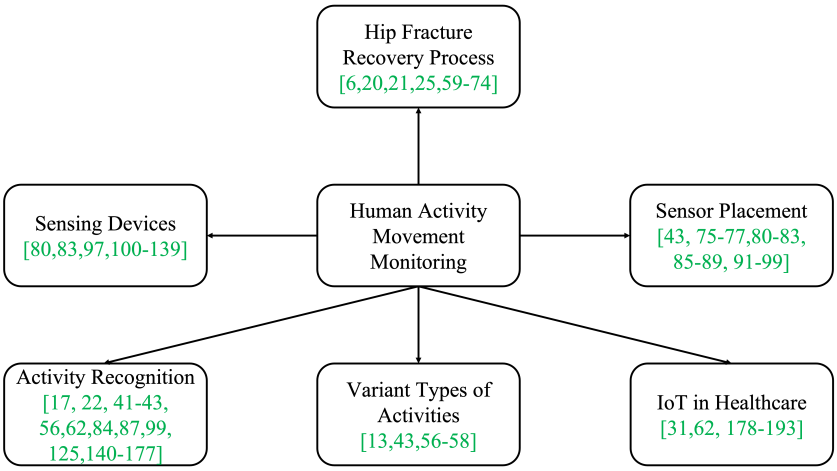


Figure 2.1: Human activity movement monitoring parameter consideration

2.3 Variant Types of Activities and Exercises

Activities can be indoor, outdoor and rehabilitation activities/exercises are application specific. The activities that are of paramount importance to healthcare, welfare and independent living as perceived from literature analysis are described below:

1. **Static Activities:** These types of activities define human posture/orientation when they are in static state such as reclining, lying, sitting and standing [48, 60, 61].

2. **Ambulatory Activities:** These types of activities relates to motion and high-intensity level exercises including walking, jogging, running and cycling (slow, fast and normal) [48, 60].

3. **Transition Activities:** Transition activities refer to changing of a person's state from stationary to dynamic. The type of activities involved are sit-to-stand, stand-to-sit, stand-to-walk, and sit-to-lie [48, 60].

4. **Basic Activities of Daily Living (BADL):** BADL is essential as part of a daily life self-care routine such as feeding, grooming, bathing, etc. [60]

5. **Instrumental Activities of Daily Living (IADL):** IADL activities are of great significance for people living independently. Examples include shopping, meal and drink preparation, managing finances, taking medications, basic household work, communication device usage, etc. [60]

6. **Rehabilitation Activities:** Referring to the type of activities that focusses more on restoring functional mobility to normal and also includes the activities discussed above. However, for faster recovery and observing the vital change at specific body parts, activities vary according to the type of disease. For hip fracture patients, activities such as timed up and go, balance tests, weight and non-weight bearing exercise, etc. [16], are important, whereas in stroke patients [62], tracking continuous human movements is necessary.

   More in-depth work is required in classifying these basic activities into sub-activities. This would help in determining the associated behaviour and in providing more knowledge outside of the initial classification. However, it is still an open research area that needs to be addressed.

2.4 Hip Fracture Recovery Process

Hip fractures are the most common osteoporotic fracture affecting both men and women and are a major concern for the society and healthcare system. The key risk factors associated with hip fractures include elderly age, impaired balance, limited activity movement, muscle weakness and low weight. Rehabilitation is a therapy where the patients perform different types of activity movements and physical exercises. It plays a pivotal role in accomplishing physical functionality, restoring injured hip-supporting muscle strength and preventing further development of physical disability. This is through supporting early post-operative mobilisation to secondary prevention using balance and exercise activity movements. It has been expressed that following hip fracture surgery, the patient should be provided with an optimal, well-coordinated, and organized rehabilitation programme for an enhanced recovery process [9].

Initially, the goal for the patient is to regain their functional mobility. Along with the improvement in the physical functionality, the event and related hospitalisation period often result in muscle's degradation. Therefore, improving and maintaining the muscle strength with the exercises involved during post-operative rehabilitation is essential [9]. Research shows that after a hip fracture, around 5-6% loss of total lean body mass and 4-11% of gain in body fat mass is observed. Most of these changes occur during the first 2-4 months following the fracture [63]. According to a study by Visser et al. [63], it is reflected that a loss in muscle strength leads to poorer mobility recovery a year following the fracture. As a result, understanding the interrelation between the muscles involved in each of the movement exercises while strengthening the hip joint is significant for more precise planning of the recovery process. Table 2.1 represents the particular muscles involved in each of these movements [9].

In summary, the movement activities of lifting thighs upwards, lying on back, walking, leg movement (while sitting), lying on stomach, swinging leg to a side, mini squats, bridging are considered the key activities for supporting these important muscles. Vliet et al. [64] discovered three important attributes a patient should regain in order to fully recover physical functionally. These are (1) mobility restoration; (2) muscle strength restoration and (3) balance restoration.

Cohort study findings show that only 40-60% of people who survive following a hip fracture recuperate their pre-fracture phase physical functionality and 70% improve BADL independence [65]. However, this is adjustable, and less than half of the people undergoing hip fractures could recover and perform IADL. In fact, around 10-20% of pa-

Table 2.1: Exercise movements, muscle and related physical movement involvement

S.no	Movements	Muscles Involved in each movements	Related physical movement
1	Hip Flexion	Iliopsoas, rectus femoris, Sartorius, pectineus	Lifting thigh upwards, lying on back, walking
2	Hip Extension	Glutes maximus, semimembranosus semitendinosus and bicep femoris (hamstring)	Leg Movement (while sitting), lying on stomach, walking
3	Hip Abduction	Glutes medius and minimus, tensor fascia latae and piriformis	Swinging leg to a side, walking
4	Hip Adduction	Adductors longus, brevis and magnus, pectineus and gracilis	Mini squats, bridging, walking
5	Hip Lateral Rotation	Biceps femoris, glutes maximus, piriformis assisted by obturators, gemilli and quadratus femoris	Lying on Stomach and lying on back, walking
6	Hip Medial Rotation	Anterior fibres of gluteus medius and minimus, tensor fascia latae	Lying on Stomach and lying on back, walking

tients transfer to a residential care facility following hip fracture in western nations. Even with these studies, it is not clear how the rehabilitation outcomes can be improved [65]. Recovery progression across eight variant functional abilities post-hip fracture rehabilitation has been expressed by Magaziner et al. [66]. Cognitive function, depression and extremity of daily living attained maximum recovery within four months. Whereas most of the gait and balance recovery attained in the first six months with a maximum of nine months. Furthermore, IADL activities such as meal preparation, cleaning the house and shopping along with lower limb physical movements took almost a year to recover. Walking 3m without assistance often took over 14 months to recover. However, in one of the studies, it is noticed that the majority of patients recovered to their pre-fracture ADL and walking movements in the first six months following the fracture. But the significance of long-term physiotherapy during rehabilitation is still yet to be analysed [67].

In a recent study by Lee et al. [26], it is discovered that measurement and comparison of both pre and post-operative scores are required to assess the recovery level and predict functional outcomes objectively. Several scoring systems that are used extensively by researchers and practitioners in assessing the patient progression during the acute phase includes Verbal Rating Scale (VRS), Cumulated Ambulatory Score (CAS), New Mobility Score (NMS), and timed up and go test. The feature of CAS in quantifying the score relates to the pre-fracture mobility, post-surgery until independence in basic mobility and short-term post-operative outcome following surgery and during the hospitalisation period. CAS is a valid outcome method that examines on a 3-point scale as indicated in Table 2.2 and the overall cumulative score varies from 0 to 6. Here, a score of '0' indicates an inability to perform basic mobility tasks, even with assistance. Whereas a score of '6' score signifies an ability to perform all the tasks independently. The measurement score includes activities such as sit-to-stand, in and out of bed, walking with or without a mobility aid and stand-to-sit. NMS feature relates to functionality level pre-fracture and valid predictor of rehabilitation outcome and mortality. It has high inter-tester reliability that examines on a 4-point scale as illustrated in Table 2.3 and the overall cumulative score varies from 0 to 9. '9' indicates activities performed independently with no aid while '0' refers to an inability to perform any of the activities. Activities such as indoor and outdoor walking, and shopping are part of this. The verbal rating scale features relates to hip fracture pain scores (ranges from 0 to 4) following the fracture. The score signifies different types of pain as mentioned in [68]. The TUG test is another reliable outcome indicator for quantification of the functional mobility level. The activities that fall under this category includes standing from the chair, sit down and walking 3-m to a specified line. It also includes time spent seated in a chair with arms [26].

Table 2.2: Cumulated Ambulation Score 3-point scale quantification method

S.No	CAS score	Functional capability
1	0	Not able to
2	1	Human Assistance of one or two persons
3	2	Independent of human assistance

Table 2.3: New Mobility Score 4-point scale quantification method

S.No	NMS score	Functional capability
1	0	Not able to
2	1	Human Assistance of one person
3	2	Using Aid
4	3	Independent with no aid

Following the surgery and during the initial phase of 6-9 months, most of the patients recover their ambulatory, balance and gait functions. In this phase, patients are discharged from hospital and live independently at home, in rehabilitation homes or in nursing facilities. During these sub-acute periods, the physiotherapy exercises are more focussed towards improving muscle functionality and safer mobility. A meta-analysis was performed by Lee et al. [69] to evaluate the effect of ongoing resistance exercises following hip fracture surgery. Findings show an overall improvement in the patient's physical functionality compared to control groups, and mobility pertaining to lower-limb strength, ADL and balance. The resistance exercise used in most rehabilitation programmes include knee extension, flexion, leg press, and lunges. However, the number of sets, repetitions and intensity varies from study to study. As a result, along with resistance exercises, intense physiotherapy and endurance, balance and functional activities are of paramount importance for a quick healing process.

The efficacy of the home-based exercise therapy is another key important parameter during the post hip fracture rehabilitation process [24]. It is found that prolonging physical therapy and rehabilitation at home may improve functional outcomes. Brovold [70], Syllias [71] and Wyller [72] studied the effect of hip fracture rehabilitation in a home setting where the patient received additional outpatient physiotherapy for up to three months. The outcome resulted in better functional performance, balance, mobility and IADL functionality. Nevertheless, prolonging it further did not yield any additional improvements except for an improvement in strength and walking. In fact, one of the studies by Bischoff-Ferrari et al. [73] reported that extended physiotherapy reduces the rate of falls significantly. Whereas Ziden et al. [74] reported that home-based rehabilitation for up to three weeks led to improvement in patient confidence, balance, self-care, mobility in comparison to the rehabilitation in a hospital ward.

In recent years' studies, home-based rehabilitation has been identified as a viable option in comparison to institutional-based rehabilitation. Kasima et al [75] provided a comparative analysis between patients discharged to home and those discharged to a rehabilitation centre. Findings show that five visits by a physiotherapist at home resulted in better ambulation outcomes than staying for a month in a rehabilitation centre. Moreover, a study by Crotty et al. [76] reported that early discharge and home-based rehabilitation improved short-term independence compared to a hospital unit. Whereas Balen et al. [77] found no changes in the ambulation, quality of life for up to four months, post-operation.

Latham et al. [23] used a rehabilitation programme instructing the patient to carry out home-based movements numerous times per week and for few months. A physiotherapist taught rehabilitation movements part of the programme by visiting patient's home and provided timely follow-up or advisory telephone calls. However, numerous studies assumed that home-based exercise are superior to normal care but the outcomes are contentious. Kuijlaars et al. [75] observed no evidence to support the interest of home-based activity movements post hip fracture. Whereas Wu et al.'s [78] findings stated that home-based recovery exercise programs have significant effect in strengthening the muscle, healing fracture, and improving quality of life and physical functionality. In fact, recent studies [75, 78, 79] found that centre-based supervised rehabilitation was not superior to unsupervised home-based rehabilitation. Considering the variability in studies, it is still unclear which findings are more reliable as the methods and outcomes measurement differs. As a result, it still lacks the evidence and standardized based approach in treatment of the patient rehabilitation process.

In summary and over the last decade, many academics have conducted extensive research around the area of hip fracture patients' post-operative rehabilitation. Different activity movements, exercise programmes and methodology have been proposed and implemented. Although patient rehabilitation processes following hip fracture is broadly researched, no generally acknowledged rehabilitation procedures for functional and mobility healing following a hip fracture exist. The potential reason relates to the fact that it may relate more to the geriatric trauma than an orthopaedic one. As a result, rehabilitation requires attention from healthcare professionals in different fields and the patient's post-operative function can be promoted if continuity in the recovery guidance from hospital to the home is maintained.

2.5 Sensor Placement

The positioning of a sensor on the human body involves sensor orientation and relative position to the body. It is significant from the perspective of human comfort, obtaining precise and accurate data, communication optimization, usability, and adaptability. From the literature analysis on human activity recognition, single and multiple wearable sensors have been worn or attached on a predefined orientation and position. Findings show that with an increase in the number of sensor attachments at multiple body locations, the activity movement recognition improves and increases their accuracy [80]. Furthermore, it is acknowledged that sensor placement is highly dependent on the type of activity performed or monitored and is application specific [81, 82]. From a critical literature analysis around sensor placement, a graphical illustration of the sensors placed by different researchers for activity movement recognition is presented in Figure 2.2.

Sensors with single and multiple accelerometers have been placed at different locations to explore the optimal sensor location for a range of activities [81, 82, 85–87]. Cle-

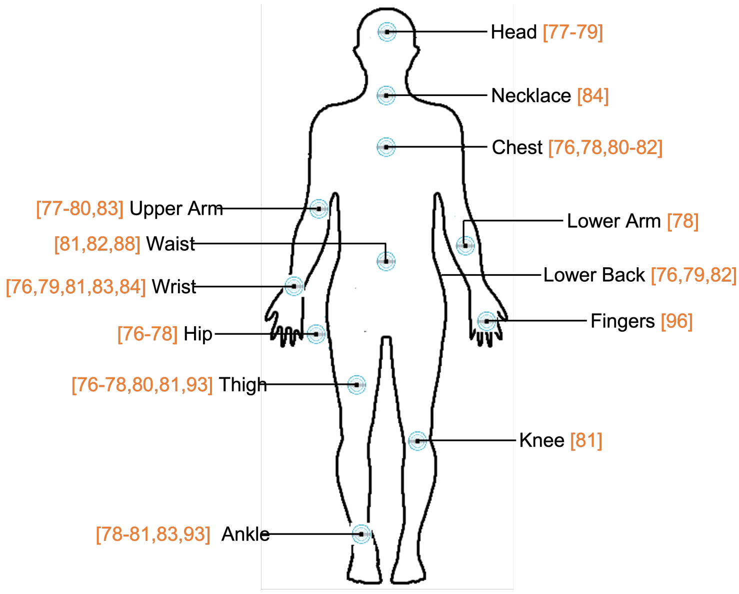


Figure 2.2: On-body sensor placement illustration for activity movement recognition from the literature

land et al. [81] investigated six different body locations to determine the optimal placement of an accelerometer sensor for recognition of basic everyday activities. Their analysis showed that sitting and standing results were poor when the sensor was on the foot. This, however, was more accurate for lying and jogging. Notably, the lower back is not considered suitable for classification, as the accelerometer tends to twist and causes irregularities in the data. Hence, Cleland et al. [81] concluded that the left hip (sensor located at the iliac crest) was the ideal location for classifying everyday activities.

Bao and Intille et al. [88] findings showed that placing the accelerometer sensor on the ankle, hip and thigh proved to be favourable indicators for activities that included posture movement and ambulation, while placement on the wrist and arm were favourable for upper body activity movements like martial arts, typing and twisting etc. Atallah et al. [86] focussed on investigating the ideal sensor location for a more complex group of activities, involving upper and lower limbs. Results showed that wrist location provided good precision and identification rates for activities like preparing food and eating, whereas a waist-mounted sensor showed good results for lower limb activities like walking and sitting. Unlike Cleland et al. [81], Atallah et al. [86] did not investigate the effect of combining accelerometer data on classification accuracy. From the detailed critical analysis, a summary of the favourable sensor location for particular types of activity movement using an accelerometer and Inertial Measurement Unit (IMU) sensor is illustrated in Table 2.4.

From the table and based on a critical review analysis around sensor placement, Pirttikangas et al. [89] used the wrists, thigh and necklace as relevant sensor locations for the identification of activities like typing, watching TV etc. According to Mathie [90], Parkka [91], Yang [92], Karantosis [48], Yeoh [93] and Atallah [86], sensors placed on the waist gave significant information about many different activities such as running, sitting, standing and lying. However, other placement locations such as the chest, wrist, thigh, and lower back have also been used to recognize activities such as cycling, running, working on a computer and walking. From one of the recent studies by Fabien et al. [94] pertaining to mobility impairments, it was discovered that there is no clear preference to sensor placement especially for gait related movements as it was placed at different locations like trunk, pelvis, shanks and feet. Moreover, ankle location was found to be efficient in estimating distance, steps , velocity and energy expenditure. In addition, the head location is used for measuring balance during walking [95].

Table 2.4: Overview of the favourable body location with a particular type of involved activity

Reference No.	Favourable Body Location	Activity Movement Type
Orha and Oniga [96]	Right thigh and hand	Sitting, standing, supine, prone, walking upstairs and downstairs, running, squats
Bulling et al. [97]	Wrist	Reading, opening/closing window, watering plant, chopping with a knife and stirring in a bowl
Manini et al. [98]	Ankle and Thigh	walking
Pirttikangas [89]	Thigh, Necklace and Wrist	Typing, drinking, watching TV, stairs Ascent and Descent
Bonomi [99]	Lower Back	Sitting, lying, standing, walking, running, cycling and working on a computer
Chamroukhi [100]	Thigh, Ankle and Chest	Walking, sitting, standing up, stairs Ascent and Descent and sitting on a ground
Yeoh [93]	Thigh and Waist	walking speed, lying and static activities
Bayat et al. [101]	Arm and Pocket	Running, climbing stairs, walking (slow and fast) and dancing
Bao and Intille [88]	Wrist and Arm Ankle, Thigh and Hip Wrist,Hip and Thigh	Ambulation and posture Sitting, reading and watching TV 20 everyday activities in total
Atallah et al. [86]	Wrist Waist Chest and Wrist Arm and Knee Waist, Chest and Knee	Lying up and down, sitting down, eating and drinking, walking, treadmill walking and vacuuming running, cycling and treadmill running, preparing food and getting down

Overall , there is limited evidence and information available about sensor placement, both in general and specifically pertaining to post hip fracture rehabilitation activity movements. No one location can be viewed as perfect, and this factor is still a subject of debate that needs to be addressed [102, 103]. Another important feature related to placement is sensor orientation. It may be directly attached to the skin, or in belts, straps etc. Developing user-independent sensing activity trackers [104] and enabling the user to adjust sensor position and placement according to their life-style and clothing choice is another significant area to be taken into consideration, which would help the users to adapt and accept with ease and comfort [82].

2.6 Sensing Devices

Sensing devices play a significant role in acquiring the relevant movement data necessary as part of the activity movement recognition and monitoring process. Smart sensing technologies like wearable and non-wearable sensors linked with enhanced predictive modelling techniques enable the recognition of variant activity movements. However, there is a third sensing-based approach group, called hybrid sensors, that use a combination of non-wearable and wearable sensors [105, 106].

Wearable sensors are the on-body worn wireless sensors attached directly to the user at different on-body locations, clothes that capture information about activity movements and exercises performed by the human. The body-worn sensors placement has been discussed in Section 2.5 that discusses how the wearable sensor positioning on various locations of the body contributes to obtaining better activity recognition. Many different wearable sensors are currently used in movement recognition; for instance, the inertial sensors that includes a three axis gyroscope, accelerometer, and magnetometer sensor, the smartphone sensors integrated with IMU's and proximity sensors. Biosensors such as respiratory information, heart rate, Electrocardiogram (ECG) and blood pressure are another category of wearable sensors used commonly in human activity recognition. However, non-wearable sensors are less intrusive, non-restricted by power consumption, have better reproductibility, repeatability and less inaccuracy from external factors interference because of a controlled environment, placed in a naturalistic environment, for example in a smart home without causing disruption in an individual daily life routine. The commonly used non-wearable sensors for human activity recognition include: Radio Frequency Identification (RFID), vision-based acquired by RGB video and depth cameras, radar, Bluetooth, Wi-Fi, image processing, floor, audio and door sensors [106]. A comparative analysis of the wearable and non-wearable sensors along with their purpose is provided in Table 2.5 [102, 105].

Table 2.5: Non-wearable vs wearable sensor comparative analysis

Non-Wearable sensors	**Purpose**	**Wearable sensors**	**Purpose**
Ultrasonic and Photoelectric	Localization/Presence detection	Accelerometer	Activity recognition, fall and motion detection
Vibration	Vibration	Accelerometer magnetometer, and pedometer	Gesture recognition and step count
Pressure	Pressure,fall and Step detection	RFID	Person action recognition with objects
Magnetic switches	Door opening and closing, object usage	Accelerometer, gyroscope, magnetometer	Action recognition movements and motion tracking
Watt meter	Electrical consumption usage	Pulse sensor	Heart rate

However, among the two types of smart sensing technologies discussed, wireless body worn wearable based technologies have gained a lot of attraction in recent years mainly in the medical area because of their small size, convenience, portability, sensor miniaturization using Inertial Measurement Units (IMU's), long battery life and non-invasive nature. Moreover, with the use of wearable sensors, it has been made possible to treat patients at home and measure physiological signals like heart rate, body temperature and activity movement, especially when going through the rehabilitation process after an operation, following a strict routine [107]. It is acknowledged that sensors like accelerometer, gyroscope and magnetometer are the extensively used sensors for human movement identification [108]. A number of studies [109–112] have presented a survey for early care and monitoring for the elderly using a wearable system; recognize gestures, activity movements and examine assistive wheel-chairs and smart walking kits using wearable sensors, respectively. In fact, a recent study by [108] provided an overview of the different wearable sensors currently used by researchers in their studies relating to the recognition of different human activities . Table 2.6 illustrates the different types of sensors used by researchers in their studies for recognition of different human activity movements and exercises [106]. In the table, complex activities involve cycling and stepping over an obstacle; transitional activities involve sit-to-stand and stand-to-sit; dynamic activities involve jogging, climbing stairs and walking; lower-body activities involve walking, running and gait phase detecting; medium-level activities involve walking and simple activities involves cooking, eating and drinking.

Table 2.6: Overview of the favourable sensor with a particular type of involved activity and its recognition

Reference	Favourable Sensor	Activity Movement Recognised
[113–117]	Temperature sensor, magnetometer, accelerometer, altimeter and gyroscope	Simple and medium level activities
[113–115, 118]	Accelerometer and IMU	Lower body activities
[113, 116, 119]	Heart rate monitor and accelerometer	Transitional activities
[115, 119, 120]	Air pressure sensor, gyroscope, magnetometer, and accelerometer	Transitional and lower body activities
[113–115]	Accelerometer and IMU	Complex and medium level activities
[119]	Accelerometer and IMU	Dynamic (upper body) activities
[121]	Accelerometer	Sitting, lying, standing and walking speed
[119]	Accelerometer	Lower body activities
[113]	Accelerometer	Complex and medium level activities

[122] and [123] did an extensive review on the sensing technologies in human movement identification. In their review, it is stated that triaxial accelerometer is the most widely used and preferred sensor. They are particularly effective in monitoring daily physical activity movements, in clinical trials and practice, fall detection, postural ori-

entation, energy expenditure, balance test and activity movement motion classification. Accelerometer sensor is popular as it quantifies movement direction of a human motion across three axes over time. The movement involves repetitive body motions like sitting, running, climbing stairs, standing and walking [124,125]. [88] provides an overview of their research work that uses triaxial accelerometer data in human activity recognition. [126] study provided information about activity movement of a particular body part and orientation by deploying a network of triaxial accelerometers over the subject's body. Whereas [127] using the accelerometer movement data collected from the hip position was able to recognise the subject's ambulation and posture movements. [128] was able to detect lower body movement motions using the three wearable accelerometers data collected from ten subjects. [129] used a wearable device for collecting triaxial accelerometer data for human activity recognition and obtained an accuracy of 94%. Whereas [130] used a single triaxial accelerometer sensor to recognise eight activities i.e. walking, vacuuming, standing, climbing stairs, sit-ups, running and brushing teeth.

Other research studies combined the magnetometer and accelerometer simultaneously [131–133], gyroscope and acceleration with magnetometer [134–136], GPS and microphone with accelerometer [137–139], and other combinations [120, 134, 140] in classification of activity movements. [141] findings shows that gyroscope-based recognition accomplishes better outcomes in comparison to accelerometer for activities like walking (upstairs and downstairs). However, in order to cover a wider range of activities along with gestures, using a combination of inertial sensors increases the recognition accuracy significantly [102]. [85] and [142] also used a combination of sensors to classify BADL, along with posture orientation. However, classifying real falls with normal falls, both the triaxial accelerometer and gyroscope are not reliable, but using the magnetometer helped in determining the actual falls [142]. Moreover, some of the researchers have used only the accelerometer and gyroscope for obtaining orientation information and in discriminating variant types of movement accurately [105, 143]. [128] and [137], integrated the inertial sensors data to recognize daily (e.g. cooking) and physical activities respectively. Whereas [144] combined sensor data from smart environments and mobile sensors to classify users' daily activity movements.

However, information like user location, lateral orientation or tilt, which are important information for activity recognition still needs to be resolved by using the accelerometer [125]. Considering these reasons, a combination of sensors or sensor fusion could be a valid solution in activity movement recognition. But the selection of sensor varies from application to application and the type of movement involved in it. Hence, this factor would be very useful in determining the reliability, accuracy and robustness of the sensing system. Furthermore, there are some design, development, implementation, utilization and fabrication challenges associated with wearable sensors, both from hardware and software aspects for continual human activity monitoring. Some of these challenges relates mostly to low energy operations, the physical impact of the sensor, safety requirements, security, data privacy, light weight, big data handling, storage, processing, interoperability, data connectivity and communication. Therefore, it is important to consider the device limitations, challenges and available resource utilization while designing a wearable tracker for human activity movement monitoring. In summary and from the aforementioned discussion, it is evident that most of the research around activity movement recognition involves dealing with complex, simple, gesture-based, transitional and dynamic activities. However, less focus has been given to more complex activities involved during the rehabilitation process, especially during the post hip fracture rehabilitation process. Hence, limited information and research studies are available that target rehabilitation activity movements where patients have to follow a stringent rehabilitation activity programme which requires further investigation.

2.7 Activity Movement Recognition Methods

From the last two decades, human movement recognition has become very popular and an active area for researchers globally. Recognition of human activity movements and exercises plays a significant role in providing information about the person's identity, daily physical changes and psychological state. This further aids in human-to-human interactions and interpersonal relations. Furthermore, the establishment of detailed activity movements is useful in many domains of human-centric applications like post-operative rehabilitation, gesture detection, home care support, exercise and fitness. In one of the recent studies [145], it is stated that the activity recognition learning module comprises data collection, initialisation, data computation and feature extraction, learning module testing and verification following with the recognition result. However, the use of machine and deep learning techniques and feature extraction from the relevant sensor data plays a significant role in delivering the precise activity recognition outcome [146].

Many scholars have contributed to activity recognition covering wide range of applications such as fall detection [27, 60], posture recognition [147], human tracking [66], and gesture-based movements [148]. Many different activity recognition methods for data analysis such as digital signal processing [149, 150], time and frequency domain features extraction methods [145, 151, 152], as well as statistical, inclination angle and threshold-based methods [46–48] have been used in the classification of static, gait-related activities and rehabilitation movement activities. The feature extraction is divided into four categories, i.e. time-domain features (e.g. max, min, average value and standard deviation), frequency-domain features (e.g. frequency and amplitude), mixed domain features (comprehensive of both time and frequency domain features) and heuristic features (Simple Moving Average (SMA), Signal Vector Magnitude (SVM) and inter-axis correlation). Table 2.7 illustrates the different features extraction based on time and frequency domains of feature [145, 152]. In addition, the common mathematical formulae used in feature extraction as extracted from different literature analysis are presented in (refer Appendix A.2).

[130] and [153] extracted the mean, variance and root mean square values from a 3-axis accelerometer data in classifying the activity movements. Spectral energy feature that helps in distinguishing sedentary activities from vigorous activities was used by [154] and [155] by presenting a classification algorithm implementing energy features. [149] and [153] calculated the frequency-domain entropy of the distinct FFT elements and findings showed that the approach helps in distinguishing activities with related energy values. Wavelet coefficients are useful in presenting walking pattern and gait related applications [156]. A study by [48] and [92] found that using SMA features is effective in identifying a period of daily static and dynamic activities. However, SVM helped in fall detection whereas inter-axis correlation accomplished good results in discriminating cycling from running.

Table 2.7: Activity recognition feature extraction methods

Reference	Feature Domain	Feature Extracted
[89, 130, 144] [157–163]	Time-domain	Mean, Variance, Max, Min,Standard deviation, RMS, Mean absolute, Amplitude, Zero or mean crossing rate, peak count, Derivative and Cumulative histogram
[20, 164, 165] [92, 130, 154]	Frequency-domain	Discrete FFT coefficient, Spectral energy, centroid, entropy, Frequency range power, mean and variance
[104, 166–169]	Time-frequency domain	Wavelet coefficient, geometric template matching, FFT, Variance, mean, correlation, index of maximum correlation, standard deviation, amplitude, peak to peak and median
[48, 154, 158]	Heuristic domain	SMA, SVM and inter axis correlation

From the aforementioned critical analysis, feature extraction from the activity data has shown its significance in recognition of different activity movements. However, for a more detailed, precise and accurate recognition of particular activity movements, different classification methods like threshold-based, pattern-based, machine and deep learning are implemented by researchers across different applications using the features extraction data-sets as inputs. Table 2.8 portrays an implementation of different classifiers along with their accuracy level in categorising different types of activities.

During the investigation, some of the limitations and advantages are observed using these classifiers. The threshold method is simple and very significant in a real-time monitoring system but for a free-living environment, the accuracy is not good in comparison to a home and laboratory environment [170]. The decision tree classifier is considered to be slow as training the data consumes time but it offers better running response. The Naive Bayes classifier proves to be effective in producing higher accuracy in real-life environment situations. However, Hidden Markov Model (HMM) on the other hand gave satisfying results due to the system algorithm robustness and better computation capabilities. The study in [171] examined the ability to determine someone's daily life activities and lifestyle. The study used random forest, SVM, the decision table and Artificial Neural Network (ANN). SVM showed better accuracy but due to vector generation, it consumed a lot of memory. Whereas the decision table was favourable for ordinary decision making. The regression technique gave the worst performance despite using low-level memory. However, the author suggested to use Convolutional Neural Network (CNN) in future models as it may provide better activity recognition outcome.

ANN also gave better results but is considered susceptible to the everyday activity data noise that might affect the training performance. [172] analysed varied deep learning models for movement recognition. The study explained how Long Short Term Memory (LSTM), CNN and Recurrent Neural Network (RNN) are used to provide better outcomes in activity recognition. Findings shows that RNN and LSTM are favourable in recognising short period activities in comparison to CNN, which is more suitable for large activities having a repetitive nature, and the pooling mechanism is better in CNN to achieve a better outcome. BLSTM has received little attention in human activity recognition [173]. However, a study by [174] using the PCA-BLSTM model achieved an accuracy of 97.64%. However, it is recommended to test the model on more complex activities having higher dimensionality. In summary, there is no standard classifier that has been proposed in categorising a specific or wide range of activities with a high degree of accuracy according to our knowledge yet. However, whether to use a classifier in combination or not for precise recognition relies on the type of movement involved and application. Therefore, the classifiers discussed above could be taken into consideration while designing the system solution and for more advanced learning where activities can be recognised with a higher precision rate.

Table 2.8: Categorisation of related work on implementation of different classifiers along with their accuracy level in categorising different types of activities

Reference No.	Classifier Type	Activity Recognized	Accuracy
[175]	Threshold-based	Static and Dynamic activities	93%(home 98%(Laboratory)
[130]	Decision-Tree	Standing, walking, running, climbing, brushing teeth and vacuuming etc.	98.53%
[130]	Decision Table	standing, walking, running, sit-ups, vacuuming, brushing teeth and climbing stairs	46.67%
[176]	Naïve Bayes	Walking at different speed, stair ascending and descending	90% (Young) 92% (Elderly)
[177]	HMM	Walking, standing, sitting up and down, running and jumping,	94.8%
[155]	Nearest Neighbor	Sitting and standing	91%
[178]	Gausian Mixture Model (GMM)	walking flat, up and down slope and climbing stairs	88.76%
[179]	Signal Vector Magnitude (SVM)	Gesture based recognition	87.36%
[180]	Random Forest	Sitting, standing, laying, walking up and down stairs, sit-to-stand and stand-to-sit	98%
[91]	Artificial Neural Network (ANN)	Walking, running and cycling	84%
[181]	Convolutional Neural Network (CNN)	vacuuming, ironing, cycling, walking stairs and standing	84.89%
[182]	Long Short-Term Memory (LSTM)	working on a computer, walking, standing and climbing stairs	91.3%(LSTM)
[174]	Bidirectional Long Short Term Memory (BLSTM)	Standing still, sitting, relaxing, knees bending, jogging, running, jumping, front elevation of arms	97.64%(BLSTM)

2.8 Internet of Things in Healthcare

Medical care and healthcare rehabilitation are the most attractive and widely researched applications areas for IoT. IoT has the potential to upsurge many healthcare applications like remote healthcare monitoring, rehabilitation care, elderly care, fitness programmes and chronic diseases. As a result, it has been anticipated that the IoT-based technology would become an inimitable means to the modern healthcare system. IoT will be the foundation for future smart rehabilitation systems with the aim to relieve the shortage of healthcare professionals and ageing population crisis. A study by Islam et al. [183] illustrated a collective representative of the current IoT-based healthcare products and prototypes. It also highlights the key IoT player in the industry which includes firms such as CISCO, Microsoft, Apple, Samsung, Bsquare, Solair, Orbcomm and Flexera that have shown the capability of developing IoT connected healthcare products.

At present, many research studies are carried out in addressing the potential of IoT in the healthcare domain in relation to different pragmatic challenges. Drawing from the analysis and according to Swapna et al. [184], the key components involved in an IoT model includes the use of sensors, cloud, user interface, intelligent analysis, actions, standards, gateways, networks and things or devices. There are many IoT-based healthcare applications in use, researched and proposed by many different scholars globally due to the rapid advancement in communication technologies like sensing devices and smartphones. Moreover, many other IoT applications include e-health [185], m-health [186], k-health [187], sleep monitoring [185], fall detection [188], rehabilitation systems [189, 190], home monitoring [66], smart medical implants and an intelligent healthcare system [191].

On the other hand, IoT-based smart rehabilitation applications have been introduced recently and have the potential to improve the concern of inadequate resources due to the increasing ageing population. An IoT-based smart rehabilitation automated system design based on ontology is proposed in [192]. Findings show that the IoT can be an efficient and successful platform to offer real-time informative interactions and connecting all the dots of relevant resources. Moreover, IoT-based technologies provide a meaningful infrastructure of remote monitoring in the overall rehabilitation process. There are many IoT-based rehabilitation systems proposed by researchers. For example, a knee rehabilitation system [193], an upper limb rehabilitation assessment system [194] and a smart city medical rehabilitation system [192].

A comprehensive theoretical survey on IoT devices for rehabilitation particularly for applications such as stroke rehabilitation is conducted by Dobkin et al. [195]. The survey portrayed that with the aid of IoT-based technology, the quality of physio-therapeutic practice can be remotely monitored and the alert warnings or feedback offered can elevate the recovery progression. The authors stated that co-active interventions for muscle strengthening and ambulation could be offered by IoT devices for rehabilitation. In addition, the authors also highlighted the use of portable assistive devices with radio transmission to a nearby router or smartphone measuring velocity, precision, repetitions and spatial-temporal movement characteristics. A systematic analysis is provided by Qi et al. [196] which discusses the use of IoT technologies in context to physical activity recognition and monitoring in health. The study was based on IoT technology, using wearable devices, and diverse mobile applications. The authors discovered new research developments and challenges in IoT, discussing the ideas in areas like smart rehabilitation, health and AAL. The discussion was from the perspective of IoT that comprising sensing, network, processing and application layer and is considered to be a successful case study within this area. From the aforementioned discussion, it is evident that different IoT healthcare applications will possess different requirements. As a result, the IoT-based architecture choice will decide the application performance. Three-layered architecture (perception, network and application layer), middleware-based architectures, service-oriented architecture (comprises of sensing, network, service and interface layer) and five-layer architecture (perception, transport, network, processing and application layer) are the different types of architectures implemented by researchers across different healthcare applications [197]. There are many existing, newly proposed architectures that are reviewed critically. Understanding the significance of these architecture across different applications would aid during the development of system design for a particular type of application.

Farahani et al. [36] proposed a holistic multi-layered IoT healthcare monitoring architecture that attempts to portray the progression from the clinic-focused healthcare system to the patient-focused system. The architectural design comprises devices, fog and cloud layers that change the conventional health system to an intelligent healthcare system. Moreover, it also discussed anomaly detection, ambient assisted living, early warning score, mobile-health and IoT-based smart gloves heart rate monitoring for Parkinson's disease.

Whereas [198] proposed cloud IoT-health by introducing a cloud computing and IoT model. In this study, an explanation of the cloud and IoT computing and their applications in the healthcare system is discussed comprehensively so that it could be incorporated into the healthcare system as a new technology. An outline of the HIoT structure was discussed and considering various use cases, different IoT design models were presented in [191]. In addition, technologies like machine learning, blockchain, edge computing, software-defined networking and big data that were applicable for the future use of HIoT were investigated and explored. A study on advanced IoT enabling personalised healthcare systems is presented in [196]. In this study, the author proposed a four-layered IoT architectural design that includes sensing, network, data processing and an application layer and was explained in detail. In comparison, Ray et al. provided a review on the current standards and solutions for edge/IoT. The authors also suggested an IoT-based edge architecture highlighting its requirements, functionalities, capabilities and operational concerns. A comparative analysis between the cloud computing and edge computing in HIoT in relation to bandwidth utilisation and latency was presented that could be considered for future design purposes.

In summary, the establishment and deployment of different IoT-based architecture across different areas of healthcare applications has shown its potential to perform real-time monitoring of human activities. However, as of yet, there is no standard architecture that could provide an overall solution and some challenges are associated with it that requires attention. Some of the challenges include; system scalability, robustness, interoperability, reliability, latency, privacy and confidentiality, continual monitoring, energy efficiency and provision of extensible services and functionality. Moreover, how each layer within the architecture could be utilized by distributing the system functionalities at different layers is still an area of concern. In doing so, the system load could be distributed and help perform each operation in an efficient, reliable and robust manner. All of these limitations along with the aforementioned advantages could be of great significance and taken into consideration while designing a post-operative hip fracture rehabilitation movement monitoring system.

2.9 Conclusion

In conclusion, this chapter outlined and provided a detailed critical review of the key components that could be of great significance in the formulation of a post-operative hip fracture rehabilitation activity movement monitoring. The analysis showed that little is known about the effectiveness of the hip fracture rehabilitation pathways in improving patient outcomes. Therefore, a requirement of a generic rehabilitation programme along with the real-time movement monitoring of any person undergoing rehabilitation from such an injury requires immediate attention. Furthermore, the insights gained from the discussion of various components such as the significance of the selection of sensors in movement monitoring, sensor placement that can cover a maximum range of activities, activity recognition methods in movement monitoring and the role of IoT in healthcare applications paved the way for structuring an IoT-based movement monitoring solution. The analysis of all these components may benefit the research on various aspects such as the design of an overall movement monitoring the IoT system's architecture, addressing the related design issues and challenges, the recognition of hip fracture activity movements, real-time continual movement monitoring, rehabilitation programme event detection and follow-up with the patient's progression.

Chapter 3

Modelling and Development Tools

3.1 Introduction

The chapter principal objective is to discuss the types of hardware, software and simulation tools selected and used for meeting the hip fracture rehabilitation movement monitoring work requirements of the research. Another objective is to illustrate the significance and characteristics of the selected tools. This could aid in activity movement data collection, data computation, data storage, data communication, testing the proof-of-concept, and in validating the activity movement recognition approach, implementation of the overall conceptual ideology on the IoT enabled with wearable movement monitoring system and testing the system performance analysis for a smooth monitoring process.

This chapter begins by providing a brief introductory review of concept development tools motivation and overview, and discussing the types of tools used by different researchers and industries in activity movement recognition. Drawing from the analysis, selected hardware, software and simulation tools, and approaches to designing and evaluating the rehabilitation movement monitoring process are presented in Section 3.3 to Section 3.4. Important characteristic features of the selected tools are also highlighted along with the evaluations to reflect the research activities. Lastly, the chapter conclusion is outlined in Section 3.5.

3.2 Concept Development Tools Motivation and Overview

In this research, it is of vital importance that testing of the post-operative hip fracture rehabilitation movement monitoring conceptual ideology requires scalable hardware, software and simulation tools. Selection of the right tools and methods based on the envisioned movement monitoring framework can effectively result in the subject's activity movement data collection and its analysis, validating the recognition approach, data communication and analysis of the overall activity movement monitoring performance within the deployed network. According to the author David et.al [199], it is believed that the activity movement recognition system is split into two stages. The first stage involves recognition methodology (i.e. sensor selection setup, sensed data processing, classifiers and fusion methods). In this stage, the collected data is mostly fed offline to conventional rapid prototyping tools such as Matlab. This tool provides a rich repository off the shelves of visualisation methods and parameterizable algorithms. As a result, the system variants can be tested at ease and quickly without being involved in time-consuming implementation work. Whereas the second stage involves the implementation of the activity recognition applications. In doing so, the algorithms are implemented in an appropriate language and transferred to the selected hardware device.

In one of the recent studies, author Sharu et al. [200] provided a survey on the IoT ecosystem with a great emphasis on the devices, gateways, operating systems, middleware and communication. The study classified three categories of IoT-devices. These are: (1) Low-end devices (Class 0) (2) Middle-end devices (Class 1) and (3) High-end devices (Class 2). Class 0 devices are low in power, have constrained computational resources and are mostly involved in sensing and for actuation purposes. Some examples of low-end devices include Telcos, Waspmote and TmoteSky. Class 1 devices have more computational resources compared to Class 0 devices but they cannot handle complex requirements. Examples of Class 1 devices include Arduino Yun, Netduino and ESP8266. Image processing and data filtration are some of the capabilities of Class 1 devices. Moreover, numerous communication technologies can be installed within them. Class 2 devices are single-board computers such as Raspberry Pi, Beagleboard, Cubicboard, Banana and Orange Pie. They have maximum computational resources and support LINUX, UNIX operating system. Furthermore, these technologies support emergent technologies like deep and machine learning, artificial intelligence and natural language processing. Such types of devices supports all communication protocols and have everything required to meet a specific application requirement.

On the other hand, simulators are generally chosen as they do not require hardware for testing purposes, and they speed up the design process, reduce expenses, time compression and sometimes become a training tool . Since the simulation depends on machine computational capabilities, complex simulations and conceptual scenarios can be created with high-performance computers. Moreover, it can solve complex engineering problems before actually implementing in real physical space and has the potential to revolutionise experiment-based decision-making [199]. Many researchers have used Matlab extensively for human movement recognition [3, 199, 201, 202].

Nevertheless, author Andres et.al [203] did an extensive review around the hardware technologies knowledge currently used by researchers and industries in activity recognition research and for product development, respectively. This hardware relates to the self-developed hardware or the commercially available hardware available in the market. Findings show that 50% of studies choose to develop and prototype hardware from scratch using boards such as Arduino, Raspberry Pi, low power micro-controllers and IMU sensors. Whereas 60% uses "plug and play" devices and systems. As a result, the different classes of hardware technologies such as wearable, assistive robotics, smartphones, video, electronic components and Wi-Fi are extensively used for activity movement classification. The selection of the hardware tools based on the critical related work analysis and research study requirements is discussed in the next section.

3.3 Selected Tools for Hardware

The importance of IoT hardware has grown tremendously especially in the area of remote healthcare monitoring. It provides the Internet linkage of embedded systems, and smart objects, including smartphones acting as IoT access centres. Moreover, it is responsible for offering significant interaction information on their network and these objects can be deployed in networks like Ethernet, BLE and Wi-Fi and other available communication standards. The comparison of these technologies is provided by author Nur-A-Alam et al. [204]. As the scope of IoT hardware and software are infinite, author Kiran et al. [205], in their study, classified IoT hardware into two categories. These are (1) gadgets and wearable devices and (2) embedded system boards.

The first category refers to the pre-assembled commercially available devices in which the IoT development is limited to the software side. Examples include Fit-Bit flex, Samsung Gear 2, FLORA and i-wallet. However, the next category allows the IoT development from both the hardware and software side. Some examples include Raspberry Pi, Arduino Yun, Beagle Bone and ESP8266. In fact, from a comprehensive study pertaining to technological features of IoT in medicine by Ali et al. [206], two important conclusions are made. This relates to the use of micro-controllers and development boards in IoT medical applications. First is that AT-mega328P and ARM Cortex-M3 family from megaAVR are the extensively used micro-controllers. However, the preferable development boards such as RPi and Arduino are extensively used in IoT-based health applications. From the aforementioned discussion and findings, Microduino, which are tiny versions of Arduino compatible boards and RPi hardware, are selected for our research. The discussion of each of these hardware platforms is presented in the following sections.

3.3.1 Wearable Design Hardware

Microduino is a low-cost tiny version of Arduino compatible electronic building board blocks. Each module blocks snap together with the connectors stacked on top of each other as depicted in Figure 3.1. There are almost 50 different modules with 30 various sensor types, where each module has its own functionality [207].

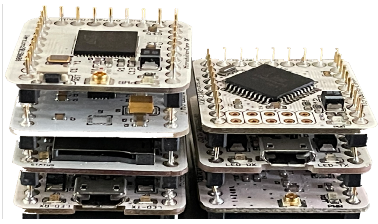


Figure 3.1: Micrdouino modules snap together with connectors on top of each other

Testing of the conceptual ideology at hardware level involves sensing of the human activity movement data, data processing (data filtering and signal processing), data storage and data communication. Considering this aspect, the Microduino modules selected as part of the research work are Core RF (data computation/ signal processing), SD card (data storage), Real Time Clock (RTC) (activity movement event detection), USBTTLC (uploading the program), nrf24 (data communication), Motion sensor (10 degrees of freedom (DOF) for sensing the real-time activity movement). The description of each of these modules and highlighting the significance of how each module satisfies the domain of our research application are as follows:

1. **CoreRF:** Microduino CoreRF is an AVR board processor that has the capability to perform data computation (like mathematical and digital signal processing) which is an essential part of movement recognition requirements. It is the main controller of our wearable hardware design. Table 3.1 illustrates the module specification. It is integrated with 802.15.4 wireless protocol and supports wireless components such as RF4CE, MAC/6LoWPAN and ZigBee that could also be used for data communication purposes. It easily provides seamless connectivity with other Microduino

related sensors and modules and is also compatible with Arduino programming IDE [208].

Table 3.1: CoreRF module specifications

S.No	Parameter	Specification
1	MCU Type	ATmega128RFA1
2	SRAM	16 KB
3	Flash	128 KB
4	EEPROM	4 KB
5	Power Supply	3.3 V
6	Clock Speed	16 MHz

2. **Motion Sensor:** Microduino 10 DOF motion sensor adopts I2C interface and is widely used in movement monitoring, self-balancing cars and robotics. The key significance of the motion sensor is that it integrates four sensors in a single module that includes: three axis accelerometer and gyroscope (MPU6050), a barometric sensor (BMP180) and a magnetic-field strength sensor (HMC5883L) [209]. Among all the available sensors, only the triaxial accelerometer is used in this research, which is responsible for sensing real-time human movement activity data. It offers four different ranges of acceleration: $\pm 2g$, $\pm 4g$, $\pm 8g$ and $\pm 16g$, where g is the acceleration due to gravity in m/s^2. In this research, the acceleration range of $\pm 2g$ is considered sufficient to detect ambulation activities [12].

3. **SD Card:** The main aim of the SD card is to read and write data from off a memory card. It is an open hardware circuit design and compatible with Arduino programming environment. In this research, the raw activity movement accelerometer data signals are stored in the SD card. However, depending on the application requirements, the data storage longevity can be extended by using an SD card of any size [210].

4. **nrf24:** It uses a 2.4GHz ISM band with the maximum transmission power of 0DBM and has an operating voltage between 1.9-3.6V. The transceiver communicates with a maximum data rate of 10Mbps over a 4-pin Serial Peripheral Interface (SPI). The specifications of this module are illustrated in Table 3.2. It is a high-speed embedded wireless data transmission module that uses its own enhanced shock-burst communication protocol for transmission and reception. It supports three air data rates, i.e. 250kbps, 1Mbps and 2Mbps and is appropriate for low-power wireless applications. The packet structure of this protocol is broken down into five fields as illustrated in Figure 3.2 [211]. Enhanced shock-burst introduced Packet Control Field (PCF) is used for more enhanced communication. This also includes the preamble, address, payload and Cyclic Redundancy Check (CRC) which was in the original shock-burst protocol. The new structure is of great significance as it allows variable-length payloads (ranging from 1-32 bytes), allows each packet sent with a particular packet ID and each packet can request acknowledgement [212]. In this research, the role of this module is significant in the establishment of data communication network connectivity (i.e. point-to-point and multi-point network) during the activity movement data transmission and reception.

Table 3.2: Nrf24 module specifications

S.No	Parameter	Specification
1	Frequency Range	2.4 GHz ISM band
2	Maximum Air Data Rate	2Mb/s
3	Modulation Format	GFSK
4	Max Output Power	Leg 0DBm
5	Operating Supply Voltage	1.9-3.6 V
6	Max. Operating Current	13.5 mA
7	Min. Current (Standby mode)	26 μ A
8	Communication range	800 +m (line of sight)

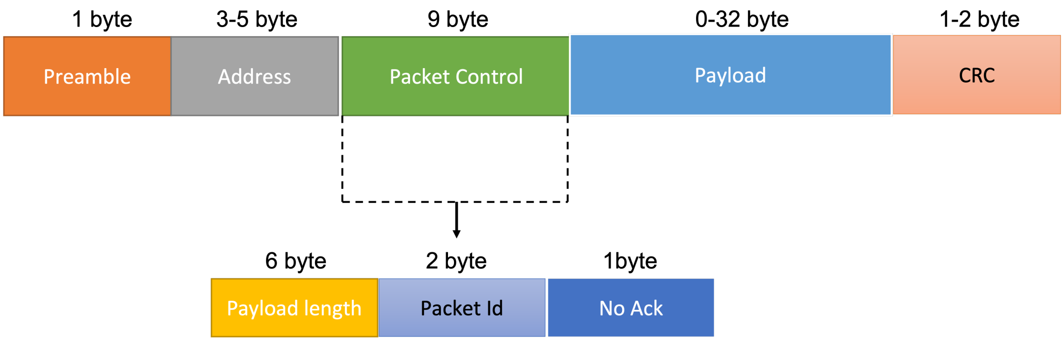


Figure 3.2: Nrf24 enhanced shock-burst packet structure

5. **Real Time Clock (RTC):** RTC is based on NXP CMOS PCF8563 and uses TWI/I2C interface for communication. It is a low power clock chip and uses EEPROM AT24C32 with I2C interface for data backup. Moreover, it has a super-capacitor XH414 that provides a power-down timing function in a time slot [213]. In this research, the subject's rehabilitation movement occurrence period is captured using this module. This will help track when the patient is active and performing activity movements.

6. **USBTTL-C:** It is a switching chip-based module that can be directly connected to the CoreRF module in order to debug serial ports , download the program and communicate with a computer. The module has a built in transceiver, supports 3.3 and 5V power voltage and is compatible with USB V2.0 [214].

After understanding the features of the aforementioned modules and their role in testing the concept ideology, a wearable activity tracker is designed using the modules discussed above. A 3-D printed enclosure is designed to fit all these components in a single box. Moreover, a commercial fabric strip is tailored based on the wearable sensor design to make it comfortable for the user wearing the activity tracker. The activity tracker is the fundamental part of the monitoring process as it involves real-time activity movement data acquisition, computation, storage and communication. Figure 3.3 portrays the proposed wearable tracker used in this work, its attachment at ankle location along with its components stack.

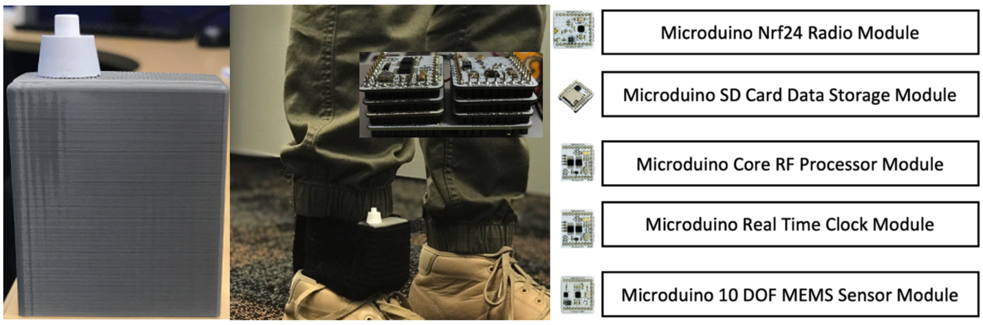


Figure 3.3: Wearable activity tracker, its attachment on the right ankle and its components stack

3.3.2 Internet-Gateway/IoT-Gateway Hardware

Internet-gateway is referred to as a high-end IoT device. It acts as an intermediate among variant sensor networks and the IoT cloud platform or high-end IoT devices throughout the Internet. The major task of the gateway is to handle heterogeneity as different kinds of data streaming from variant sensors is collected and sent to the cloud platform. Therefore, it acts as a bridge across different IoT architecture layers lying in different networks. Furthermore, the gateway can act as a high-end device and middle end-device when the IoT ecosystem is large and small, respectively. Gateways are robust to environmental conditions and can perform tiny operations like data filtration, pre-processing or local processing, data conversion to a unique format, data storage, ability to handle power break, and overcome failure and communication gaps [200]. Commonly, gateway communicates through Wi-Fi, Ethernet, Bluetooth and Global Positioning System (GPS) [204]. However, in large IoT ecosystems, local intranet is available at the controller and gateway level that support real-time monitoring applications such as healthcare monitoring [200]. Table 3.3 presents the different types of edge/gateway devices used by researchers in different applications.

As discussed earlier, Raspberry Pi and Arduino are the two most investigated boards and are in use for the IoT applications development in the healthcare monitoring domain [206]. RPi is considered an excellent choice for IoT projects and with the Pi community, along with Arduino, it is massive and software support is always secured. RPi3 is a third-generation Linux computer (64-bit) that can do the same operation as a Linux desktop. It is a single board running on a 1.4GHz 64-bit processor and has Power-over-Ethernet support. Figure 3.4 portrays the components and specifications of a RPi 3 Model B+. The feature of Bluetooth and Wireless LAN is considered very useful for the development of IoT applications [200]. Numerous operating systems such as IoT core, raspbain Linux, Ubuntu Mate and Windows 10 can easily run on RPi. For our research, the Raspbian operating system is used in RPi and comes preloaded with Python which is the official programming language for RPi. A sample presentation of the Raspberry Pi serial port communication code written in Python is illustrated in Figure 3.5. However, RPi supports other programming languages such as C/C++ and JavaScript [215].

In this research, a portable RPi is connected through the serial communication port with a Microduino nrf24 radio module (discussed in the previous section) using serial peripheral interface (SPI) and is powered by two AA batteries of 2500 mAh (i.e. equivalent to 5000 mAh) as shown in Figure 3.6. The main purpose of making the gateway device portable is to allow subjects to carry it anywhere and with ease while moving out of their allocated residence. However, other devices such as smartphones, laptops and super gateway nodes can be used depending on the application requirements.

Table 3.3: Different categories of IoT gateway devices used by researchers in different healthcare applications

Reference	Application	Edge device	Device Utilization
[216]	ECG signal measurement	Raspberry Pi (RPi)	RPi saves sensor data in text file and computes in MATLAB computer environment
[217]	Temperature measurement	RPi and Arduino	Exchange of data between RPi and Arduino using ZigBee
[218]	Diabetic patient monitoring	Smartphone	Determine risk-level of diabetic patient using decision tree classifier
[219]	cancer recognition	iPhone	Skin lesions detection using CNN model operating on iPhone.
[220]	Parkinson's disease teletreatment	Intel Edison	Intel Edison extracts acoustic features and sends to cloud for categorization
[221]	Falls monitoring	LCP2148 ARM7 micro controller	Wireless sensor communication and push notifications of abnormal events
[222]	Activity recognition	PC server	Classification and prediction of different activities using random forest and SVM
[223]	Pulse rate, Temperature measurement	Raspberry Pi	Remote healthcare monitoring using Bluemix Cloud

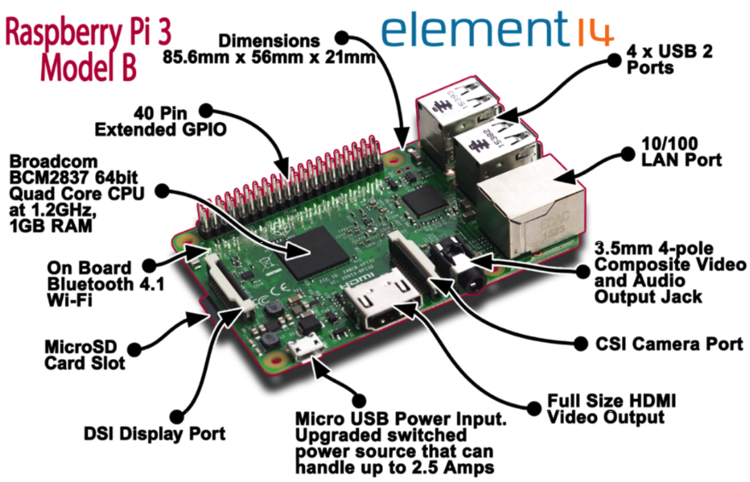


Figure 3.4: Raspberry Pi design

```python
import serial
from time import Sleep
serialport = serial.Serial('COM1',115200)
sleep(4)
serialport.write('H')
sleep(1)
#check bytes in input buffer
while True
    if(serialport.in_waiting>10)
        DataIn = serialport.readline()
        sleep(1)
        serialport.flush()
        sleep(1)
    sleep(10)

serialport.close()
```

Figure 3.5: Raspberry Pi 3 Python script

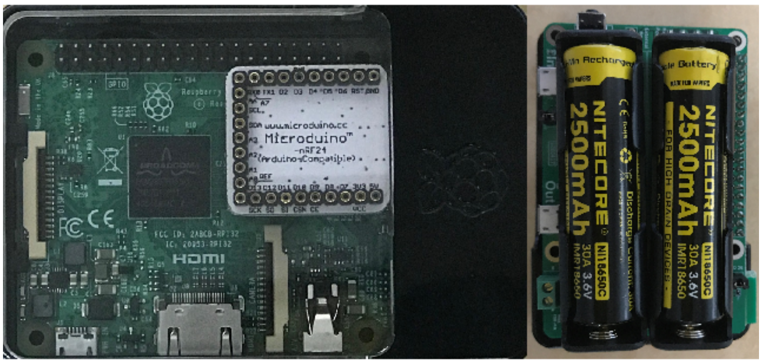


Figure 3.6: Portable Raspberry Pi with Microduino nrf24 radio module top and bottom view [2]

3.4 Selected Tools for Software and Simulation

After the selection of the hardware comes the software selection which is the crucial aspect of IoT product development. Kiran et al. [205] study provided a comparison of the IoT software platforms that are compatible with different IoT hardware. It is important to know which software platform will support the selected hardware module. It is normally driven by Integrated Development Environment (IDE) and API availability for accessing the data and notifications . Moreover, the study divided the IoT software domain into two categories: (1) IoT languages and (2) IoT platforms. For the first category, the most common IoT languages used are Python, C++, JavaScript and HTML5. Apart from these languages, a study by Ali et al. [206] reveals that MATLAB is extensively used and preferable programming language for validation of the research in scientific and technical computing. Whereas the IoT platform is currently available and used by researchers and industries, including ThingSpeak, Ubidots, Pinnocio and smart living. The selection of IoT platforms is significant from the perspective of device management, connectivity, database, interfaces, intelligent data analytics, data visualization and action management based on sensor data and its conditions. From the aforementioned critical analysis and based on the hardware selected and its requirements, the software selected for our research study includes Arduino IDE, MATLAB and ThingSpeak IoT cloud platform, which are discussed in the following sections.

3.4.1 Arduino IDE Programming Software

Arduino software is an open-source electronic platform that is flexible and easy to use. The software includes a text console and sketch for writing a code, a series of menus, message fields and toolbars for common functions. It simplifies the process of working with micro controllers and has several advantages such as: It provides a simple, clear programming environment, it is inexpensive, and it has a cross-platform, meaning the software can run on Windows, Mac or Linux operating systems. Moreover, it also provides the capability to write codes and upload a sketch to the board online, using a web browser. The programming language used is C programming. However, the language could be expanded to C++ programming, too. Programs written using Arduino IDE are called sketches. A sample representation of it is illustrated in Figure 3.7, along with a debug screen. In this research, Arduino Integrated Development Environment (IDE) or Arduino software has been used to write programs (for sensing activity movement acceleration signals, basic statistical data filtration and frequency-based signal processing) and upload programs to the Microduino modules part of activity tracker and communicate with them for debugging purposes [224].

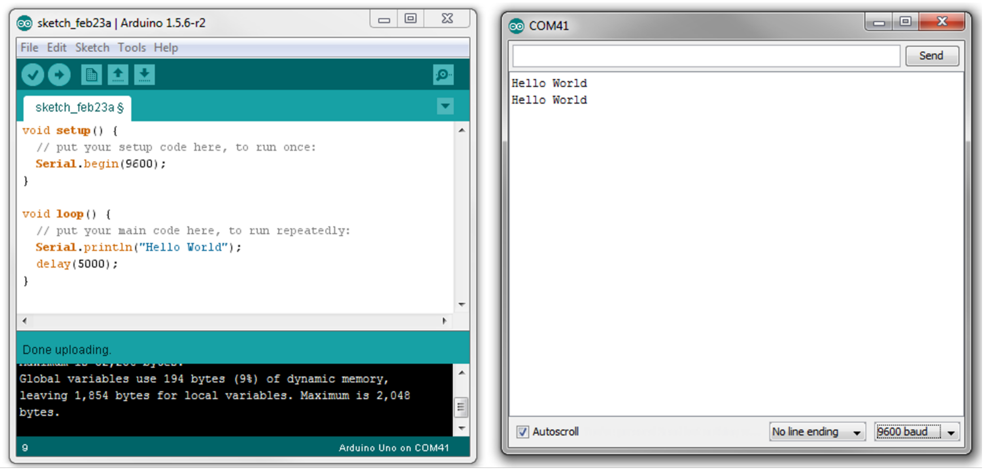


Figure 3.7: Arduino IDE program sketch

3.4.2 Matlab and Simulink Software

Matlab is a highly performance based language collaborative system that integrates computation, programming in an easy-to-use environment, automatic generation of C source code and visualisation. It also includes algorithm development, modelling, simulation, data analysis and prototyping the concept. Here, problems and solutions are expressed in mathematical notation. On the other hand, Simulink is a time-based Matlab graphical programming interface used for analysing, simulating and modelling dynamical systems. Because of its efficiency, flexibility and ability for quick iteration, it is widely used in embedded systems [206, 225].

In this research work, Matlab software has been used for testing the proof of concept before implementing it in an actual physical space. This involves designing an activity movement recognition design model, mathematical movement processing algorithm software, preliminary validation of the algorithm based on the movement data collected from different healthy subjects, intelligent computational analysis using machine learning or logical processing, plotting graphs and data visualization.

3.4.3 Thing Speak Cloud Software

For this research, ThingSpeak, an IoT-based cloud platform, has been used. The platform allows to collect, store movement information in real-time, visualise, offer alert warnings and analyse streams of data in the cloud. It allows developing IoT-based processing and visualisation for the application. Computational tools such as Matlab are integrated within the platform that could be used for any data computation like signal processing and machine or deep learning process to make sense out of the activity movement data . The usage of such tools could be significant in making a more precise sense out of the data as the computational resources are relevant to most of the operational requirements of the process. It provides the capability to run IoT analytics automatically based on events or schedules [34, 226].

The fundamental part of ThingSpeak relies on its communication channels where each channel accommodates a maximum of eight fields of different data types, three location fields and one channel field for the status value. It updates the data every one second and accommodates around 90,000 messages per day, which also overcomes the lag associated in transmission with the processed data from the gateway to the cloud [2]. Moreover, it also provides the capability for uploading the data in bulk, where the limit of a single bulk update is up to 14400 pieces of data and the time limit between each sequential bulk update should be 15s or more [2]. ThingSpeak has a plugin that provides the functionality of triggering a notification using Thing HTTP from IFTTT. IFTTT refers to " If this, then that" which is a web service that allows users to create applets which act in response to another action. Moreover, it allows users to automatically act on the data and communicate or follow up with required personnel by sending alert messages, emails or calls [2, 226].

3.5 Conclusion

In conclusion, this chapter provided an outline of the commonly used and available tools for activity movement recognition. It discussed the significance of selection of modelling and development tools for testing a particular application conceptual ideology. It presented Microduino and Raspberry Pi 3 hardware , Arduino, Matlab and ThingSpeak software and Simulink simulation tools selected for this research and discussed the role of each of them in contributing towards the validation and implementation of the application proof-of-concept.

Chapter 4

Post-Operative Hip Fracture Rehabilitation Movement Monitoring Concept Development

4.1 Introduction

This chapter focusses on the development of an online activity movement monitoring system to help monitor and assess the follow-up of a patient's progress in implementing a rehabilitation programme after leaving hospital after a hip fracture operation. The main contributions from this chapter include compiling a conceptual model out of existing rules and health programmes for post-operative hip fracture rehabilitation. This is presented in Section 4.2. The model reflects the key stages a patient undergoes straight after hospitalisation and provides clarification of the process involved, main physical movements of interest and its associated events across all stages of care. To support this design model process, a high-level "IoT-enabled with wearable post-operative hip fracture rehabilitation long-term movement monitoring system" design highlighting all the key operational functionalities is proposed and presented in Section 4.3. The detailed design functionality of each of the suggested operational components is discussed in Section 4.4 that is responsible for the overall movement monitoring process. Lastly, the chapter conclusion is outlined in Section 4.5.

4.2 Proposed Rehabilitation Model

Following the hip fracture operation, the patient is required to follow a structured rehabilitation programme for the recovery of the affected muscles. However, there are no specific guidelines accessible pertaining to the key activities involved at different stages of rehabilitation following a hip fracture [12]. Until now there was no evidence that discussed the specific time frames of switching the activity movements from one stage to another, as the patients are generally elderly with a wide range of cognitive and physical abilities. Prior to their fracture, some were very frail to start with, while others exercised regularly. Similarly, their resilience, confidence and anxiety levels vary, and these factors affect how they progress. Because it is so multi-factorial, it is hard to discern or declare exact milestones [9]. As a result, some key factors are taken into consideration while proposing the rehabilitation pathway design model. These are four-fold and involves the following:

1. Identification of the different progression phases involved from the hip fracture injury to the rehabilitation process. This ranges from the time the patient first experienced a hip fracture, and underwent a surgical operation to the rehabilitation recovery process.

2. Analysing the different types of activity movements involved during the healing phase. Along with the analysis, understanding the interrelation between the muscles involved in each of the movement exercises while strengthening the hip joint (refer to literature review chapter under section 2.4: hip fracture recovery process). This is significant in order for a more precise plan of the recovery process as, according to a study [9], it is shown that loss of muscle strength leads to poorer mobility recovery a year following the fracture.

3. Investigation of the key performance indicators such as how often the activity movements should be performed by an individual during the day (referred to as daily frequency practise), how many repetitions should be performed and the duration of each activity. These parameters are of great significance while recognising a particular activity, as it would help the healthcare professionals in understanding the vital changes/ improvement levels taking place within an individual. Furthermore, it will also help in deciding how well the patient is progressing and whether they are ready to proceed on to the next stage of the recovery process or not.

4. An understanding of each of the activity movement description/instruction so that the activity is performed correctly by an individual and has a direct impact on the type of muscles involved within each activity. This is essential while capturing the raw activity movement data and for recognition purpose, as some of the activity movements are supervised (when the patient is in hospital) while some are unsupervised (when the patient is at home or living independently).

Considering the aforementioned design attributes and based on the information provided from the related work in Chapter 2, with the help of a physiotherapist and medical domain expert knowledge, it is apparent that there are different activities at each stage of treatment that occur for hip fracture patients [12]. Therefore, an overall layout of the post-operative hip fracture rehabilitation pathway in stages is proposed as represented in Fig 4.1 [9]. The rehabilitation model involves a number of stages and covers the rehabilitation requirements at the hospital, indoor-at-home activities and outdoor activities [12]. It exhibits the number and name of stages involved, key involved activity types and names across each stage, how frequently the exercises should be practised, which activity is supervised, unsupervised or is a combination of both, the duration of a particular activity to be performed and an activity image illustrating the movement direction and pattern [9]. The model structure is divided into three rehabilitation phases spread across four different stages [3, 9]. Three phases of rehabilitation recognised from the existing practices are:

1. **Phase 1:** Supervised rehabilitation at hospital.

2. **Phase 2:** Guided/Unsupervised rehabilitation at home.

3. **Phase 3:** Unsupervised rehabilitation outdoors.

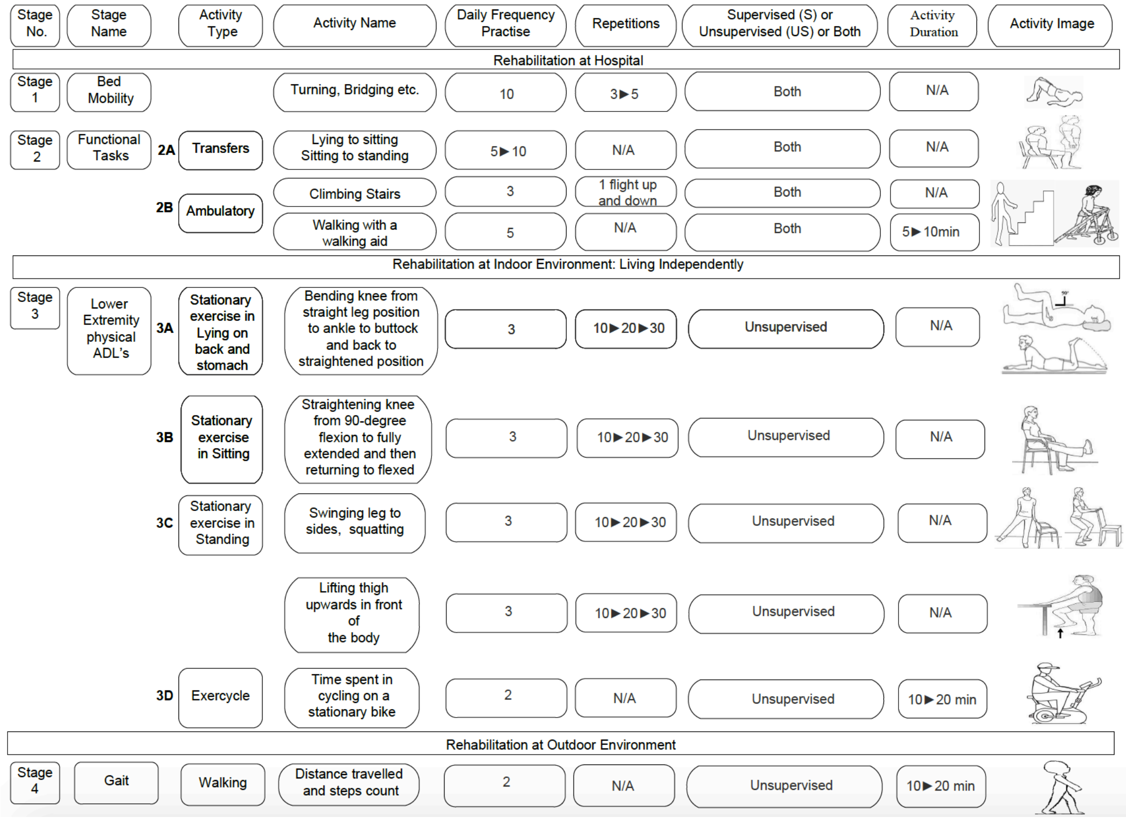


Figure 4.1: Post-operative hip fracture rehabilitation model illustrating the significance of involved activity movements across different stages of hospitalisation, indoor living, and outdoor activities [3]

During the first phase of the rehabilitation process, i.e. supervised rehabilitation at the hospital, the objective of the rehab just after the operation at the hospital aims to improve the patient's independence [3, 9]. This is performed by attempting a range of motions resulting in a strengthening of the muscles. These exercises are: Bed mobility (turning or bridging) which requires a daily frequency practise of ten times with 3-5 repetitions; transfer (lying to sitting and sit-to-stand) with a daily frequency practise of 5-10 times; and ambulation (walking with a walking aid five times with a total duration of 5-10 min and climbing stairs three times where one flight up and down refers to one time of frequency practise). These movements are both supervised and unsupervised and are part of stages 1 and 2 of the first phase of the rehabilitation process. It assists in the returning of their daily physical functionality, allowing them to be safe ambulators within their home environment. Before being discharged from the hospital, a team of health professionals consisting of nurses, social services and therapy staff observe their improvement levels based on CAS, NMS and VRS as mentioned in Chapter 2. Following the observation's findings, health professionals work closely with the patients to accord on achievable goals for a secure discharge [9].

In the second phase of the rehabilitation process i.e. guided/unsupervised rehabilitation at home, a hospital-based physiotherapist provides an exercise programme for the patient to undertake at home. This is aimed at increasing joint range of motion, strength and endurance with a view to improving lower extremity physical activities of daily living and particularly ambulation. The activity movements part of stage 3 of the second phase of the rehabilitation process involves stationary exercises in lying on back and stomach, stationary exercises in sitting (i.e. leg movement), stationary exercises in standing (i.e. swinging leg to a side, squatting, lifting thigh upwards in front of the body) and exercycle. All of these activity movements, unsupervised, require a daily frequency practice of three times starting with ten repetitions and could go up to 30 repetitions depending on the patient's progression and improvement level. However, exercycle exercise needs to be performed only two times for a total duration of between 10 to 20 min. It has been reported that home-based exercise programmes with minimal supervision have a reasonable effect on improving physical functionality, mobility and balance [11]. However, due to the lack of supervision, the patients' compliance with performing their exercises and gait activities is not objectively quantified and hence healthcare providers rely only upon subjective commentary from the patient, its validity being questionable. The current implementation reflects random operation with significant uncertainty in the expectation of the outcome. The process, if implemented correctly, should help improve the mobility to the level of moving to the outdoor exercises. It could also help in identifying possibilities to fine-tune the programme to be more suitable to the particular person (i.e. personalisation of the programme) [3, 9].

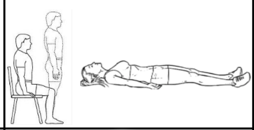
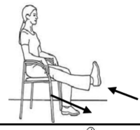
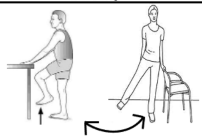
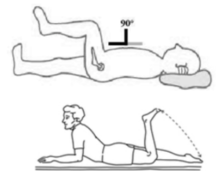
The last phase of the rehabilitation process, i.e. unsupervised rehabilitation outdoors aims to improve the patient's mental health along with the physical functionality by enabling them to ambulate outside of the home environment. Gait related movements such as walking are part of stage 4 of the last phase of the rehabilitation process and requires a daily frequency practice of two times where each practice accommodates a total duration of between 10 to 20 min. In doing so, exercise programmes can advance/progress much more effectively, as is the ability of the patient to re-integrate within their local community [3, 9].

In summary, the main movements of interest as part of the activity movement recognition analysis in this chapter are categorised into two. The first category involves the static state and ambulatory activities of Slow Walking (SW) and Fast Walking (FW). The second category involves hip joint and related muscle strengthening movements like Leg Movement (LM), LTU, SLTS, Lying On Back (LOB) and Lying On Stomach (LOS). Table 4.1 represents the main rehabilitation physical activity movements along with their associated movement description and image.

However, apart from the three key rehabilitation phases discussed above, there are situations where some patients receive supervised rehabilitation once home irrespective of how they are progressing. The reason is that their exercise at home is limited by the lack of equipment that can be utilised. This is most relevant to strengthening exercises where increased resistance is needed in the form of weights or special equipment to obtain a more efficacious improvement. Resistance training exercises are needed for plantar flexors, knee extensors, and particularly hip extensors and abductors. Additionally, balance exercises are often undertaken in a supervised environment where the risk of a fall is less likely. Whether a patient receives supervised rehabilitation depends upon factors such as perceived progress, resources available in the local community and provision within the patient's insurance programme [9].

The significance of knowing these progression stages in systematic order is important while developing an online automated decision-making system model and fuzzy indicator based on activity recognition. For instance, a system can recognise the swinging leg to a side activity has been performed two times with ten repetitions each time. Based on the particular movement recognition and accumulated data over the days, weeks, or

Table 4.1: Hip fracture rehabilitation involved activity movements, its description and illustration

S.No	Activity Name	Activity Description	Activity Image
1	Static state	Activities like sitting/ standing/lying holding a single position	
2	Slow Walking (SW) and Fast walking (FW)	Activities helping in paying attention to the movement, improving posture, stride and arm motion movements	
3	Leg Movement (LM)	Straightening knee from 90-degree flexion to fully extended and then returning to flexed	
4	Lifting Thigh Upward(LTU) and Swinging leg to a side(SLTS)	Standing with your feet together, arms holding a fixed object for support, then lifting one knee up to the waist level for LTU. For SLTS , move your leg out to the side keeping knees straight	
5	Lying on back (LOB) and Lying stomach(LOS)	LOB: Flex hip and bring knee towards chest not more than 90-degree and slowly return limb to extended position. LOS: Flex knee and bring heel towards buttocks and return to extended positions.	

months, the system will automatically recognize the activity stage, patient improvement and progression levels [9].

With the rehabilitation system design in place and multiple patient data availabilities pertaining to these activity movements through the help of intelligent machine or artificial intelligence techniques could aid researchers/clinicians in actively monitoring the patient progression in a personalised manner, accessing the patient data remotely, observing the vital changes taking place on a regular basis, comprehending how slow or fast a patient is progressing and adjusting the repetitions and exercise accordingly, analysing the average amount of time required for a patient to switch from one activity to other and sending necessary feedback to the patients in case of emergency or for a follow-up [9].

As a result, the key performance parameters of interest while recognising a particular activity precisely during online movement monitoring are:

1. Daily frequency practices i.e. how many times a particular activity is performed by a patient.

2. Number of repetitions i.e. how many repetitions are done each time an activity is carried out and

3. Activity duration i.e. how long a particular activity is carried out.

The next section discusses the potential for an online rehabilitation programme implementation by proposing an IoT-enabled with a wearable post-operative rehabilitation movement monitoring system design solution.

4.3 Movement Monitoring System Architecture

A generic post-operative rehabilitation movement monitoring system architecture is proposed as represented in Figure 4.2 [9]. The architectural design functionalities utilise computational resources at three main levels. These are: Wearable wireless activity tracker level, IoT gateway or edge level and Internet-cloud level functionalities. Each of these levels play a unique and significant part in offering the key functionalities for smooth operation of the overall rehabilitated patient movement monitoring process [34].

In the proposed system architecture, human subject is considered as the fundamental part with the wearable activity tracker, which can be embedded with different inertial sensors and attached at different body locations (for example hip, thigh, ankle, back and waist), thereby formulating a wireless body area network. The consideration of different body locations (i.e. hip, thigh, waist and ankle) is used to investigate the optimal sensor placement that can cover/target the maximum coverage of key activities involved during the post-operative hip fracture rehabilitation process. The tracker is responsible for sensing the real-time human activity movements and reports wirelessly to a local gateway through embedded standard protocols like ZigBee, Bluetooth or Wi-Fi. However, other customised protocols may also be facilitated depending on the type of modules used and their associated protocol. They may involve one or more sensing types and the rate of data acquisition and reporting could be configured to suit the application. The gateway (for example RPi, a workstation, laptops and smart devices) may handle one or more wearable trackers involved with one or more sensing types. These may relate to multiple users or multiple wearable sensors on the same subject.

Both the wearable activity tracker and IoT gateway offer the role of communicating the data to the cloud. They could be involved in edge computing and data backup storage. Hence, this could be handled as a generic solution. Alternatively, the two-network modules (i.e. wearable activity tracker and IoT gateway) could be implemented and driven as software-defined functions [34]. This could be accomplished by operating the two modules in handling local or edge computation for data compression and decision-making capabilities by offering some level of activity classification and as a data backup storage. In doing so, the involved computation, size of history information, the data packet size and data transaction rate would have a direct impact on the system key performance metrics such as wearable energy expenditure, communication latency, movement information transparency and activity recognition accuracy. Managing the scenario of utilising these resources may have a direct impact on the handling of the big data generated by the process and hence relieving the cloud from the lower level processing details, thus helping in the data packet size reduction.

At the cloud level, both the user interaction and higher-level data analysis over the span of the rehabilitation process takes place. Both real time and long-term process data and event monitoring over the overall rehabilitation cycle are taking place. The support of the data accessible within the cloud repository and various knowledge components related to the monitoring can serve in delivering detailed computational tasks. These are; correction of the logically incorrect movement activity classification by looking at the past one min history data, recognising the activity movements precisely in deciding the rehabilitation progression model event detection, the virtual sensor system for virtualising the interconnection of sensing, activity recognition, rehabilitation events detection and health service systems and creation of various screens for data visualisation. Therefore, the information available in the cloud could be personalised, tailored and made available

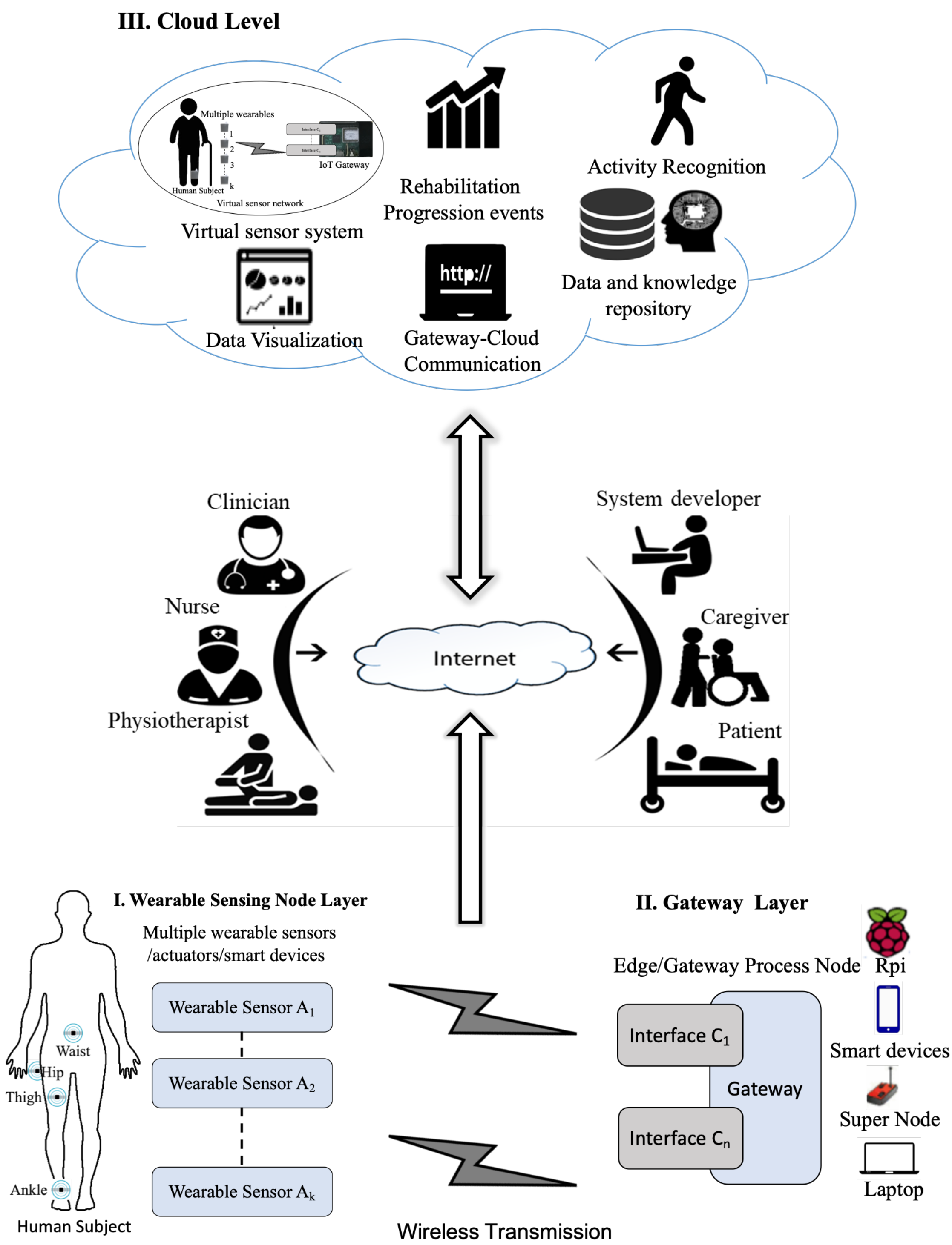


Figure 4.2: Post-Operative rehabilitation movement monitoring system architecture

to offer transparency according to key user interaction with various parties such as patient, caregiver, physiotherapist, clinician and nurse. This is important as each of them plays a key part in contributing towards the enhancement and accomplishment of the patient's rehabilitation recovery progression goals.

4.4 Architecture Key Operational Functionality Description

This section provides a detailed description of the architectural operational functionalities involved at each of the three levels [34]. These are:

4.4.1 Wearable Wireless Activity Tracker Level Functionality

The wearable activity tracker level comprises four key functionalities, as illustrated in Figure 4.3 for offering a modular and software-driven configurable system [2].

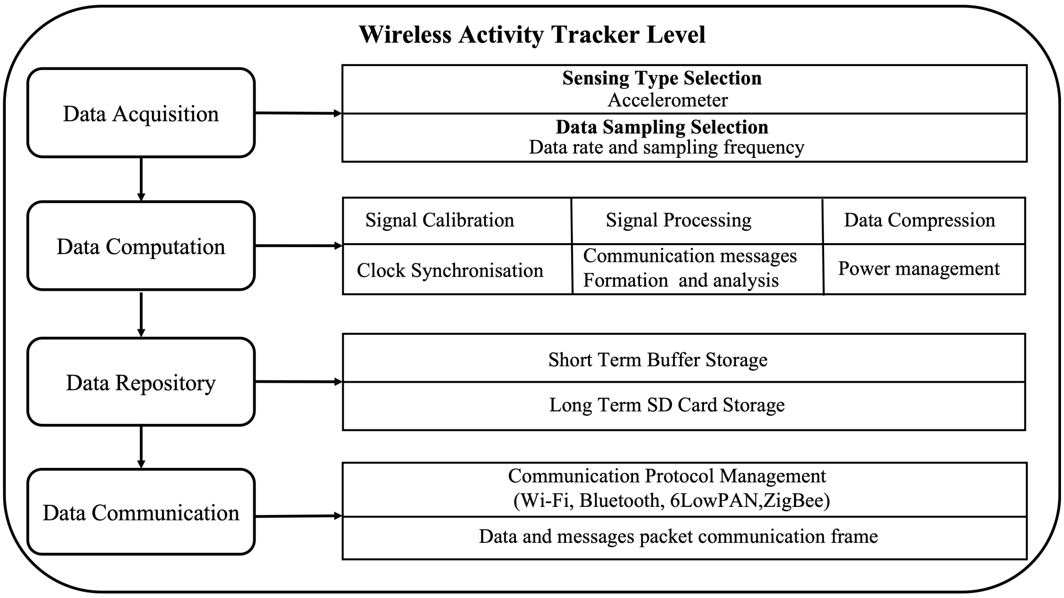


Figure 4.3: Wearable monitoring level key possible functionalities

Data acquisition involves a sensor selection, the sampling rate (rate at which data is collected) and acquisition duration. As mentioned in Chapter 3, micro-electromechanical sensor (MEMS) triaxial accelerometer is considered for real-time human movement data collection and classification. The data is collected at a sampling frequency of 128 Hz for each activity over a five-minute period. Five minutes is selected as the preference for the data collection due to the following reasons: First, it will provide a sufficient number of activity samples. Second, it offers good coverage for the range of activities especially for slow movement activities such as leg movement while sitting, slow walking, and swinging the leg to the side while standing. Lastly, it will also help in analysing the dynamic switching from one activity to the other [3].

The sampled sensed raw movement data is then subjected to the data computation. This may involve digital signal processing, signal calibration and data compression. Other processing activities may involve managing the analysis and formation of communication messages, the mode of operation and time synchronization [2, 34]. An activity movement recognition mathematical model part of data computation functionality for filtering the raw movement data signals is created in the MATLAB software package. These include the mathematical expressions involved in the data processing algorithm techniques for the recognition of hip fracture rehabilitation activity movements [12]. These are: mean (m), standard deviation (σ), skewness (S), kurtosis (K), maximum amplitude (MA), and the corresponding frequency of the maximum amplitude Cf_{MA} [12].

$$m = \frac{1}{N}\sum_{i=1}^{k} c_i \times n_i \tag{4.1}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{k} (c_i - m)^2 \times n_i} \tag{4.2}$$

$$S = \frac{1}{N\sigma^3}\sum_{i=1}^{k} (c_i - m)^3 \times n_i \tag{4.3}$$

$$K = \frac{1}{N\sigma^4}\sum_{i=1}^{k} (c_i - m)^4 \times n_i \tag{4.4}$$

$$MA = max|\alpha_{128}(1 : (5/FS))| \tag{4.5}$$

$$Cf_{MA} = (l-1) \times FS \tag{4.6}$$

From the aforementioned equations, N represents the total number of data samples, c_i is the centre value at interval i, n_i refers to the data sample number at interval i, k is the number of intervals, α_{128} represents every fourth sample of the total FFT sample dataset, l (output samples of the frequency spectrum) = 1:(5 / FS), and Frequency Scalar (FS) = (sampling frequency / N_4) / 128. N_4 is equal to a value of four. It takes the average of every fourth sample from the collected accelerometer data, left with 128 samples. These 128 samples represents the final input samples that is subjected to perform FFT operation on. This is represented by α_{128} [12]. Following the FFT operation, 20 output samples (l) are selected with a resolution bin having the step size of 0.25 Hz. The reason for such selection is most of the high amplitude peaks of the everyday activities were found upto a range of 5 Hz (refer appendix A.6, figure A.4) [150].

Using the aforementioned mathematical equations, the raw acceleration movement signals can be converted to filtered signals by combining all the three-axis samples (the purpose of combining the sensor axes is to make the algorithm immune to potential errors in aligning the sensors with body or anatomical axes), taking the mean, eliminating the DC offset and taking the moving average of every four samples (represented in Equation 4.5 as α_{128}). This will down-size the sampling rate to 32 Hz to comply with the 20 Hz suggested for everyday activities [2, 3, 12, 34].

Data storage functionality comprises raw and processed data repositories. A circular buffer can be used for short-term storage of the continually processed data and SD card for long-term storage of the raw activity movement data. Another important functionality is that of managing the data communication protocol (for example Wi-Fi, Bluetooth and ZigBee) [2,34]. This, in effect, configures the physical and data link layers of the communication protocol and regulates data and message communication patterns. As discussed in Chapter 3, the Nordic nrf24 chipset that uses its own enhanced Shock-Burst communication protocol can be used for data communication purposes. Considering the data packet transmission, analysing the activity tracker energy consumption is essential [2, 34]. This performance measure could be investigated based on two settings. The first involves the transmission of only filtered movement signals, while the other involves the transmission of final compressed movement signals. The next section describes the IoT gateway or edge level functionality and their interaction with the wireless activity tracker.

4.4.2 IoT Gateway or Edge Level Functionality

IoT gateway or edge level also comprises four key functionalities, as illustrated in Figure 4.4.

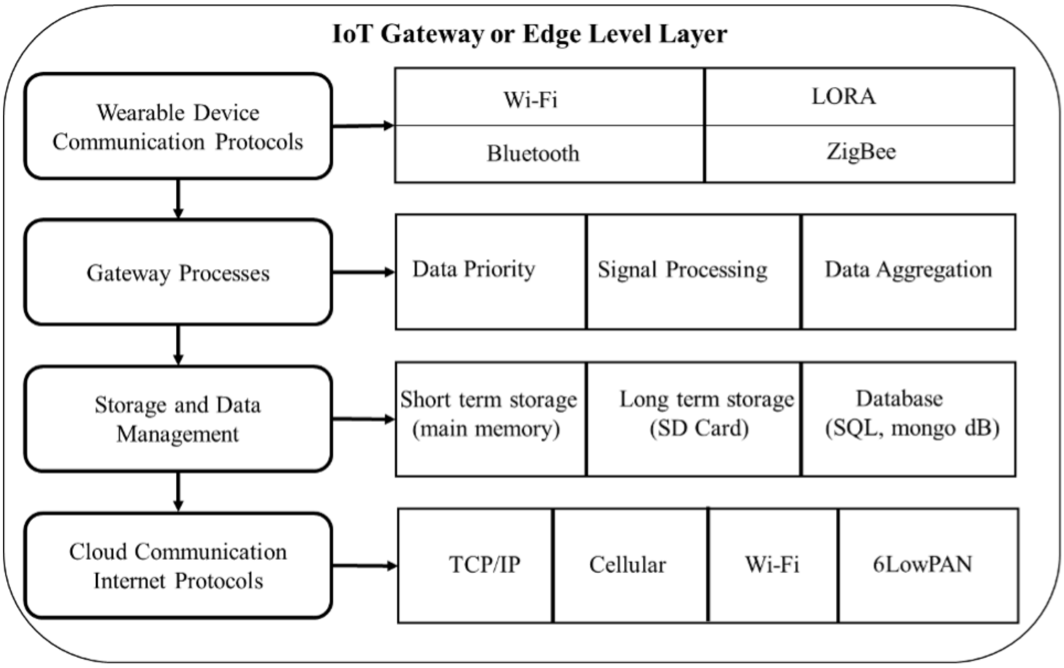


Figure 4.4: IoT gateway or edge level key possible functionalities

First is the wearable device gateway communication protocol (for example Wi-Fi, Bluetooth, LORA and ZigBee) that relates to the protocol used and as a protocol converter. This function helps in receiving the incoming data from the wearable device wirelessly and passing it through the serial communication [34]. As discussed in Chapter 3 , the Nordic nrf24 chipset connected to a portable RPi through serial communication can be used for data reception.

The incoming data from the activity tracker in either form of setting as discussed in the previous section, can be stored for either short-term storage available within the main memory (1 GB RAM) or long-term storage in the SD card (16 GB) and the data can be managed using databases like MongoDB and MySQL [34]. As a result, receiving the data under these two settings at IoT gateway level would help in investigating the overall system key performance metrics such as: (1) activity movement information transparency; (2) data Packet loss and (3) IoT gateway energy consumption. The setting with better performance measures would then be considered suitable for a remote monitoring system.

The third functionality is the local computational capability analysed at the gateway level like FFT signal processing, data aggregation and using if-then-else threshold personalised rules before connecting to the cloud and transmitting using the fourth functionality, i.e. cloud communication internet protocol such as TCP/IP, cellular and Wi-Fi [2, 34].

The next section describes the Internet-Cloud level functionality and its interaction with the IoT gateway.

4.4.3 Internet-Cloud Level Functionality

Internet-cloud level comprises five key functionalities, as illustrated in Figure 4.5.

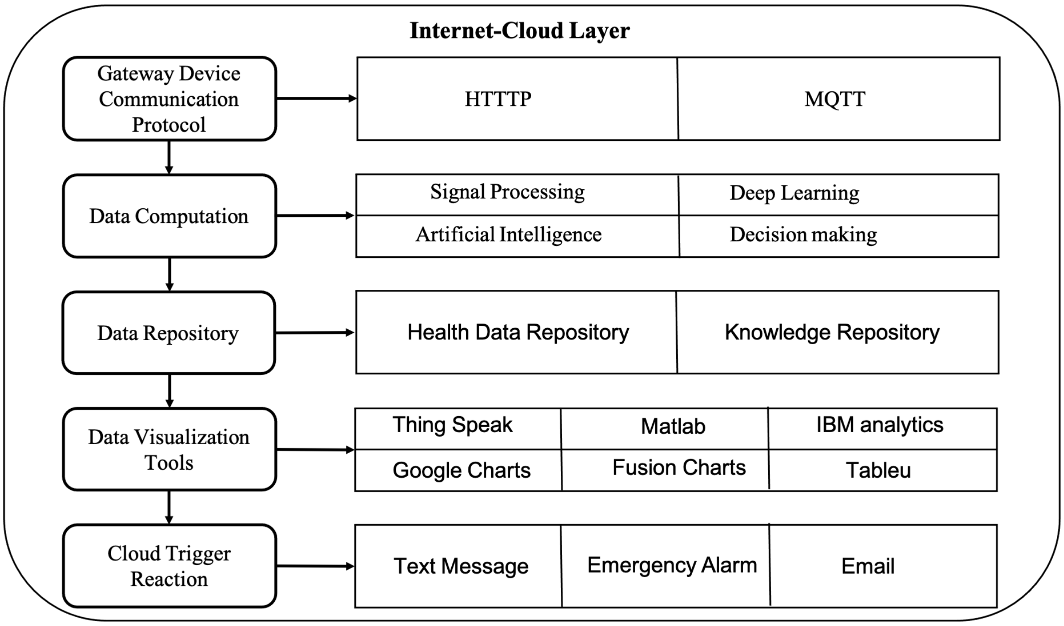


Figure 4.5: Internet-Cloud layer key possible functionalities

Communication protocols such as Hypertext Transfer Protocol (HTTP) and MQ Telemetry Transport (MQTT) can be used for a data acquisition frame from the gateway or edge device. The cloud has its own data repository that can be used for storing the patient activity movement data or any other related knowledge data and can be managed at ease. With the use of the data available in the cloud repository, data computation techniques like FFT signal processing, artificial intelligence and machine learning techniques can take place at different levels. In addition, cloud resources play significant role in data presentation, activity event detection, and triggering a reaction in case of an emergency. Examples of commercially available tools include ThingSpeak, IBM analytics, Google and Fusion charts, Tableau and MATLAB. The triggering of a reaction could be accomplished using different services such as sending a text message or email and/or buzzing an emergency alarm so that immediate action can be taken [2, 34].

4.5 Conclusion

In conclusion, this chapter proposed a model for a post-operative hip fracture rehabilitation process that facilitates the stages for patients to undergo straight after hospitalisation. While the programme has emerged out of an analysis of existing recommendations within the science and practice of the hip fracture rehabilitation process, it offers grounds for automating the process and allowing for effective utilisation of the modern digital environment. Keeping the proposed model in mind, the chapter proposed an IoT-enabled with wearable movement monitoring system architecture highlighting all the key operational functionalities at different levels for a smooth and robust system operation. Following that, an examination of the key factors that are considered and significant for the activity movement data collection process, mathematical analysis and on-body sensor localisation was provided.

Chapter 5

Concept Modelling and Implementation

5.1 Introduction

The chapter principal objective is to develop and test the conceptual ideology as defined in Chapter 4. Firstly, it involves data analysis in recognition of the hip fracture rehabilitation activity movements based on the frequency-domain analysis approach (as discussed in Chapter 4 under section 4.4.1) and reflecting the testing of each movement group under its associated test conditions. Based on the activity movement data analysis, the second objective is to identify the optimal sensor placement (waist, thigh, ankle and hip) that can cover/target maximum coverage and recognition of key post-operative hip fracture rehabilitation activities involved, and improve the sensing capability. Drawing from the data analysis and suitable location of choice, the third objective is to investigate the minimum data collection time suitable for recognising an activity movement without any loss of information or signal distortion. The fourth objective discusses the approach in which the overlap among the activities can be reduced and how personalisation could play a significant role in addressing such concerns. The fifth objective is to implement, test and display result scenarios of the key competent functions (wearable activity tracker, IoT gateway or edge and internet-cloud functions) involved in IoT-enabled with wearable post-operative hip fracture rehabilitation activity monitoring system architecture. The final objective is to investigate the overall system architecture performance analysis by considering the architectural scenarios and role of network functions in affecting both information transparency and operational lifetime. The role of wireless sensor edge computing, gateway edge and cloud computing are taken into consideration for assessing the possible organizations and related performances.

The chapter starts by representing the experimental data analysis of hip fracture rehabilitation activity movement concerning the sensor localisation. Section 5.3 illustrates the sensor location-based activity recognition coverage discussing the suitable sensor location that could provide maximum coverage of key post hip fracture rehabilitation activity movements. Section 5.4 presents the activity classification overall summary of a young healthy individual at the ankle location. Section 5.5 presents the investigation of the minimum data collection time required for recognising an activity precisely. Section 5.6 discusses the overlap among the activities based on the proposed approach and how this could be minimised by grouping the activities and looking past the one-minute movement behaviour. Moreover, it also displays the significance of personalisation and provides a comparative analysis of the subject's overall recognition parameter range. Section 5.7 presents the architectural functionality implementation on hip fracture rehabilitation movement monitoring. Section 5.8 discusses the system performance for possible scenarios of architectural implementation, taking into consideration the available network functions, information transparency and wireless sensor lifetime. Lastly, the chapter conclusion is outlined in Section 5.9.

5.2 Analysing Movement Type Recognition Against Wearable Placement

In this section, a wearable monitoring device (proposed in Chapter 3 under section 3.3.1) has been used to collect rehabilitation movement acceleration data signals from a healthy young individual. The wearable device is attached individually at four different body locations (waist, hip, thigh and ankle). The data collection process is of five-minute time period (as discussed in Chapter 4 under section 4.4.1) and is captured at a sampling rate of 128 Hz. The structure of the five-minute period as represented in Figure 5.1 is divided into 10 data collection tests where each test collects data for 24 s followed by a 6-s halt. The test is subsequently repeated until the required time is completed. The 24-s (3072 samples) epochs with 6-s rest are chosen ad-hoc. Raw acceleration movement signals are collected for all of the activity movements of interest (discussed in Chapter 4 under section 4.2). The movement data is stored in SD (a slot provided within the activity tracker). An activity movement recognition mathematical model for filtering the raw movement data signals is created in the MATLAB software package and analysed offline. The analysed data is then used to validate the activity movement recognition approach (using the mathematical equations defined in Chapter 4 under section 4.4.1) and to identify which sensor location is the most suitable to cover most of the proposed activity. The description of the preliminary activity movement recognition validation model is represented in Figure 5.2. The experimental data analysis of each of the activities with respect to sensor localisation is as follows:

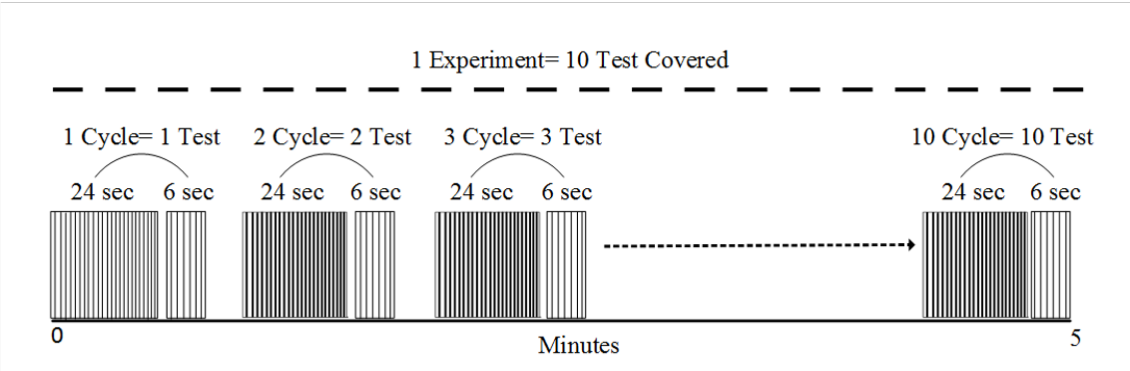


Figure 5.1: Activity movement data collection process

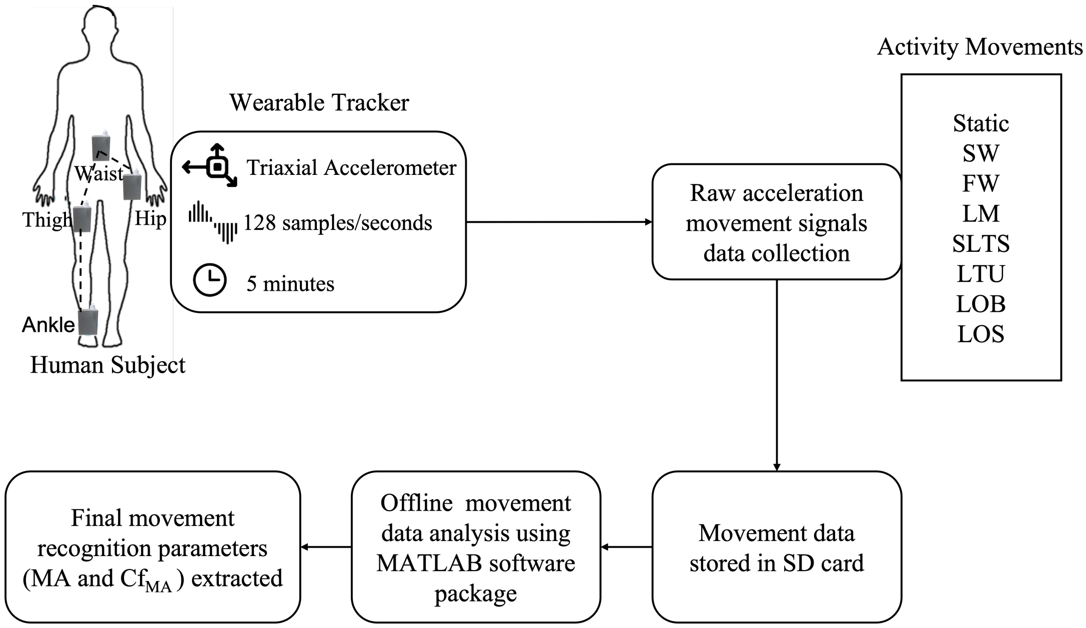


Figure 5.2: Preliminary activity movement recognition validation model

5.2.1 Static Activities: Sitting Vs Standing

Two types of static activities i.e. sitting and standing positions, are considered a part of post-hip fracture rehabilitation movement monitoring. Figure 5.3 shows the illustration of both the activities.

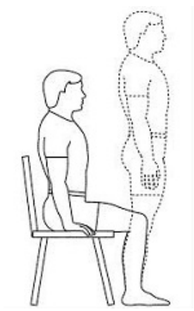


Figure 5.3: Sitting and standing activity illustration

Test data analysis for two static activities, sitting and standing, are shown in Figure 5.4 and Figure 5.5. From the two figures, it is observed that the sitting activity has a maximum amplitude value of 0.6 m/s^2 whereas for standing activity, it is 0.9 m/s^2. Therefore, it seems appropriate that a low amplitude (value < 1.0 m/s^2) can be utilised to categorise the static state of the person.

Figure 5.6 and Figure 5.7 provide evidence that the standard deviation parameter is suitable for sitting and standing activity categorisation. In Figure 5.7, standard deviation values in Test 3 and Test 5 using the thigh sensor are high. This might be due to the medium or large shifts in forward and backward thigh movement generated by the individual while maintaining the position, as observed during the data collection. Hence, the ankle location was considered more suitable for categorisation where standard deviation values for sitting and standing are 0.015–0.0187 and 0.020–0.0440, respectively.

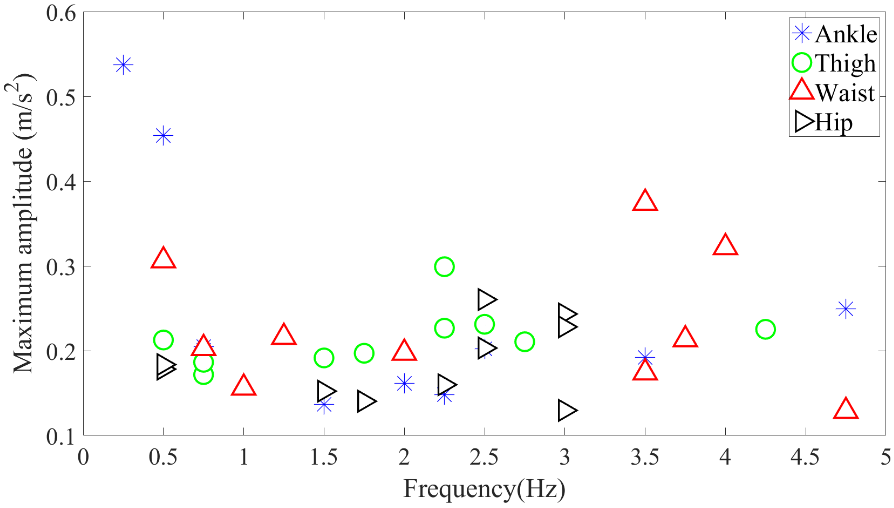


Figure 5.4: Frequency vs maximum amplitude: sitting

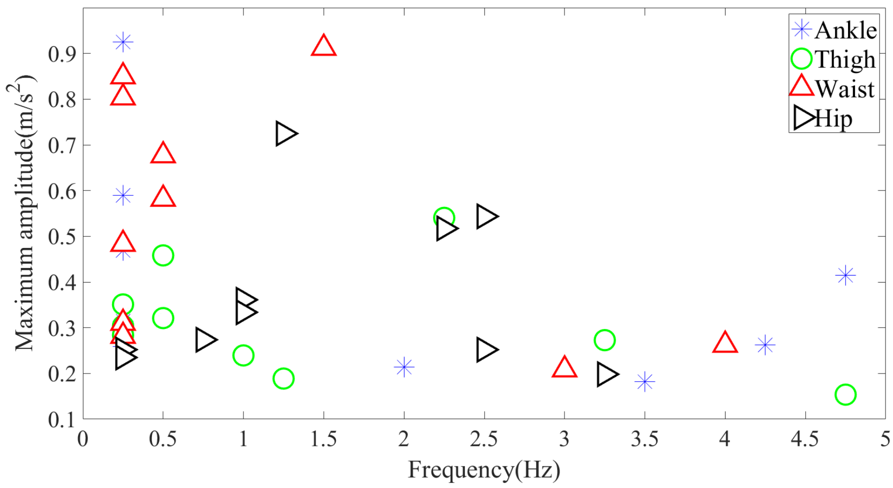


Figure 5.5: Frequency vs maximum amplitude: standing

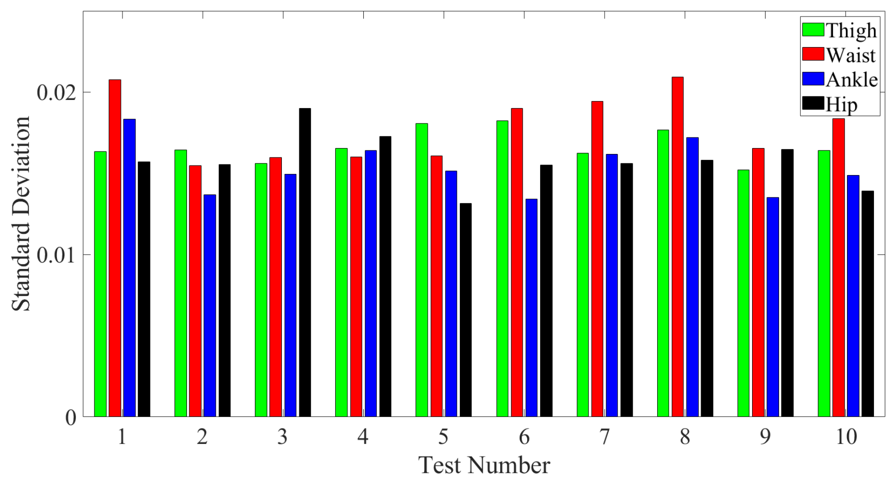


Figure 5.6: Standard deviation: sitting

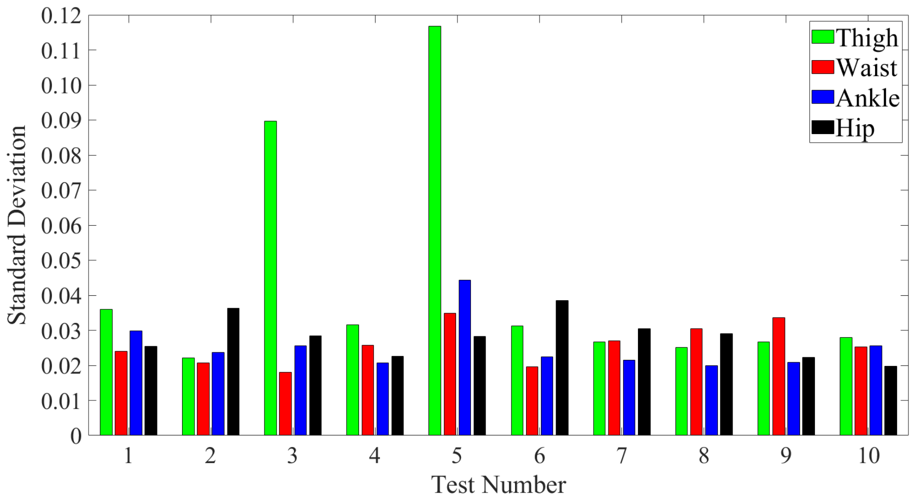


Figure 5.7: Standard deviation: standing

5.2.2 Ambulatory Activities

Two ambulatory activities, i.e. slow and fast walking, are considered under two different environmental conditions. These are free-living and corridor environmental conditions. The description of each of them are as follows:

5.2.3 Fast Walking

Figures 5.8 and 5.9 represent a comparison of fast walking in a free-living environment such as a large park and a corridor environment with obstacles such as the presence of people and objects.

For the free-living environment, the FFT data points for the three locations, i.e. thigh, waist, and hip reflected a frequency range of 1.5–2 Hz, but with a varying amplitude. In contrast, at the ankle location, the frequency was notably lower, although at a similar amplitude to the thigh. The ankle location reflected small variations across the free-living and corridor environments.

Considering the corridor environment, data points for the ankle location lay within a frequency range of 0–1 Hz with a slight variation in amplitude. For thigh, waist, and hip locations, the frequency was notably higher, between 1.5 and 2.5 Hz.

There are two key reasons for the changes in frequency and amplitude observed between footfalls. First, there will be times when footfall impact is high during initial ground contact that may increase the amplitude of the acceleration. Second, at times when the foot is still on the ground (magnitude $\approx$ 1 g having no impact), it is likely producing low-frequency data.

Considering the above comparative analysis, it was concluded that for fast walking in free-living and corridor environments, the thigh and ankle could be considered as the best locations. This is because the data points lay within a certain frequency range and had overlapping amplitude values. The ankle location could be of merit to extract foot impact data.

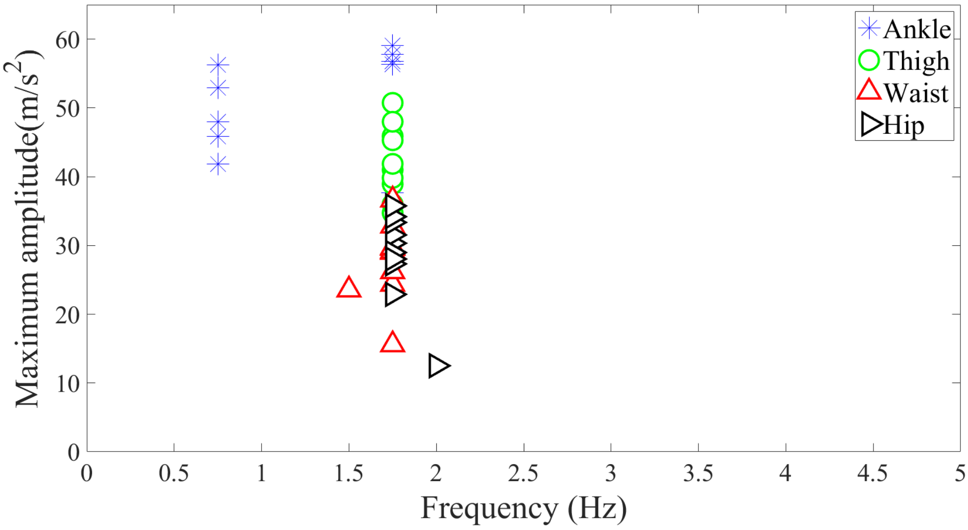


Figure 5.8: Free-living environment: fast walking

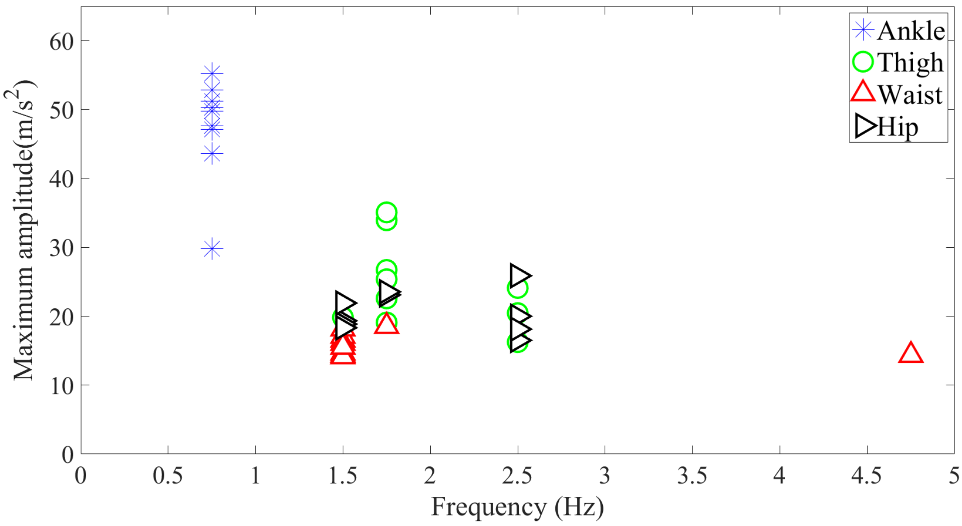


Figure 5.9: Corridor environment: fast walking

5.2.4 Slow Walking

Figures 5.10 and 5.11 represent the comparison of slow walking in both free-living and corridor environments. In the free-living environment, data points of the ankle and thigh locations were within the same frequency range (0–1.8 Hz) with different amplitude values, whereas for the waist, the accuracy was much higher, as 90% of the data points lay within a frequency range of 1–1.5 Hz. However, for the hip, data points were randomly distributed across a wide frequency range. For the corridor environment, data points for the thigh, waist, and hip locations were also widely distributed; however, the ankle location lay within a frequency range of 0.5–1.25 Hz. Two different locations (waist and ankle) were shown to be suitable for slow-walking activity categorisation in both environments.

Recognising both fast and slow walking is a concern, as they differ in amplitude and frequency across the walking environments unless different locations are utilised. This is problematic. First, placing the sensors at two different locations to recognise these walking activities in two different environments would be cumbersome for the user wearing the sensors. Secondly, recognising activity based on the frequency threshold only would not be suitable, as it overlaps with both slow and fast walking.

It is apparent that acceleration intensity or amplitude is one of the distinguishing parameters that can help in categorising both slow and fast walking when the sensor is located at the ankle. From Figures 5.8–5.11, it is evident that for both environments, the amplitude for slow walking ranged from 10–28 m/s^2, whereas for fast walking, it was notably higher, i.e., 40–60 m/s^2. Therefore, setting an amplitude threshold would be significant in classifying these two walking activities.

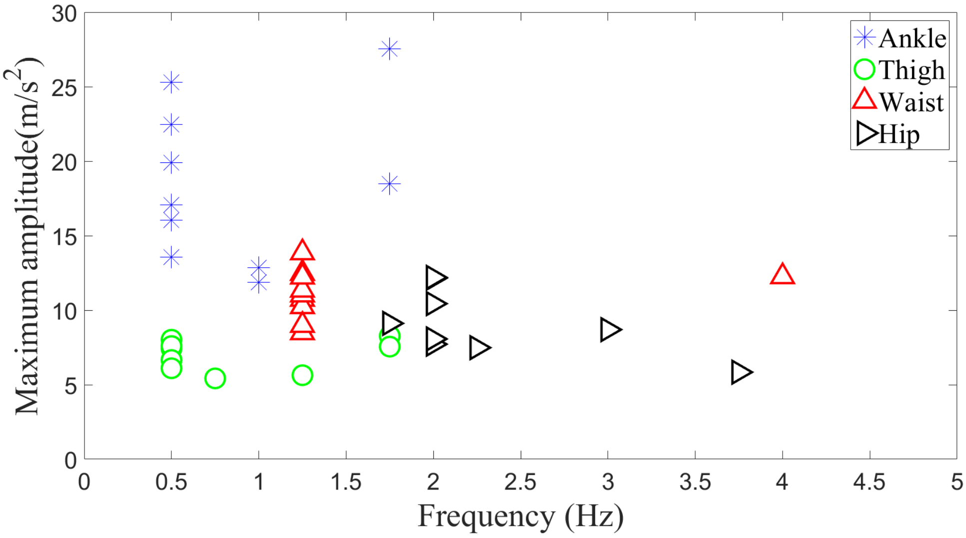


Figure 5.10: Free-living environment: slow walking

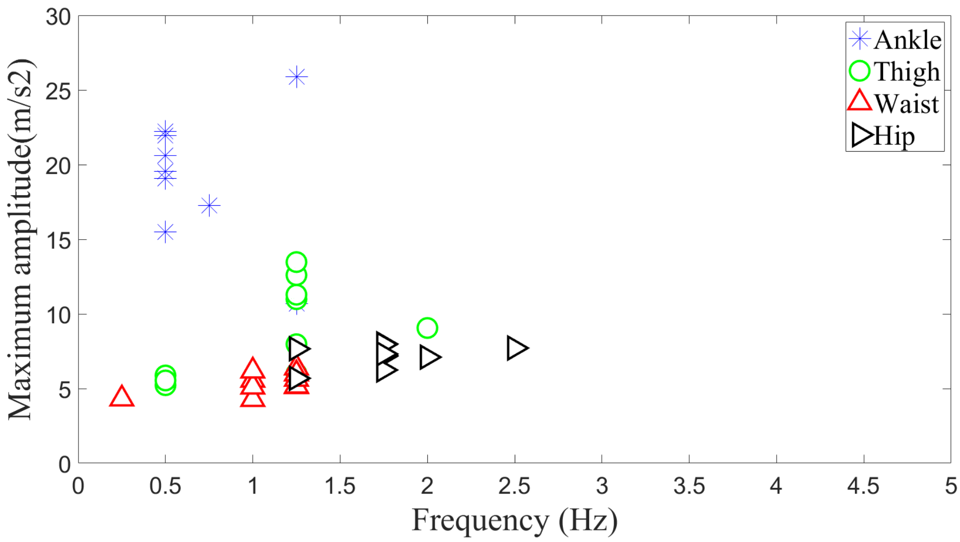


Figure 5.11: Corridor environment: slow walking

5.2.5 Stationary Exercise

The two types of stationary exercise involved in the recovery process are; (1) stationary exercise while lying on the back and (2) stationary exercise while lying on the stomach. The discussion of each of these are as follows:

1. **Lying on the back:** Figure 5.12 (a) represents the illustration of stationary exercise while lying on the back whereas from Figure 5.12 (b), data points for hip, thigh, and ankle locations lay within a specific frequency range of 0–0.4 Hz, whereas for the waist location it was more widely spread. However, both hip and thigh locations can be considered suitable locations for classification, as they have a similar range of amplitude and frequencies. Considering these locations, the frequency and amplitude threshold values that could be used for classification would lie from 0–0.4 Hz and 5–14 m/s^2.

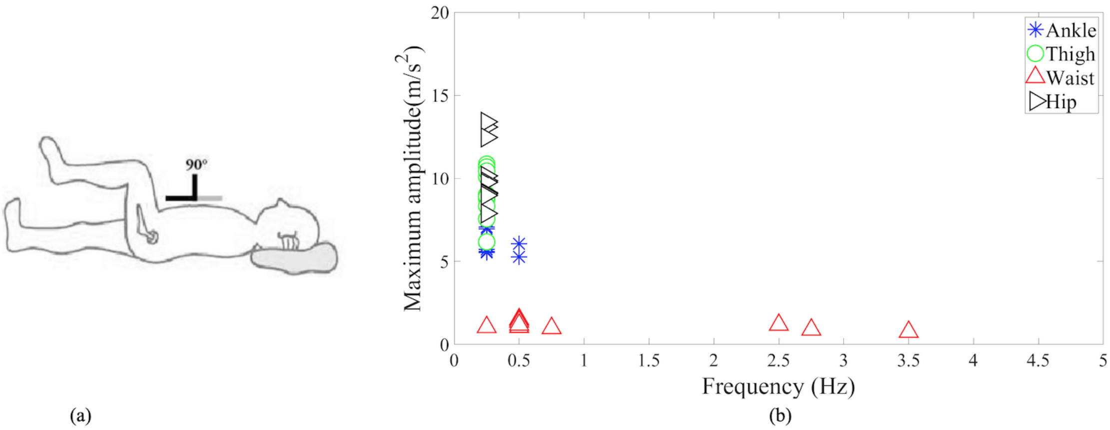


Figure 5.12: (a) Lying on the back activity illustration and (b) Data analysis

2. **Lying on the stomach:** The illustration of stationary exercise while lying on the stomach is represented in Figure 5.13 (a) while Figure 5.13 (b) shows the analysis of a stationary leg exercise (flexing and extending the knee) when lying on the stomach with a sensor on four different locations.

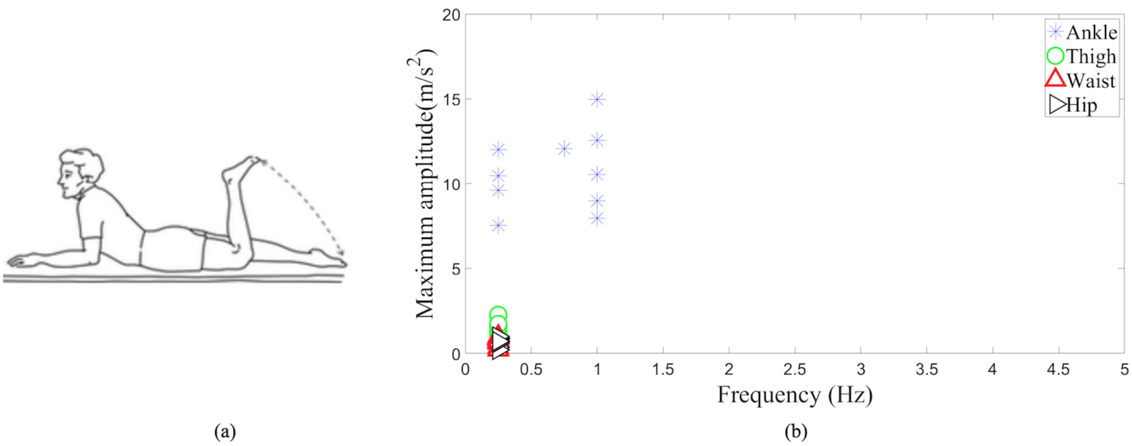


Figure 5.13: (a) Lying on the stomach activity illustration and (b) Data analysis

Hip, waist and thigh location data points lie within a frequency range of 0 to 0.3 Hz with similar low amplitudes. As for ankle location, the data points are placed in a slightly wider frequency range but are in a distinct amplitude range. Hence, any of these locations could be utilised for the categorisation of exercise performed on the stomach.

When comparing locations for exercise on the stomach and back, the thigh would be a suitable location to consider as the amplitude value range was between 1 and 3 m/s^2; and did not overlap in this range.

5.2.6 Swinging Leg to a Side

The illustration of swinging leg to a side exercise is represented in Figure 5.14 (a), whereas Figure 5.14 (b) shows the analysis of swinging a leg to the side with four different sensor locations. Data points for ankle, hip, and waist location had a varying frequency range. This negatively affects the level of accuracy for categorisation. However, the thigh location would be best as it lay within a frequency range of only 1.4–1.6 Hz and the amplitude range was from 11–17 m/s^2.

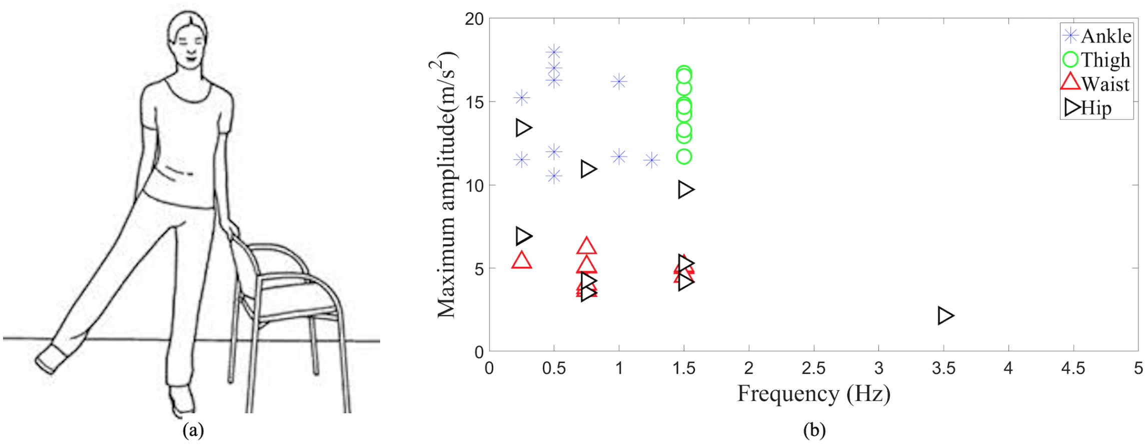


Figure 5.14: (a) Swinging leg to a side activity illustration and (b) Data analysis

5.2.7 Lifting Thigh Upwards

The illustration of lifting thigh upwards exercise is represented in Figure 5.15 (a); Figure 5.15 (b) represents the analysis of lifting the thigh upwards in front of the body at four different sensors' locations. Frequency data for thigh, hip, and waist location were widely distributed, compared to the ankle location, where data points were focused at a frequency range that lay within 0.9 and 1.1 Hz and the amplitude was between 11 and 19 m/s^2. Hence, the ankle location was favoured for categorisation.

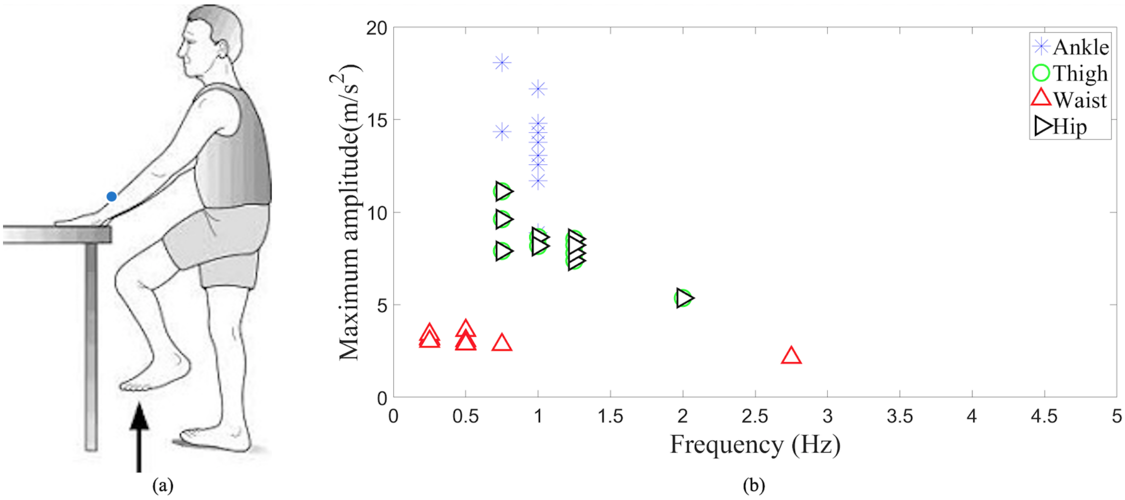


Figure 5.15: (a) Lifting thigh upwards activity illustration and (b) Data analysis

5.2.8 Stationary Exercise While Sitting (Leg Movement)

The illustration of leg movement exercise is represented in Figure 5.16 (a) whereas Figure 5.16 (b) represents the analysis of stationary exercise while sitting (hip and knee flexion and extension) at four different sensor locations. The ankle location was favoured for categorisation as the frequency range was low (0–0.4 Hz) and the amplitude was distinctive, lying between 23 and 37 m/s^2. After analysing the proposed activity recognition model

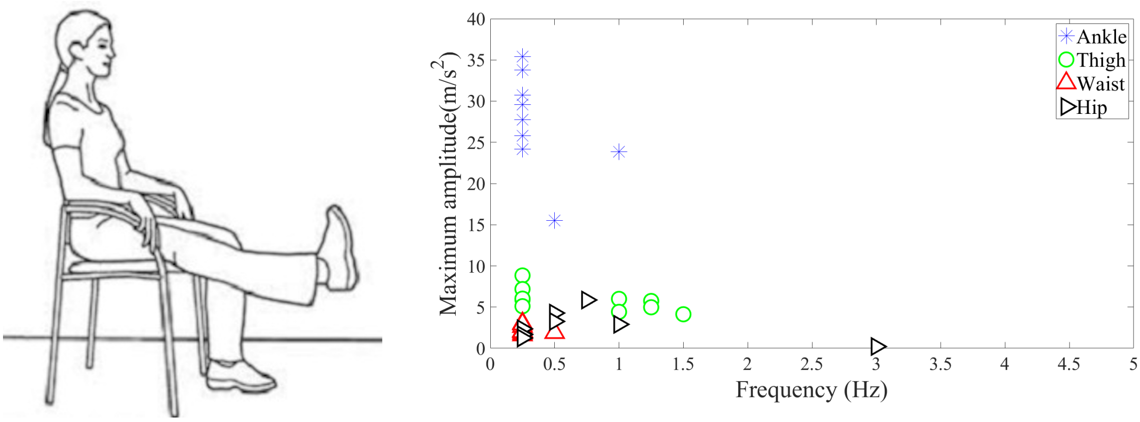


Figure 5.16: (a) Leg movement activity illustration and (b) Data analysis

across different types of activities, it is evident that the model proved to be effective at categorising most of the exercises and activities that were practised in the process of rehabilitation of hip fracture patients (refer Section 5.4 for overall summary). The results of implementing the recognition model on the collected data reveal that the standard deviation plays a key role in static activities. Furthermore, the maximum amplitude of the activities acceleration signal's frequency content is associated with ambulatory activity recognition and both maximum frequency and amplitude for hip fracture-related activities. The next section illustrates the activity recognition coverage based on the chosen sensor location.

5.3 Sensor Location-Based Activity Recognition Coverage

Figure 5.17 (a) and (b) provides a summary of the extent to which a particular sensor location could identify or categorise activities. Based on this figure, it is apparent that the ankle joint is the location of choice.

As ankle location is considered the suitable location for recognition of hip fracture rehabilitation activity movements, the next section discusses the activity classification summary of a young healthy individual at the ankle location.

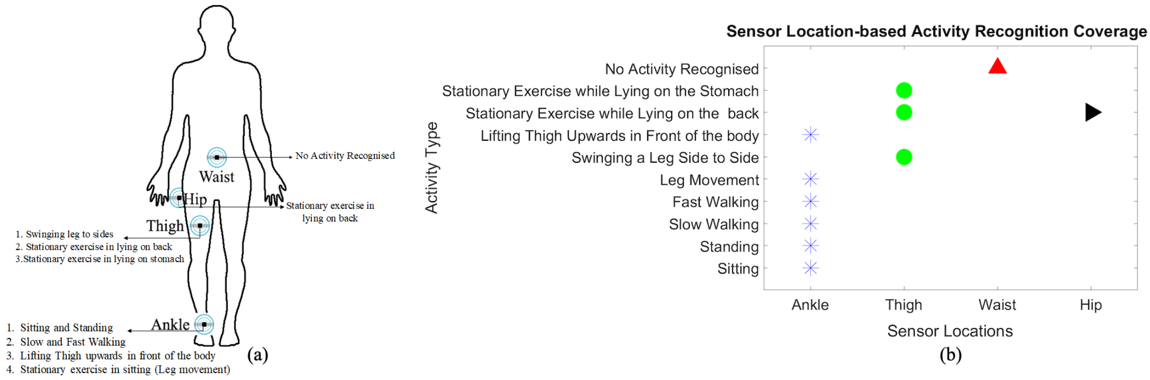


Figure 5.17: (a) Human subject activity recognition based on sensor locations (b) Sensor location-based activity recognition coverage

5.4 Activities Classification Overall Summary at the Ankle Location

The specific parameters that are frequency and amplitude, are shown across all the activities graphically in Figure 5.18, while Table 5.1 provides the precise values relevant to this figure. Notably, all the activities fell under a frequency of 2 Hz and an amplitude of 60 m/s^2.

Table 5.1: Activities classification overall summary at the ankle location

Activity Type	Amplitude(m/s^2)	Frequency(Hz)
Slow Walking	12-28	0.5-1.75
Fast Walking	40-60	0.5-1.75
Lying on Back	5-9	0-0.5
Lying on Stomach	7-15	0-1
Swinging Leg to Side	10-18	0-1.3
Lifting Thigh Upwards	11-19	0.9-1.1
Sitting (Leg Movement)	23-37	0-0.4

For dynamic physical activities, amplitude values of corridor fast walking overlapped with free-living fast walking. In addition, corridor slow walking overlapped with free-living slow walking. However, the frequency content values remained the same for both

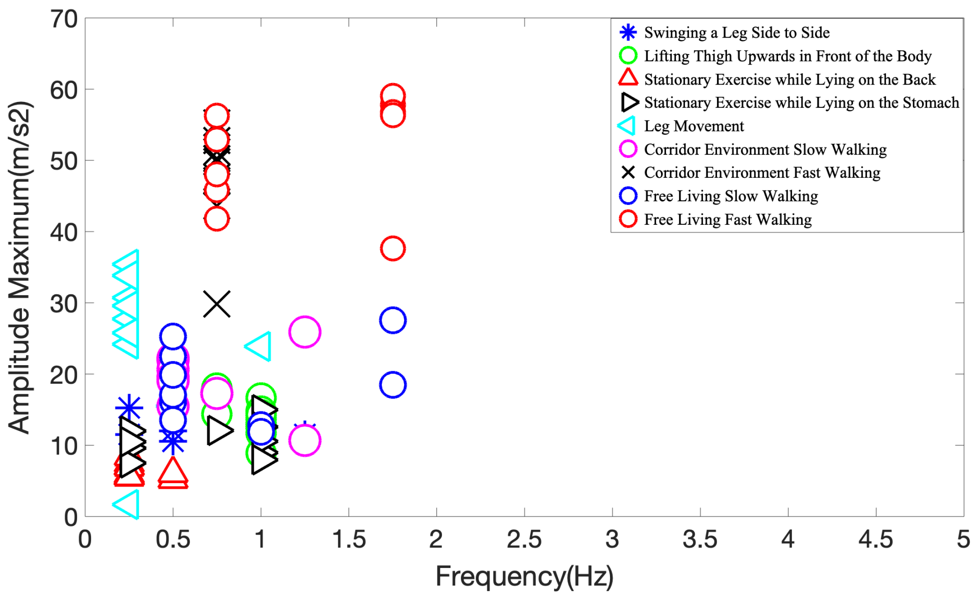


Figure 5.18: All activities manifestation with the sensor placed at the ankle location

slow and fast walking. The amplitude values offer a good indicator for recognising walking activity, irrespective of the environment. For stationary exercise while lying on the back and stationary exercise while sitting, frequency values almost overlapped, but amplitude values showed large variations, allowing for better categorisation. It becomes difficult to differentiate the exercise of lying on the stomach and swinging a leg to the side when the wearable sensor is at the ankle location. This is because both the amplitude and frequency ranges almost overlapped with each other. Additionally, the amplitude and frequency for lifting the thigh upwards and swinging the leg to the side overlapped.

5.5 Activity Recognition Minimum Data Collection Time Analysis

In the previous section, it has been concluded that the ankle location is the suitable location for recognising an activity movement accurately. Considering the favourable location of interest, six other different times; 1s (128 samples), 2s (256 samples), 3s (384 samples), 4s (512 samples), 6s (768 samples), 12s (1536 samples), and 18s (2304 samples)) along with 24s chosen previously are also explored on a given case using the same dataset. This is performed to identify the minimum data collection time to process the human activity movement signals without any information loss or signal distortion leading to a precise recognition.

A sample representation of the extracted recognition parameters of a lifting thigh upward activity movement is used here as an example and is presented in Figure 5.19. As seen from the graph, the recognition parameters MA and Cf_{MA} have a value of 8.8964 m/s^2 and 1 Hz respectively. Following that, an overall comparison of the extracted recognition parameters across the proposed time intervals (1, 2, 3, 4, 6, 12, 18 and 24 s) is portrayed in Figure 5.20. From the result, it is evident that no differences were observed from reducing the data collection time to 4, 6, 12, 18 or 24 s for each set, as the activity recognition results (MA=8.8964 m/s^2, Cf_{MA}=1Hz)are the same. However, upon reducing

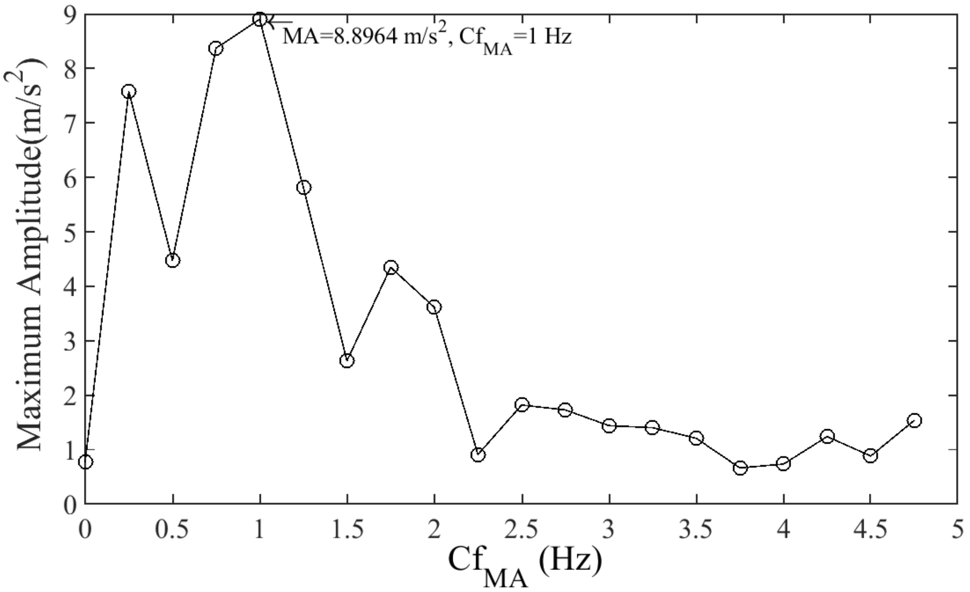


Figure 5.19: Lifting thigh upward extracted recognition parameters

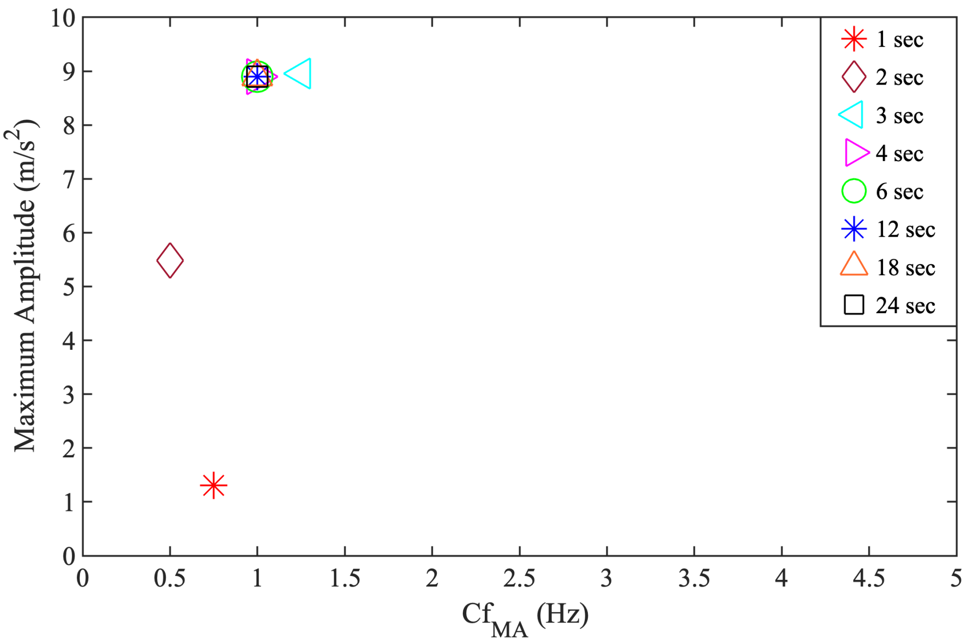


Figure 5.20: Lifting thigh upward extracted recognition parameters different time interval comparison

the data collection time to 3s, a minimal difference (MA=9.5 m/s^2, Cf$_{MA}$=1.25 Hz) in the maximum amplitude and frequency value is observed that might affect the recognition accuracy during the long-term monitoring process. Finally, on reducing to two and one seconds, an inconsistency in the data is observed for both maximum amplitude (5.4806 and 1.3075 m/s^2) and frequency (0.75 and 0.5 Hz) across all the activities. Hence, it is concluded that reducing the time interval below four seconds causes data to appear inconsistent across all the proposed activities. Therefore, a data collection time of four seconds is considered to be the minimum time for recognising an activity without any loss of information or signal distortion. The next section discusses the significance of personalisation and how it plays a crucial role in improving the activity movement overlap solution.

5.6 Activity Movement Overlap Solution and Significance of Personalisation

The preliminary validation of the proposed approach has shown that four seconds of data collection time is sufficient to recognise a particular type of activity. Moreover, it is also concluded that the ankle joint is the most suitable location for the classification of hip fracture rehabilitation activity movements. Moreover, some activities overlap partially or with high degrees of freedom. Considering all of these aspects in mind and using the similar aforementioned approach of categorising the activities, an experimental analysis is conducted to further improve the recognition process. The activity movement data is collected from ten different healthy young individuals (five male and five female subjects in their early twenties). While these subjects are not the best representatives of the real-life hip-fractured elderly, they offer the necessary preliminary trials before stepping towards the healthy elderlies, and then the injured elderlies.

For finding threshold parameters of each subject when performing any of the individual movements relevant to hip fracture rehabilitation, the data is collected continuously over a time period of three minutes for each of the activities. Here, for all of the activities (i.e., static, slow and fast walking, leg movement while sitting, swinging leg to a side, lifting thigh upwards, lying on back and lying on stomach), each subject is instructed to perform the individual activity continuously for three minutes. The reasons for choosing three minutes are that it offers a minimum of 45 samples of logically complete groups of data. Each of these groups is sufficient for FFT analysis. This will also help us track the dynamic changes for each exercise as the subjects transition from energetic to steady to slowing down. The outcome helps in setting a specific threshold range for a particular individual with some level of precision.

From the outcome of the FFT process, recognition threshold parameters for all the activities are extracted for five male subjects based on MA and Cf_{MA} parameters. Subsequently, the threshold feature range of each activity for all five subjects is combined together to form an overall male subject range. This is represented in Figures 5.21 and 5.22. Findings show that for the static state, MA is always less than 1m/sec^2 as there is no movement from the subject and the acceleration axis is orientated in a particular direction. For the slow walking activity, male subjects 1, 3 and 5 have a similar threshold range in comparison to the male subjects 2 and 4 which also have similar patterns in comparison with each other. In the case of the fast walking activity, subjects 3 and 5 have similar patterns whereas subjects 1, 2 and 4 are distributed with slight margins but overlap with each other. The key reason for these differences is because each subject's fitness level and body composition vary. Other potential reasons could be from the footsteps (shorter or longer steps) taken by a subject while performing this type of activity.

In the case of other activities i.e., LM, LTU, SLTS, LOB and LOS, the overall subject range has a high degree of overlap among each other. However, if we consider the individual subject range, the overlap is observed only among some activities. For example, in the case of male subject 2, LM, SLTS and LOB overlap with each other and LTU overlaps with LOS. A similar trend is observed where different activities overlap, and it varies from subject to subject. On the other hand, if we take the Cf_{MA} parameter (refer to Figure 5.22) into consideration, the overall subject range similarly has a high degree of overlap with almost all the activities. Whereas for each individual subject range, some activities overlap partially and others with a high degree. For example, in the case of male subject 2, activities such as LM, LTU, LOB and LOS overlap with a high degree

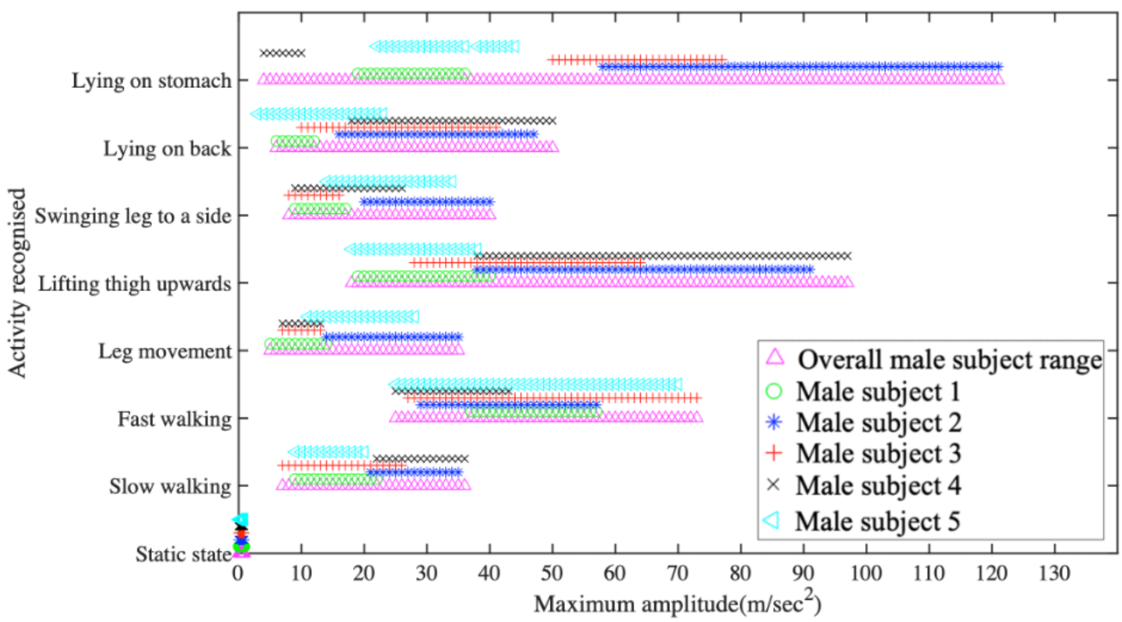


Figure 5.21: Personalised activity recognition comparison of five male subjects vs. overall subject range with respect to maximum amplitude

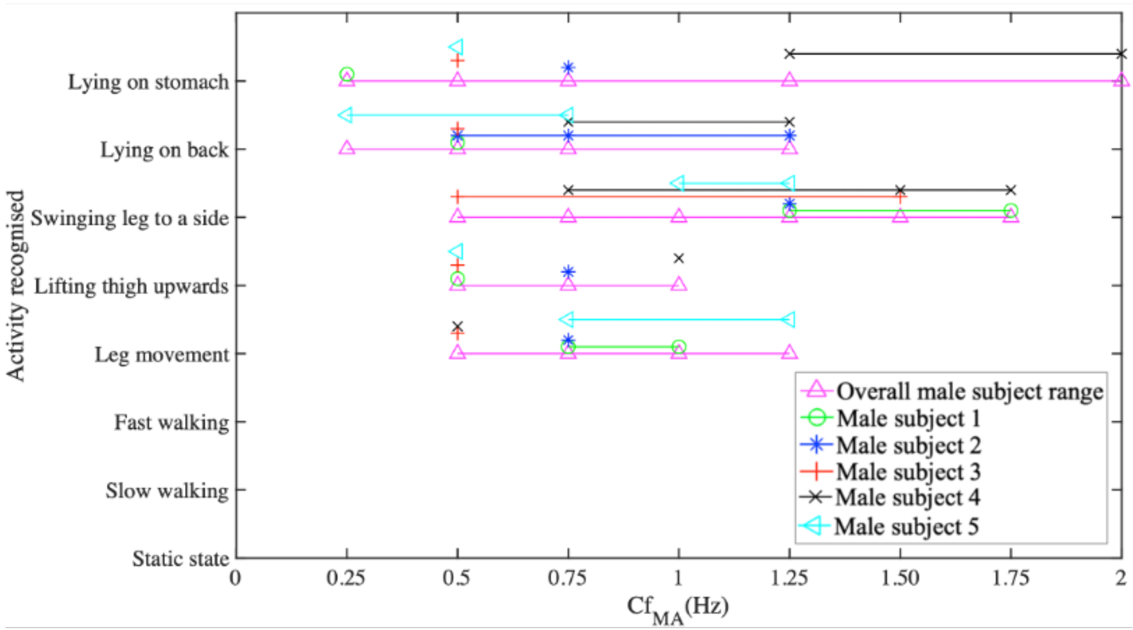


Figure 5.22: Personalised activity recognition comparison of five male subjects vs. overall subject range with respect to Cf_{MA}

among each other, but their amplitude varies which makes it easier to classify such types of activities. Whereas for male subject 1, only LTU activity overlaps with LOB. Therefore, based on the aforementioned comparative activity data analysis and discussion on five male subjects, it is evident that setting a particular threshold range for all the subjects in recognizing an activity is not feasible. This is because the activity parameters overlap with a high degree and it would be difficult to classify one activity from the other. Herein, personalisation can play a crucial role. With personalisation, the recognition parameters can be adjusted and specified for a particular subject.

Based on personalised approach, activities such as static state, slow and fast walking can be easily recognised with high precision as only the amplitude parameter is considered for classification and very marginal overlap is observed due to the nature of the activity behaviour. While for the other hip movement related activities, both amplitude and frequency parameter are considered for recognition and have some degree of overlap among them. This overlap could be avoided to some degree, based on the personalised and activity-transitional rules implemented on the movement history data for the past one minute as described in the next section.

5.6.1 Personalisation and Activity Transition Rule Significance

To investigate the significance of personalisation across the overall subject range in recognising a particular activity, each subject was instructed to perform long-term group-based activities for a time period of three minutes (where each activity is conducted for a time period of one minute) and analysed considering different scenarios. A sample example of such a scenario is illustrated, considering two specific cases. These are as follows:

Case 1: In case 1 and as presented in Figure 5.23, the subject was instructed to perform LTU (1-min), static state (1-min) and SLTS (1-min). This is highlighted in black marker as the activity is performed. Findings show that based on the personalised approach as highlighted in purple marker, the LTU activity is 87% accurate, overlapping with LOS by 13%. The static state of a subject is 100% accurate for both personalised and overall subject range, as there is no movement from the subject and the axis is oriented in a specific direction. SLTS is 74% accurate and overlaps with LM by 26%. In comparison to the overall subject range, which is highlighted with orange marker, it is observed that the LTU activity overlaps with four different activities i.e., LM, SLTS, LOB and LOS. However, the same is observed with SLTS activity too which overlaps with four different activities i.e., LTU, SLTS, LOB and LOS. With the overall subject range approach, it is difficult to discriminate and recognise a particular activity as the degree of overlap is quite high.

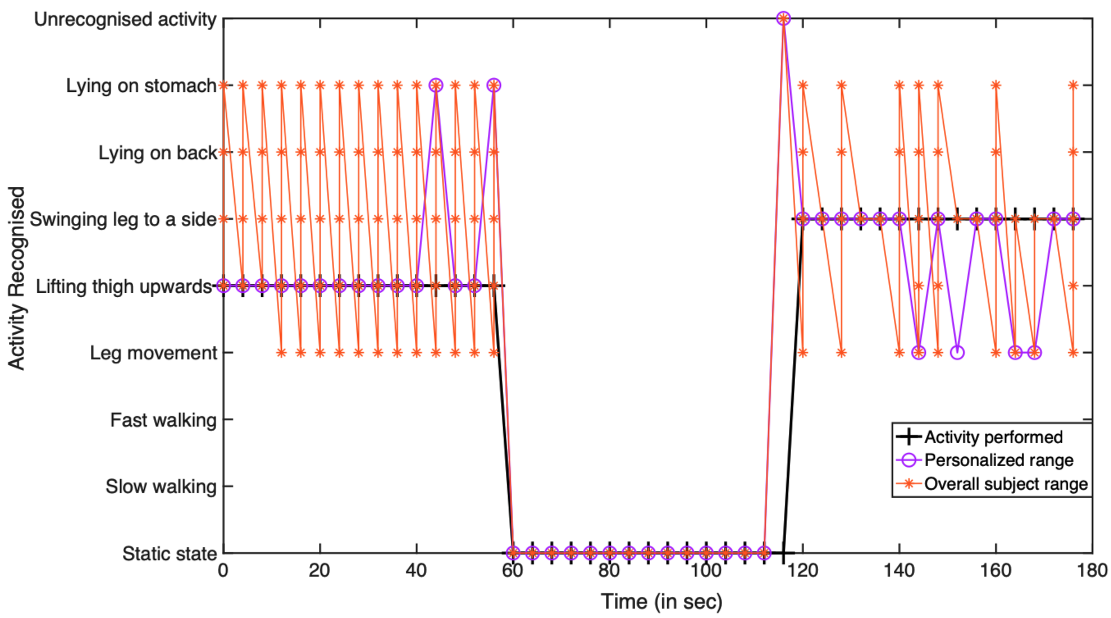


Figure 5.23: Long-term group-based activity (LTU, Static and SLTS)

Case 2: In case 2 and as presented in Figure 5.24, subject was instructed to perform LOB (1-min), static state (1-min) and LOS (1-min). Analysis portrays a 66% recognition

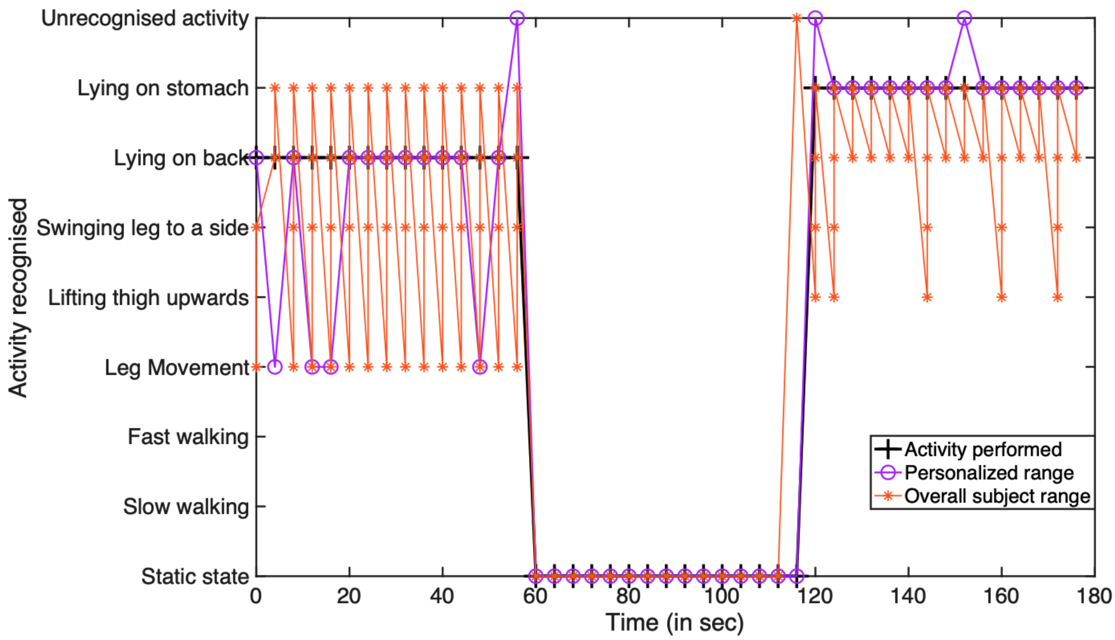


Figure 5.24: Long-term group-based activity (LOB, Static and LOS)

accuracy of LOB activity, where 26% overlaps, with LM and 8% accounts for unrecognised activity. Again, the static state of a subject is 100% accurate. LOS is 87% accurate and 13% activity is unrecognised, but no overlap is observed with other activities. In comparison to the overall subject range, LOB activity overlap with four different activities i.e., LM, SLTS and LOS. Whereas LOS overlaps with three different activities i.e., LTU, SLTS and LOB.

From the above analysis of two cases, it is evident that personalisation is a better approach to recognition of a subject's activity movement behaviour. As a result, it represents the first level of the recognition process that reduces the overlap among the activities in comparison to the overall subject range. The second level of improving the recognition process is based upon looking at the logical switching of activity transition rules and the number of occurrences of a particular activity performed or overlapped. This would help in the correction of any misrecognised activity behaviour observed during the past one min. Table 5.2 represents the overall summary of the two case findings.

Table 5.2: Case 1 and 2 activities performed, overlap and recognition findings summary

Activity Performed	Overlap Activity	Correct Recognition	Incorrect Recognition
Case 1:LTU	LOS	13/15 times	2/15 times
Case 1: Static	None	15/15 times	None
Case 1: SLTS	LM	11/15 times	4/15 times
Case 2:LOB	LM	11/15 times	4/15 times
Case 2:Static	None	15/15 times	None
Case 2:LOS	None	13/15 times	2/15 times

Findings show that for case 1, the subject performed LTU activity 13 times, where two times it overlapped with LOS. Since LOS activity is performed in a lying position compared to LTU which is performed in a standing position, overlapping two times clearly shows that the activity is misrecognised. Therefore, the subject's LTU activity is recognised with 100% accuracy. It has also been observed that the SLTS activity is performed 11 times where four times it overlapped with LM activity. It is clearly evident that LM activity is misrecognised as it is performed in a sitting position and quick switching over to the SLTS activity, performed in a standing position, is not feasible. Hence, the SLTS activity is recognised with 100% accuracy.

In case 2, the subject performed the LOB activity 11 times. Four of those times, it overlapped with the leg movement activity. As the LOB activity is performed in a lying position, leg movement activity is misrecognised as the activity is performed in a sitting position. Moreover, the sudden transition from lying to sitting may result in the capturing of erroneous movement transition data instead of a particular activity movement data. Therefore, LOB activity is recognised with 100% precision. In another scenario, the LOS activity is recognised 13 times. Two of those times, the activity was unrecognised. As a result, the LOS activity is recognised with 100% accuracy. This shows that personalisation and looking at the past one min activity movement behaviour based on logical switching and occurrences of the activity movement types has considerably improved the recognition accuracy. The next section portrays the conceptual architectural functionality implementation on hip fracture rehabilitation movement monitoring at three different levels. The discussion of the three main levels are:

5.7 Rehabilitation Movement Monitoring System Architecture

Based on the architecture proposed in Chapter 4, the aforementioned recognition process requirements and the hardware or software used (discussed in Chapter 3) for testing the overall architectural functionality are reflected in Figure 5.25. The architectural functionalities utilise computational resources at three main levels. These are the wearable monitoring tracker level, the IoT gateway (or Internet edge) level, and the Internet-cloud level. Each of these levels plays a significant part in offering the key functionalities for the smooth operation of the overall rehabilitated patient movement monitoring process.

5.7.1 Wearable Monitoring Tracker Level Functionality

In monitoring the hip fracture rehabilitation activity movement, a wearable activity tracker is designed based on Microduino's existing modules (illustrated in Chapter 3 under section 3.3.1). From our previous experimental investigation, it has shown that ankle joint location is selected as the favourable location for recognising post-hip fracture rehabilitation movement activities. As a result, the tracker is placed at the ankle location. As part of the experimental testing purpose, a young healthy participant was selected and provided with a wearable tracker. The participant was instructed to perform different sets of post-operative hip fracture rehabilitation activities (illustrated in Table 4.1 of chapter 4) in ad-hoc manner for a time period of thirty minutes. As mentioned in Chapters 3 and 4, the triaxial accelerometer sensor is used and data is collected at a sampling frequency of 128 Hz.

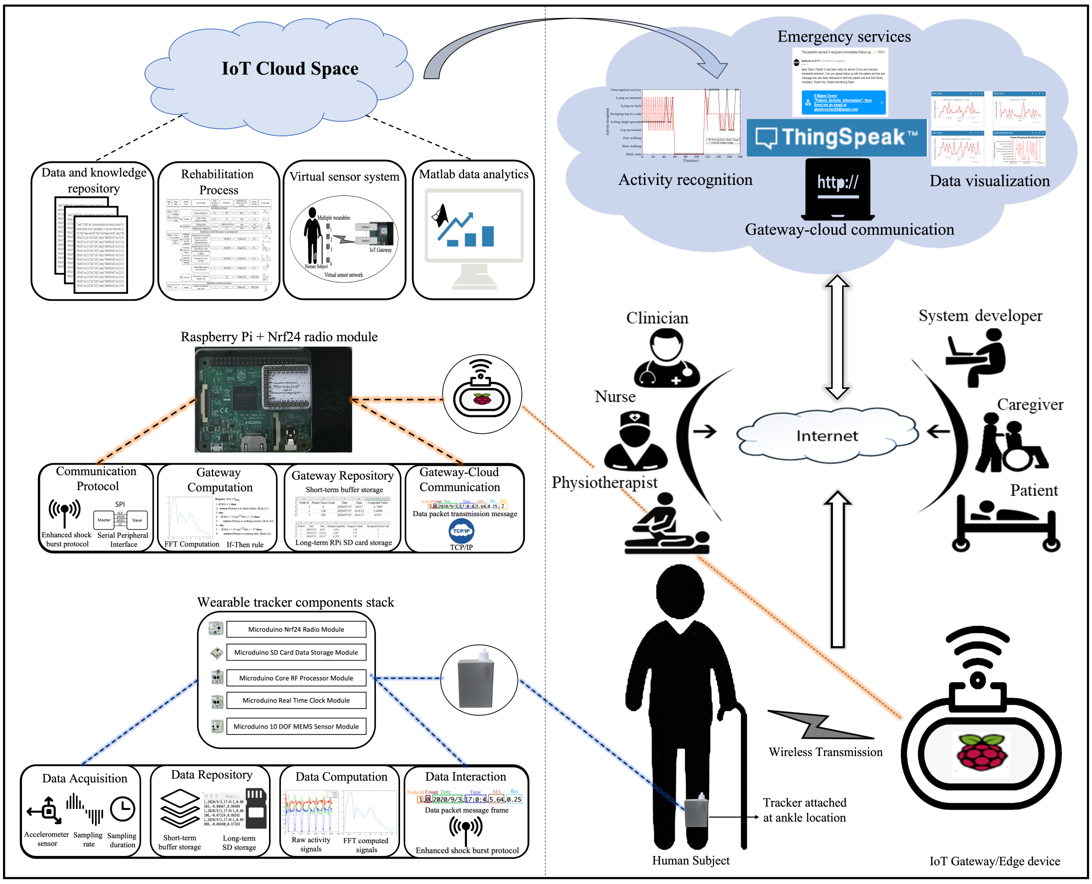


Figure 5.25: IoT-enabled with wearable hip fracture rehabilitation movement monitoring system architectural design highlighting operational functionalities at three different levels (wireless sensing; IoT edge; and Cloud level).

The continual raw acceleration activity movement data signals are stored in an SD card for long-term storage purposes. An SD card of 64 GB was used in this research, which can store data for around 30 days when run continuously for 24 hours a day. However, depending on the application requirement, an SD card of any size can be used for extending the data storage longevity. Moreover, the availability of the raw activity data can aid clinicians or researchers in carrying further processing and confirmation to lower-level analysis. The stored data can act as a backup in the event of misconnection or loss of connectivity to the gateway and the cloud.

Figure 5.26 represents the sample accelerometer activity's data stored in the SD card. The data packet format of the unfiltered data packet stored in the SD card comprises of node id, timestamp and triaxial (x, y and z axis) accelerometer readings.

Whereas Figure 5.27 presents the sample representation of the raw/unfiltered activity movement data from the 30-min trend. From the small and large ripples observed across all three axes, findings show that the human subject is dynamic and is performing some type of activity movement. Moreover, there are situations where all the axes data is steady and linear which means the subject is static and not performing any activity movements.

After capturing the raw activity movement data, it is then subjected to a filtering method. This is carried out by combing all the three-axis samples that would eliminate the tracker orientation problem, taking the mean, removing the DC offset and taking the moving average of every four samples. This would down-size the sampling rate to 32 Hz

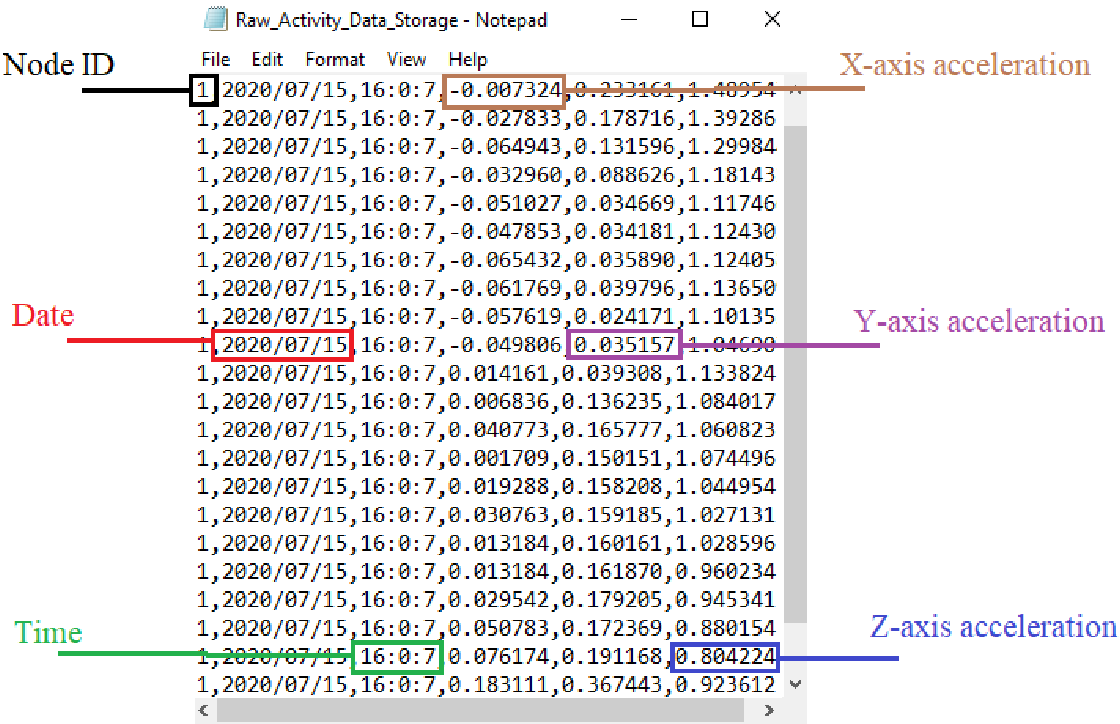


Figure 5.26: Sample raw activity movement SD stored raw accelerometer data

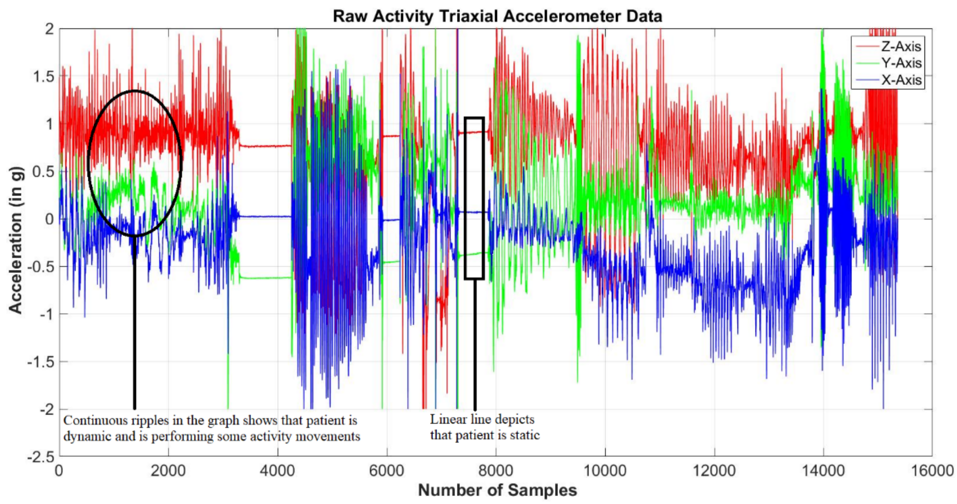


Figure 5.27: Sample trend of the raw activity movement

to comply with the 20 Hz suggested for everyday activities [150]. Here, a circular buffer has been used for short-term storage of the continually processed data. The sample representation of the activity tracker's computed data vs the five-minute activity time period event is represented in Figure 5.28. The computed data graph is smoother and consistent compared to the raw activity movement graph shown in figure 5.27.

The smoothness and consistency are because of the pre-cleaned processing happening at the activity tracker level, and refer to the first computational architectural scenario. From Figure 5.28, different ripples have been observed marked with different coloured circles that indicates that the subject has not been static all the time and has performed

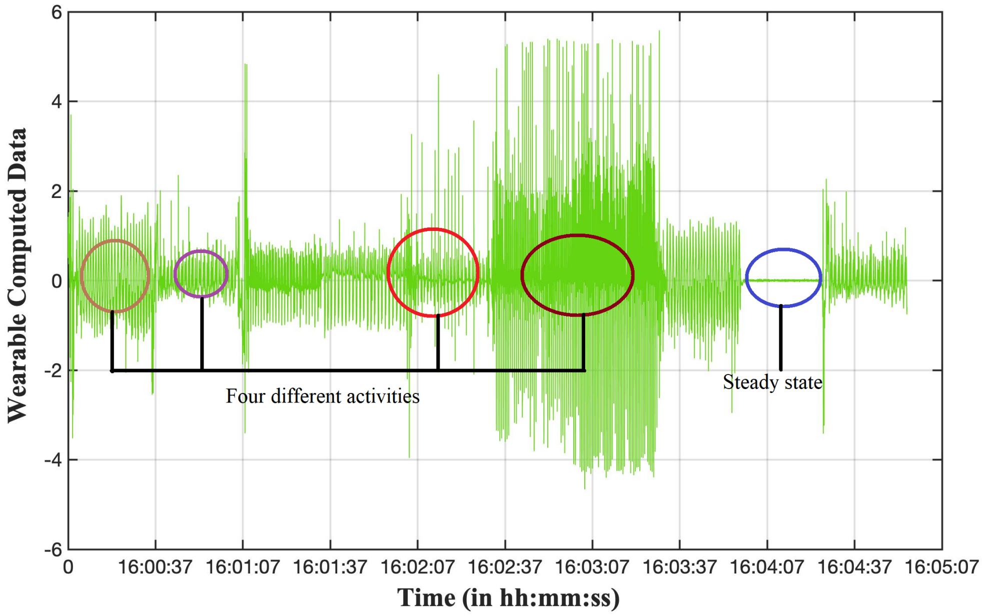


Figure 5.28: Wearable computed data vs five-min activity time period event plot

different types of activity movements. Moreover, a linear line marked with blue coloured circle indicates that the subject was static. Therefore, it would be hard to discern which activity movement subject has been performed based on the wearable tracker-computed data. Hence, it requires further data computation and compression.

This could be accomplished by using FFT-based signal processing as discussed in Chapter 4. The mathematical equations involved in this computational process are illustrated in equations 4.5 and 4.6 (refer to section 4.4.1 of Chapter 4). Using equations 4.5 and 4.6, the process identifies Maximum Acceleration Amplitude (MA) and Corresponding Frequency Content of the Maximum Acceleration Amplitude (Cf$_{MA}$) for each of the four second batch of data transmitted by the tracker and received by RPi. The timestamp of the final compressed data is associated with the end time of the activity movement sampling snap. The final computed data refers to the second computational architectural scenario.

Based on the two computational architectural scenarios discussed above, point-to-point communication is established for transmission of the activity movement data packet. The radio data packet is transmitted at a data rate of 250kbps. For transmission and reception in the first scenario, the radio pipe address is of 5-byte, 2-byte each for node id, packet trace, date, time and 4-bytes for processed data. The packet is transmitted once every four seconds from the activity tracker to the IoT gateway. One reading has a data packet size of 12 bytes and 128 such packets are sent to the gateway containing 1536 bytes of data. The data packet communication frame for the first scenario is presented in Figure 5.29.

Whereas for the second scenario, the radio pipe address is of 5-byte, 2-byte each for node id, packet trace, date, time and 4-bytes each for MA and Cf$_{MA}$. The packet is transmitted once every four second from the activity tracker to the IoT gateway. One reading has a data packet size of 18 byte and 1 such packet is sent to the gateway. The data packet communication frame for the first scenario is presented in Figure 5.30. As discussed in Section 5.5, the reason for sending it every four seconds is mainly related to the FFT

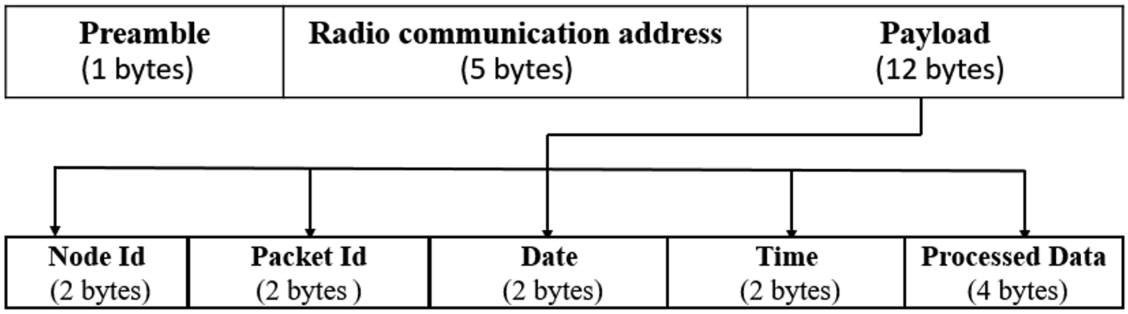


Figure 5.29: First architectural scenario data packet communication frame

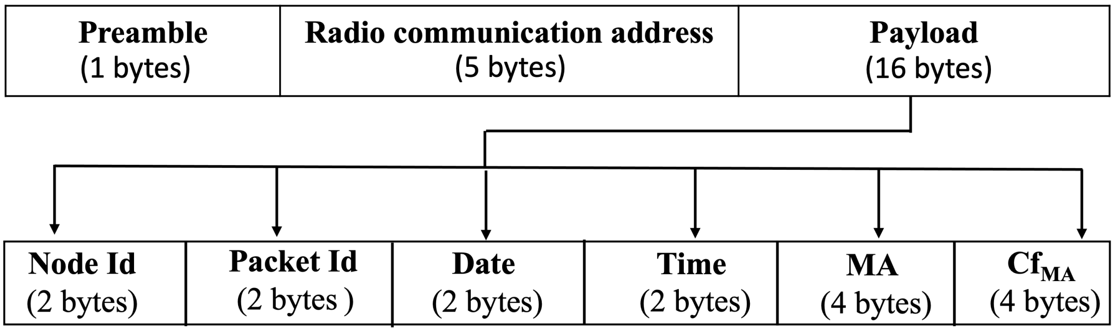


Figure 5.30: Second architectural scenario data packet communication frame

process as it is the minimal time for activity detection without any loss of information or signal distortion. A portable RPi attached with a nrf24 radio module is functioning as a gateway here whose functionality is discussed in the next section. Considering the constrained resources (data collection, processing and radio data packet transmission) available within a wearable tracker, it is important to investigate the energy consumption of the wearable tracker to observe how long the wearable tracker could be worn by a user when run continuously. The analysis has been completed by comparing the energy consumption when the tracker is in idle mode with that of a fully functional operational mode.

Since Microduino's module ran on 3.3V, the tracker is powered by a $\frac{1}{2}$ AA rechargeable battery of 800 mAh at 3.7V where the cut-off voltage is 2.75V. The selection of the battery is random so that the tracker can operate for a full day. Table 5.3 represents the current in idle and operational (op) modes (for two architectural scenarios) for each module used in the tracker.

From the practical measurement values provided by Table 5.3, a total current of 22.91 mA is used by the tracker in an idle mode. Whereas for the two architectural scenarios, a total current of between 28-31 mA and 26-27 mA is used by the tracker during its operational mode . The total power consumed by both idle and two operational modes are 84.8 and between 104-115 mW and 96-100, mW respectively. During transmission and reception, findings showed a minor fluctuation in the current consumption and are mostly 28-31 mA. This could be due to numerous reasons, but one potential reason is that it draws more current when the data is stored in the SD card.

From the calculations and as shown in equation 5.1, it is observed that battery capacity is adequate to collect, store and transmit the data continuously for a total duration of 26 hrs during the first operational mode. Whereas for the second operational mode and as

Table 5.3: Wearable tracker modules current and power consumption

Serial number	Sensing modules	Idle mode current (mA)	First operational mode current(mA)	Second operational mode current(mA)
1	Core RF	18.6	21-22	20
2	10 DOF	0.01	0.02-0.06	0.02-0.06
3	SD card	1.5	3-4	3-3.5
4	NRF24	2.8	4-5	3-3.5
5	RTC	0.032	0.05-0.1	0.05-0.1
Total current consumed		**22.91 mA**	**28-31 mA**	**26-27 mA**
Total power consumed		**84.8 mW**	**104-115 mW**	**96-100 mW**

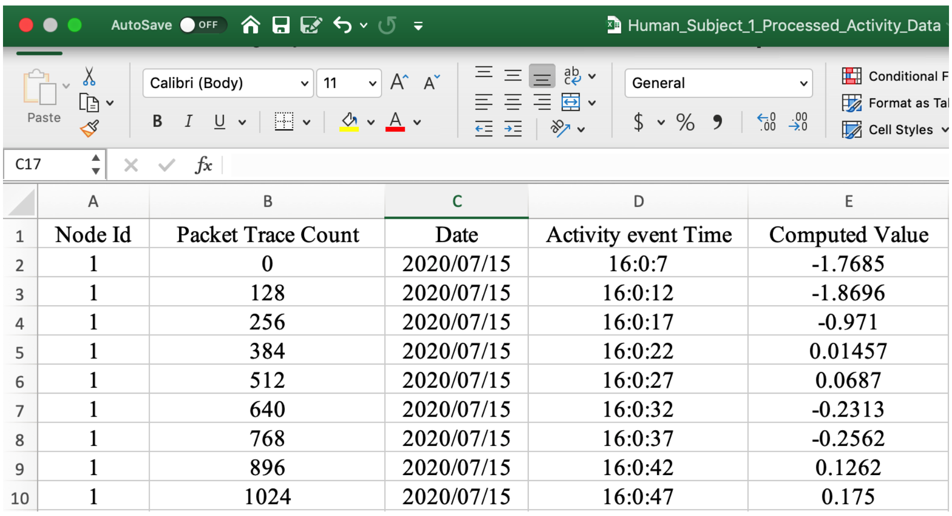
shown in equation 5.2, the battery capacity is around 30 hrs and must be recharged using a USB cable when a human subject is going to bed.

$$First\ operational\ mode\ battery\ life = \frac{800\ mAh}{31mA} = 25.80 \approx 26hrs \qquad (5.1)$$

$$Second\ operational\ mode\ battery\ life = \frac{800\ mAh}{27mA} = 29.6 \approx 30hrs \qquad (5.2)$$

5.7.2 IoT Gateway or Edge Level Functionality

For IoT gateway or edge level functionality, a portable RPi connected through the serial communication port with a Microduino nrf24 radio module (refer Chapter 3 under section 3.3.2) has been used as a gateway. Considering the first architectural scenario, a complete 128 pieces of filtered data, representing the four seconds of data acquired by the wearable sensor is received. Whereas for the second architectural scenario, one piece of final FFT computed data is received regularly by the RPi through serial communication. This incoming data packet is stored continually in the SD card residing within RPi in the form of text and CSV file format. The screenshot of the data packet received at RPi in CSV formats for two architectural scenarios is shown in Figures 5.31 and 5.32.



Node Id	Packet Trace Count	Date	Activity event Time	Computed Value
1	0	2020/07/15	16:0:7	-1.7685
1	128	2020/07/15	16:0:12	-1.8696
1	256	2020/07/15	16:0:17	-0.971
1	384	2020/07/15	16:0:22	0.01457
1	512	2020/07/15	16:0:27	0.0687
1	640	2020/07/15	16:0:32	-0.2313
1	768	2020/07/15	16:0:37	-0.2562
1	896	2020/07/15	16:0:42	0.1262
1	1024	2020/07/15	16:0:47	0.175

Figure 5.31: First architectural scenario activity tracker data packet format received and stored in RPi

Node Id	Packet Trace Count	Date	Activity event Time	MA (m/sec2)	CfMA (Hz)
1	0	2020/07/15	16:0:7	20.34	1
1	1	2020/07/15	16:0:12	10.33	1
1	2	2020/07/15	16:0:17	8.97	0.5
1	3	2020/07/15	16:0:22	14.45	1.5
1	4	2020/07/15	16:0:27	16.98	1
1	5	2020/07/15	16:0:32	18.65	0.75
1	6	2020/07/15	16:0:37	22.37	1.5
1	7	2020/07/15	16:0:42	26.55	1.25
1	8	2020/07/15	16:0:47	28.9	0.25

Figure 5.32: Second architectural scenario activity tracker data packet format received and stored in RPi

For the first scenario, the data packet format comprises of node id, packet trace count that increments by one and is used to keep a track of which packets have been received or lost during the transmission, date, activity event time and computed data value at the wearable activity tracker's level. The computed data received at the gateway is subjected to FFT-based filtering, using the mathematical equations discussed in Chapter 4. Whereas for the second scenario instead of computed data value, MA and Cf_{MA} are received by the gateway and requires no further FFT signal processing. Based on the FFT computed data, the activity threshold condition is set for a particular user based on the if-then-else condition, as illustrated in Figure 5.33 .Here, MA refers to the maximum amplitude and MF refers to maximum frequency. Hence, activity recognition is implemented at the gateway level based on MA and Cf_{MA} parameters. After recognising an activity, MA, Cf_{MA} and Recognised Activity Code (RAC) features are sent to the cloud. Here, RAC denotes a number that ranges from 0-8 and is identified in Table 5.4. For example, if an activity recognised was swinging leg to a side, an RAC of 5 will be sent to the cloud.

Pseudo Code for Subject 1:

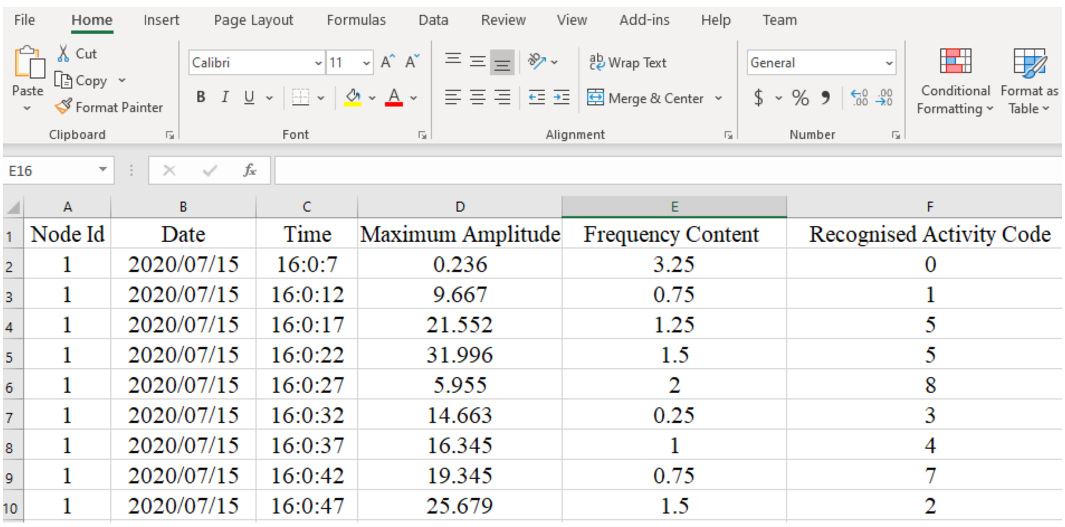
```
Require: MA,MF
if MA<=1 then
 return (Patient is in Static State) {Rule A1}
else
  if MA >= 8 and MA <= 17 then
    return (Patient is walking slowly) {Rule A2}
 else
   if MA >= 42 and MA <= 69 then
     return (Patient is walking fast) {Rule A3}
  else
    if MA >= 10 and MA <= 22 and MF>=0.25 and MF<=1 then
      return (Patient is performing leg movement) {Rule A4}
   else
     if MA >= 25 and MA <= 40 and MF=0.50 then
       return (Patient is performing lifting thigh upwards) {Rule A5}
    else
      if MA >= 13 and MA <= 26 and MF>=1 and MF<=1.75 then
        return (Patient is performing swinging leg to a side) {Rule A6}
     else
       if MA >= 10 and MA <= 21 and MF=0.75 then
         return (Patient is performing lying on back) {Rule A7}
      else
        if MA >= 15 and MA <= 27 and MF=0.25 then
          return (Patient is performing lying on stomach) {Rule A8}
      endif
     endif
    endif
   endif
  endif
 endif
endif
endif
```

Figure 5.33: If-then-else subject's movement threshold rules pseudo code

Table 5.4: RAC for hip fracture rehabilitation activities

S.No	RAC	Activity type
1	0	Static state
2	1	Slow walking
3	2	Fast walking
4	3	Leg movement
5	4	Lifting thigh upwards
6	5	Swinging leg to a side
7	6	Lying on back
8	7	Lying on stomach
9	8	Unrecognised activity

Along with the incoming wearable tracker data, the final compressed data (MA, Cf_{MA} and RAC) for both the architectural scenario is also stored in the RPi SD card in the form of a text and CSV file. The sample of the final compressed data stored in RPi is illustrated and represented in Figure 5.34. The stored data in the RPi could be used to validate the packet loss, and in case the connectivity to the cloud is lost, the activity movement data can still be recovered. The reasons for storing the data within RPi the following: First, to validate the data samples packet loss. Second, if the subject goes out of the allocated residence/ rehabilitation care centre or due to any other reason and it results in a loss of connectivity to the cloud. In this scenario, the incoming wearable tracker's data and the activity recognition data can be recovered and sent to the cloud once it finds the connectivity.



	A	B	C	D	E	F
1	Node Id	Date	Time	Maximum Amplitude	Frequency Content	Recognised Activity Code
2	1	2020/07/15	16:0:7	0.236	3.25	0
3	1	2020/07/15	16:0:12	9.667	0.75	1
4	1	2020/07/15	16:0:17	21.552	1.25	5
5	1	2020/07/15	16:0:22	31.996	1.5	5
6	1	2020/07/15	16:0:27	5.955	2	8
7	1	2020/07/15	16:0:32	14.663	0.25	3
8	1	2020/07/15	16:0:37	16.345	1	4
9	1	2020/07/15	16:0:42	19.345	0.75	7
10	1	2020/07/15	16:0:47	25.679	1.5	2

Figure 5.34: FFT based signal processing data packet format in CSV format stored in RPi SD card

As discussed in Chapter 3 under section 3.4.3, ThingSpeak provides the capability for uploading the data in bulk, where the limit of a single bulk update is up to 14400 pieces of data and the time limit between each sequential bulk update should be 15 seconds or more [2]. With the availability of this functionality, an algorithm flow chart is designed that represents the data transmission operation based on the Internet connectivity establishment. This is illustrated in Figure 5.35.

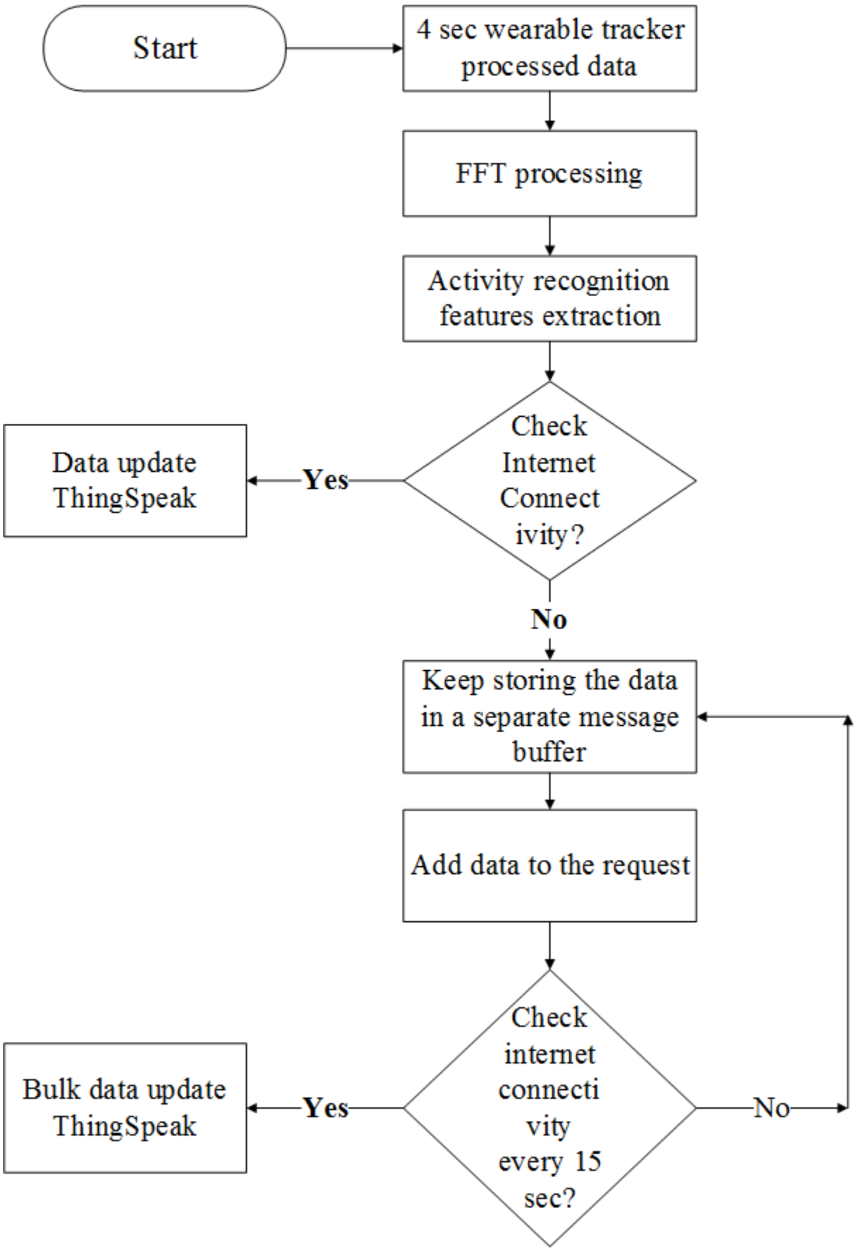


Figure 5.35: Bulk data transmission operation based on Internet connectivity establishment

The algorithm starts by receiving the four seconds wearable tracker activity movement data. The data is then subject to FFT processing that extracts the activity recognition features (MA and Cf_{MA}) for the first scenario. Whereas for the second scenario, the final FFT computed is received by the gateway every four seconds. Following that, the portable RPi device checks for Internet connectivity. If the connectivity exists, it updates ThingSpeak with the current data. However, if there is no connectivity, it stores the data in a separate message buffer and adds the data to the request. After putting the data to request, it continues checking Internet connectivity existence every 15 seconds. However, this time could be adjusted based on the application requirement. When it finds the connectivity, the complete data put to request is sent in bulk to ThingSpeak for an update. This process is executed repeatedly in a loop. In this way, it will backtrack and fill the lost-time activity movement data.

To validate the algorithm and its functionality, a simple experiment was conducted around a similar situation where the subject was instructed to perform the rehabilitation activity movement in an outside environment for around five minutes where there is no Internet connectivity and then return to the lab to get connected to the Internet to observe the bulk data upload to ThingSpeak. A sample illustration of such a scenario is depicted in Figure 5.36. It clearly represents that the five min data, i.e. around 75 activity movement data points are uploaded in bulk to ThingSpeak.

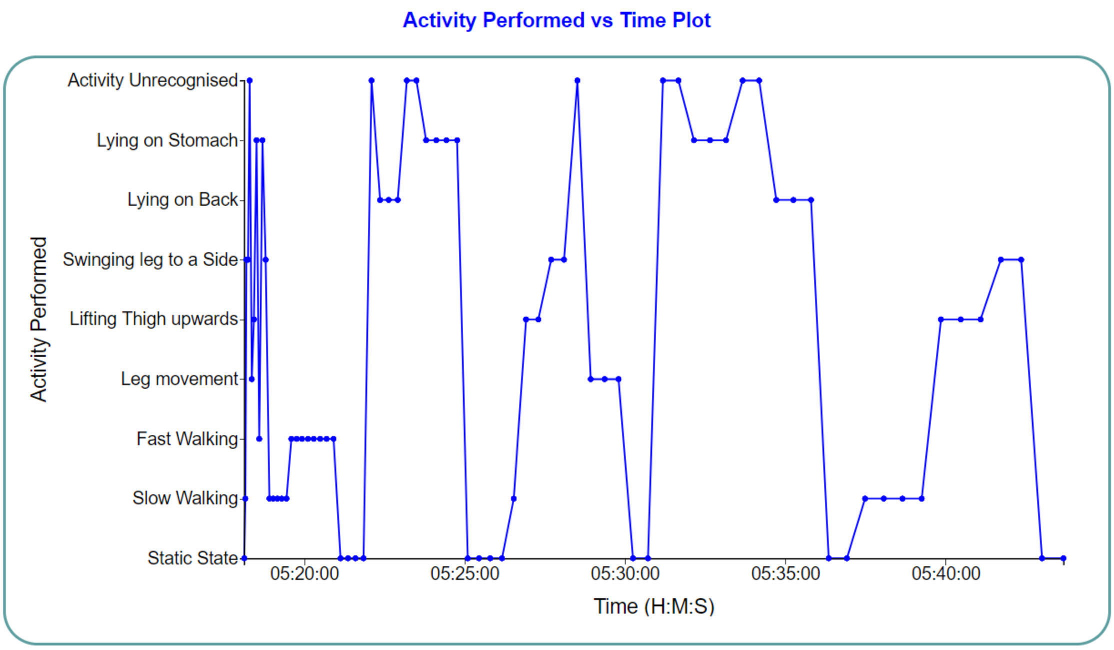


Figure 5.36: Bulk data upload to ThingSpeak when it finds the Internet connectivity

Another important aspect to consider along with the data packet reception, computation and sending of the data to the cloud, is to investigate the power consumption of the portable device. As discussed in Chapter 3, a portable gateway is powered by two AA batteries of 2500 mAh at 3.6 V. RPi recommended input voltage is 5V with a tolerance level of $\pm 5\%$. This means voltage between 4.75-5.25 could be supplied. RPi current and power consumption when it is in idle and fully operational mode is represented in Table 5.5.

Table 5.5: RPi current and power consumption in idle and operational modes

Serial number	Raspberry Pi modes	Current consumption (mA)	Power consumption (mA)
1	Idle mode	260	1.3
2	Sd card file storage	285	1.425
3	Operational mode	670	3.35

Considering the operational mode current consumption of RPi, calculations as represented in equation 5.3 indicate that battery capacity is adequate to collect, store and transmit data continuously for a time period of around 7 hrs. Battery power is only needed when the subject is outdoors. As a result, 7 hrs should be enough to cover the data collection time before recharging again.

$$Battery\ life\ of\ a\ Raspberry\ Pi3 = \frac{5000\ mAh}{670mA} = 7.46 \approx 7hrs \tag{5.3}$$

5.7.3 Internet-Cloud Level Functionality

The ThingSpeak platform (discussed in detail in Chapter 3) has been used to test the functionality at the Internet -Cloud level. The final compressed data from the RPi gateway (used within our implementation) is sent to the ThingSpeak platform using HTTP protocol. The data is spread across six different fields (Field 1: Node Id, Field 2: Date, Field 3: Time, Field 4: MA, Field 5: Cf_{MA}, Field 6: RAC) and is stored in the ThingSpeak cloud repository in three different formats i.e. JSON, XML and CSV format. This is represented in Figure 5.37.

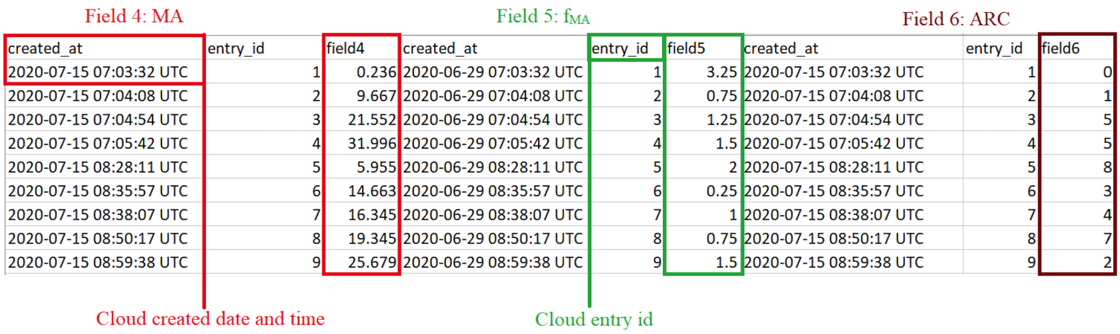
Export recent data

Data Fields	Data Format
Hip Fracture Rehabilitation Activity Monitoring Channel Feed:	JSON XML CSV
Field 1 Data: Node Id	JSON XML CSV
Field 2 Data: Date	JSON XML CSV
Field 3 Data: Time	JSON XML CSV
Field 4 Data: Maximum Amplitude (MA)	JSON XML CSV
Field 5 Data: Frequency Content (fMA)	JSON XML CSV
Field 6 Data: Activity Recognition Code (ARC)	JSON XML CSV

Figure 5.37: ThingSpeak Cloud data packet field storage

The sample screenshot of the data format stored in CSV format across fields 4, 5 and 6 can be seen in Figure 5.38. In the figure, “created at” represents the date and time when the data is received by the cloud. ”Entry id” is created automatically by the cloud as part of the record for each field data transaction. Fields 4, 5 and 6 represents the MA, Cf_{MA} and RAC, respectively.

Using the data available within the cloud repository and utilizing the Matlab analytical tools available within ThingSpeak for computation purposes, the overall processed and activity data presentation is created and is represented in Figure 5.39. The first three plots represent the compressed parameters i.e. MA, Cf_{MA} and RAC, while the last plot, i.e. human movement monitoring track represents the overall summary of the hip fracture rehabilitation movement performed by a young healthy subject over a given duration. The young healthy subject’s activities that have been recognised are static, slow and fast walking, leg movement, lifting thigh upwards, swinging leg to a side and lying on the stomach. The activity that was unrecognised is lying on the back. This information offers near-real-time trend monitoring to assist in motivating the patient, helping healthcare professionals in follow-up, emergency or decision making, etc.



created_at	entry_id	field4	created_at	entry_id	field5	created_at	entry_id	field6
2020-07-15 07:03:32 UTC	1	0.236	2020-06-29 07:03:32 UTC	1	3.25	2020-07-15 07:03:32 UTC	1	0
2020-07-15 07:04:08 UTC	2	9.667	2020-06-29 07:04:08 UTC	2	0.75	2020-07-15 07:04:08 UTC	2	1
2020-07-15 07:04:54 UTC	3	21.552	2020-06-29 07:04:54 UTC	3	1.25	2020-07-15 07:04:54 UTC	3	5
2020-07-15 07:05:42 UTC	4	31.996	2020-06-29 07:05:42 UTC	4	1.5	2020-07-15 07:05:42 UTC	4	5
2020-07-15 08:28:11 UTC	5	5.955	2020-06-29 08:28:11 UTC	5	2	2020-07-15 08:28:11 UTC	5	8
2020-07-15 08:35:57 UTC	6	14.663	2020-06-29 08:35:57 UTC	6	0.25	2020-07-15 08:35:57 UTC	6	3
2020-07-15 08:38:07 UTC	7	16.345	2020-06-29 08:38:07 UTC	7	1	2020-07-15 08:38:07 UTC	7	4
2020-07-15 08:50:17 UTC	8	19.345	2020-06-29 08:50:17 UTC	8	0.75	2020-07-15 08:50:17 UTC	8	7
2020-07-15 08:59:38 UTC	9	25.679	2020-06-29 08:59:38 UTC	9	1.5	2020-07-15 08:59:38 UTC	9	2

Figure 5.38: ThingSpeak Cloud data packet format across field 4, 5 and 6.

Figure 5.39: Human Movement monitoring ThingSpeak cloud data presentation

In fact, a further advanced intelligent computational is performed at the cloud level to correct the unrecognised activity. This is performed by looking at the activity movement past one-min behaviour as discussed in section 5.6. The final recognised activity movement data is then used to relate the subject activity movement recognition with the rehabilitation model discussed in section 4.2 of chapter 4. Figure 5.40 presents the sample representation of the real-time activity movement recognition performed by a subject during a day. In support of the sample representation illustrated in Figure 5.40, an overall summary representation of the daily frequency practice of the activity performed by a subject during the day is presented in Figure 5.41. The numbers related to daily frequency practice refers to the number of each repetition performed every four seconds by a patient for a particular activity. For instance, the patient was doing slow walking activity 10 times of four seconds recognition.

Results show that the subject was static most of the time. The ambulatory movements, namely slow and fast walking, were performed 9 and 10 times, respectively. Hip fracture related activities such as LM, LM, LTU, SLTS, LOB, and LOS were performed 6, 4, 5,

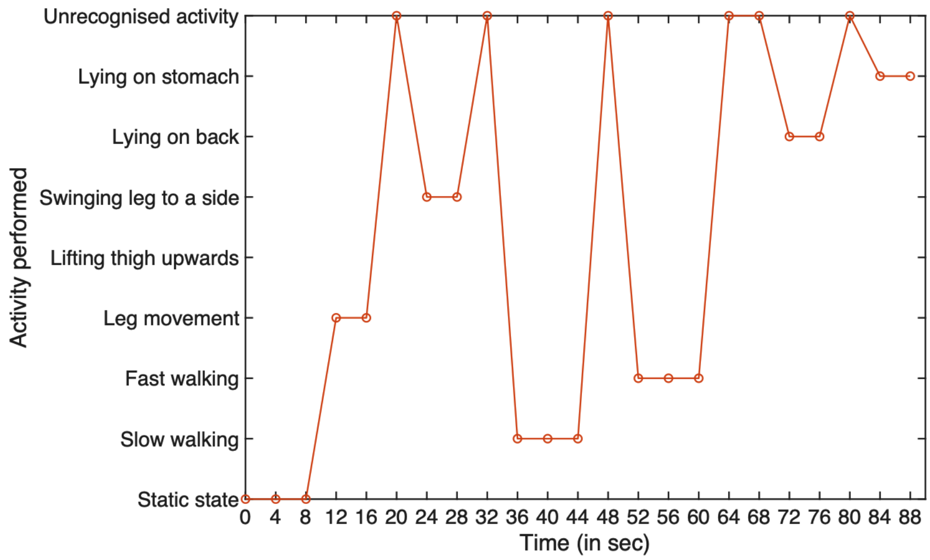


Figure 5.40: Sample representation of the real-time activity movement recognition performed by a subject during a day.

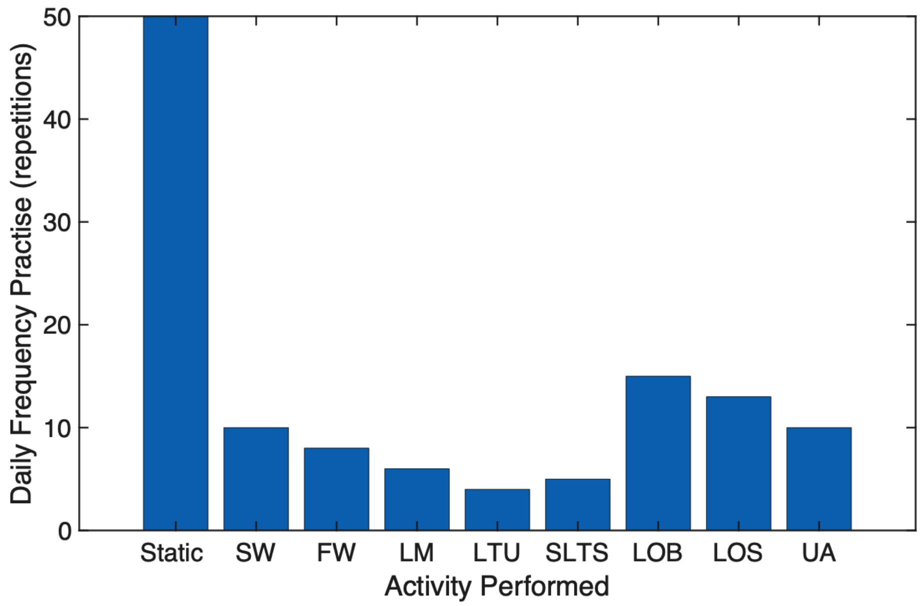


Figure 5.41: Overall summary sample of the daily frequency practice of the activity movement performed by a young healthy subject.

15, and 13 times, respectively. UA refers to the unrecognised activity and 10 times the activity was unrecognised. This is because the patient might be performing other ADL as part of their daily routine and unrelated to the rehabilitation activity movements or some of the activity movements overlapping with each other. This type of information is useful for the physiotherapist and medical professionals to observe how the patient is performing on an hourly, daily, weekly, or monthly basis depending on one's requirements. Moreover, such information is of great significance for mapping the proposed rehabilitation model. This would help in determining the stage at which the patient is at and their progression level, so that a follow-up can be performed when required and in case of an emergency.

Furthermore, with the available information, it is also essential to send alert text messages or emails to the patient, their caretakers and the healthcare professionals in case of an emergency or essential follow-up. This would not only alert the required persons for an urgent follow-up or immediate action, but the availability of such functionality is significant for the patient's well-being, motivation and gaining confidence. Hence, making them feel that the staff is there in case of a need for them and urgent situations.

Again, as discussed in Chapter 3, ThingSpeak has plugins that provide the functionality of triggering a notification using Thing HTTP from IFTTT. A sample illustration of an automatic email sent to the patient using IFTTT when no movement is observed for around 12 hrs. is represented in Figure 5.42. However, based on the application requirement, different sets of conditions could be set and the system would respond to the query automatically either by sending an email or text message or both. The next section illustrates the overall IoT system performance testing analysis considering different architectural scenarios.

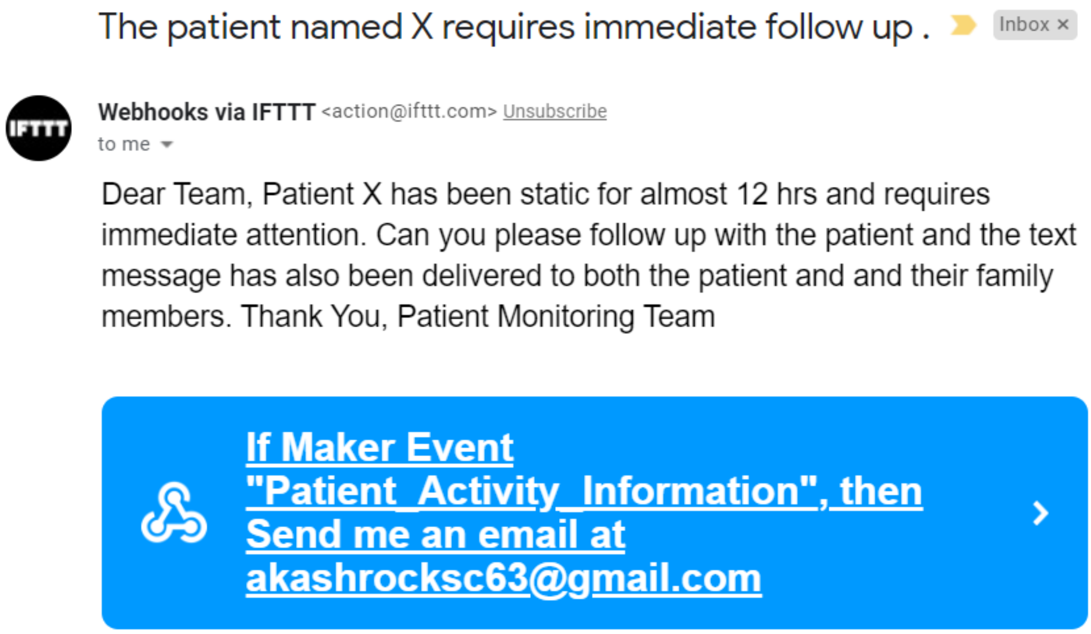


Figure 5.42: Sample illustration of an email sent using IFTTT

5.8 IoT System Performance Testing

This section investigates the data communication performance with emphasis on packet loss analysis. Data stream communication rates of four different time intervals of one, two, three and four seconds are tested. While the four second interval is considered typical for the FFT analysis of accelerometer data of an elderly user, faster rates are considered to examine the system communication capability for other users. The test has also considered the trade-off of FFT computation performed at the wireless sensor edge against the gateway edge. Four seconds is suitable for detection of hip fracture rehabilitation activity movements as it represents slow activity movements, particularly for elderly people. However, if we consider athletes or young individuals who have the ability to perform the activity movements faster and may recover quickly, in such cases, collecting the activity movement data at a higher sampling rate could help in recognizing the movement behaviour much earlier and with more precision. Considering all these possibilities in mind, one, two and three seconds time intervals are also taken into consideration and as part of the investigation. Furthermore, this section also provides a comparative analysis of the wearable energy consumption when FFT based computational processing is happening at two different levels and at four different time intervals.

5.8.1 Wireless Sensor Edge vs Gateway Sensor Edge

As part of the investigation, two architectural scenarios are considered. In the first scenario which is related to the wearable sensor edge, FFT-based signal processing is embedded within the wireless sensor where only one frame of 16 bytes of data packet size transmits to the gateway at four different time intervals chosen. These are intervals of one, two, three and four seconds, respectively. However, in the second scenario where the FFT computation is embedded at the gateway's edge while the wireless sensors just perform the acquisition and calibration of data samples. Here, fine-tuning of the raw activity movement signals through basic filtering methods like mean, removing DC offset and taking the average of every fourth sample is performed at the wearable wireless sensor edge. In doing so, a single frame has a data packet size of 12 bytes and 128 such readings are sent to the gateway again at four different time intervals where FFT-based signal processing is performed at the gateway level. The experimental description of each of these scenarios and their effect on the packet loss analysis are as follows:

Experiment 1:

The first experiment investigates the effect of increasing the number of data gathering nodes on the data drop rate while transmitting the data at different time intervals. Here, we used a network of up to five nodes feeding the gateway with a fixed rate of sensors data. Five different network setups have been considered where each wearable node is static and transmitting the data packet based on the first and second scenario as discussed above. Carrier Sense Multiple Access (CSMA) technique is used, where all the nodes report at the same time to the coordinator attached to the gateway (RPi). The experiment is repeated five times and each experiment is performed for a time duration of fifteen minutes. Each time one more node is added in feeding data to the gateway. All five sensors are stationary and are placed on the same bench without being obstructed with any obstacles around and between the nodes.

At the wearable sensor edge level, no packet loss was observed for all the nodes in the network. At the gateway edge level and as represented in Figure 5.43, no packet loss was observed for one node network and is almost negligible i.e., 1%. Taking two node networks as an example, the average packet loss for one second time interval was around 37% and decreased subsequently to 3%, 3% and 2%, respectively, as the time interval rate was increased. However, similar trend were observed for the other three node networks also. Therefore, especially in the case of bulk data transmission, it clearly indicates that as the number of nodes in the network increases, percentage packet loss also increases exponentially. They also decrease as the time interval rate increases, as it provides enough time for the data transmission to happen successfully.

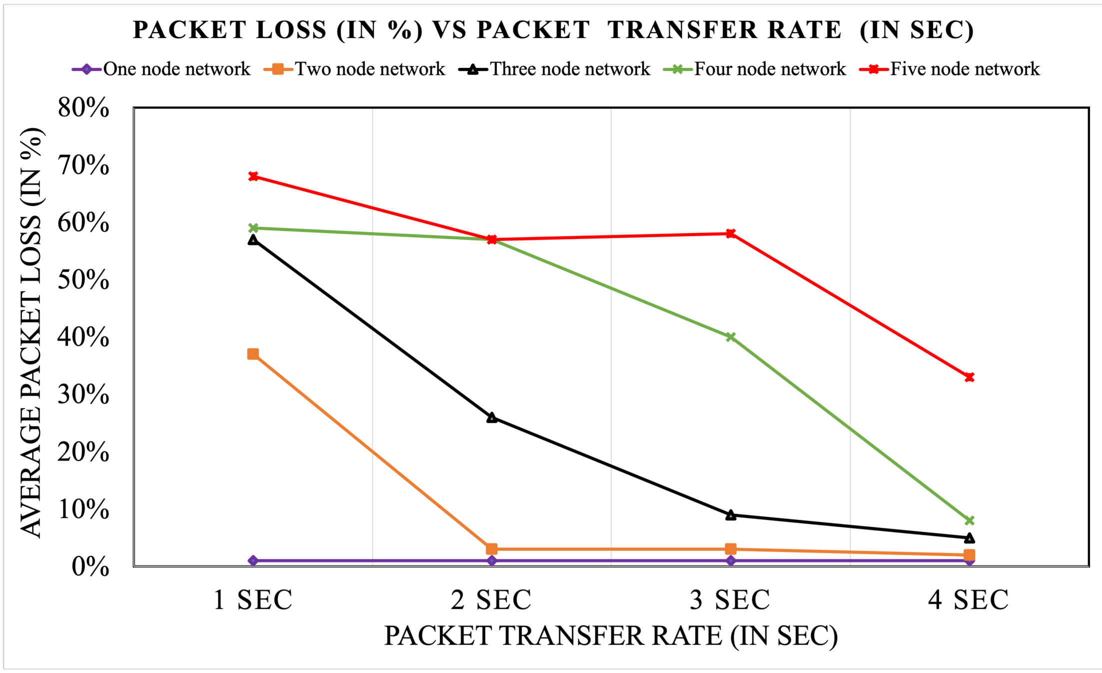


Figure 5.43: Gateway edge average packet loss analysis for a static node network

Experiment 2:

In the second experiment, all five nodes are active and attached to the human subject at five different body locations (hip, thigh, ankle, waist and chest) who is performing slow-walking activity movement. Figure 5.44 represents the wearable edge and gateway edge packet loss comparative analysis when all the five nodes are active and transmitting data to the coordinator.

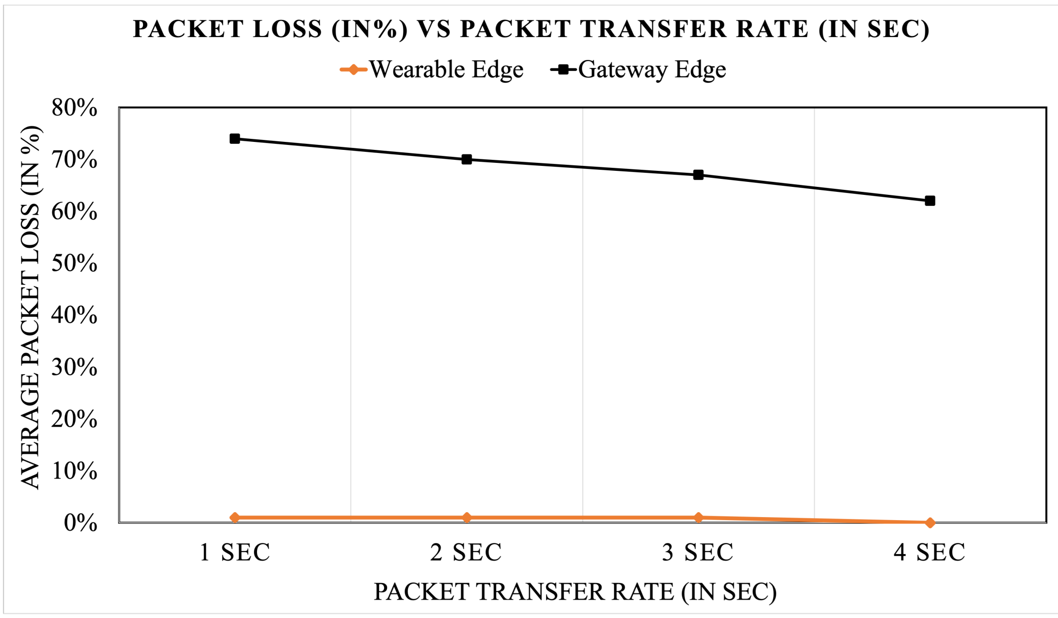


Figure 5.44: Wearable edge vs gateway edge average packet loss analysis for active five node network

From the analysis it is reflected that an average packet loss of 1% has been observed when FFT-based computation is performed at the wearable tracker level. In contrast, at the gateway edge level, the packet loss is quite high, i.e. 74% when the data transmission rate is one second. However, as the time interval rate increases to two, three and four seconds, the percentage packet loss% also reduces to 70%, 67% and 62% respectively.

In summary, the main reason for no or minimal packet loss at wearable sensor edge level is because the final data is compressed to one communication transaction of 16 bytes and does not overload the communication system during the transmission process. On the other hand, at gateway edge level, data is not completely compressed and requires 128 communication transactions with data packet size of 12 bytes to be transmitted. Therefore, all 128 readings are required to be received by the gateway for the FFT process to be accurate. Missing one or more readings out of the 128 would affect the FFT process and hence end up discarding a complete set of data collected at the specified interval. As a result of such losses, an increase in the percentage packet loss has been observed for all the nodes and across all the networks at the gateway edge level.

Considering the radio packet transmission and computational processing happening at wearable and gateway edge level, analysing the wearable device energy consumption and how long it would last at four different time intervals chosen in the packet loss analysis is essential. Since the Microduino modules can run on 3.3V, the wearable device is powered with a $\frac{1}{2}$ AA rechargeable battery of 1000 mAh at 3.7 V where the cut off voltage is 2.75 V. The battery selection is random in order to cover a day. Figure 5.45 represents the wearable and gateway edge energy consumption at four different time intervals i.e., one, two, three and four seconds. Findings show that at the wearable edge level, the current consumption for all the time intervals ranges from 20 mA to 26mA. Whereas at the gateway edge level, it ranges from 26mA to 31mA. Therefore, the gateway's edge current consumption is higher as compared to the wearable edge because 128 communication transactions with a data packet size of 12 bytes are transmitted continually.

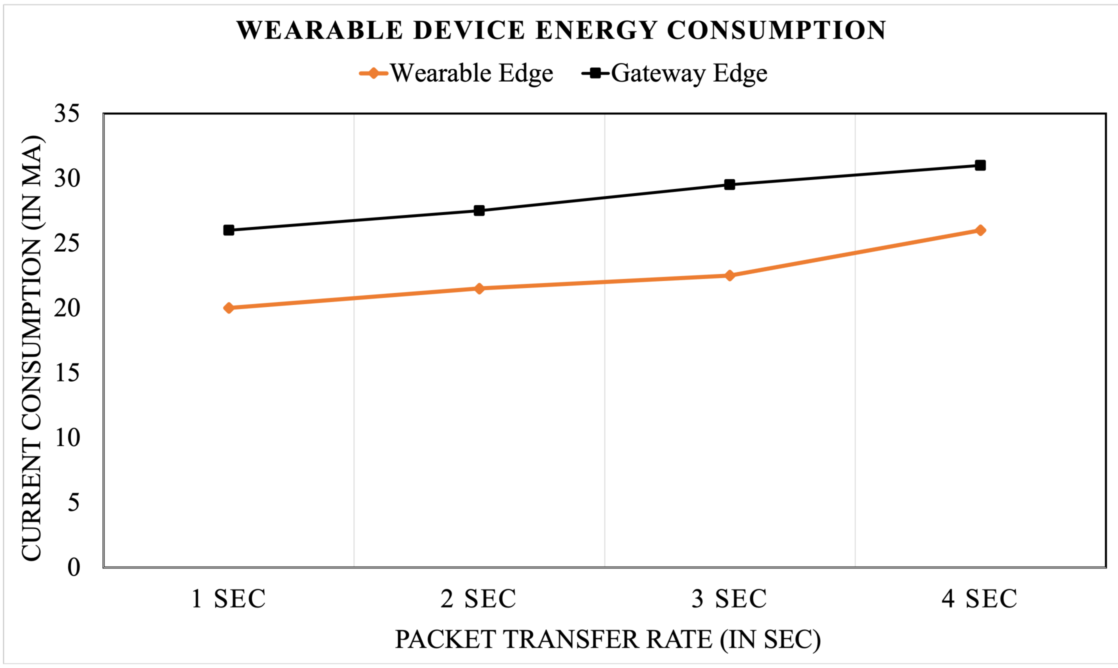


Figure 5.45: Wearable and gateway edge energy consumption

5.9 Conclusion

In conclusion, this chapter presented Chapter 4's conceptual ideology through experimental modelling and implementation. The chapter tested and validated the proposed recognition approach with the data collected from healthy young individuals. Through the data analysis, it then presented the optimal sensor location suitable for covering most of the proposed rehabilitation activity movement of interest. The experimental results reflected the impact of personalisation and the logical analysis of movement dynamics on the alignment with reality and further improvement in the recognition process. Moreover, it also presented the architectural implementation at three different levels and its system performance. Analysis of the system functionalities at the three main levels reflected the importance of edge computing at the wireless sensor edge in improving the system's overall performance.

Chapter 6

Rehabilitation Online Follow-Up Programme Use Case

6.1 Introduction

The chapter principal objective is to exhibit a more clearly-defined post-operative hip fracture rehabilitation follow-up programme for the development of an online real-time remote monitoring system. Considering the programme's requirements, another objective is to propose an IoT-enabled with a wearable hip fracture rehabilitation follow-up system that decides the patient's progression levels at each stage and offers support for decision-making through ticking its validity indicators. This chapter begins by presenting a more structured hip fracture rehabilitation follow-up programme. The programme presents the overall structural flow, starting from the surgery to rehabilitation care. It highlights the rehabilitation activity movements performed at different stages of recovery, its follow-up requirements and achievable goals at all stages of care. All of these factors are illustrated in Section 6.3 by providing sample examples, using the movement data collected from healthy young subjects discussed in Chapter 5. This section also presents an overall IoT-enabled with a wearable rehabilitation system design, highlighting all the key short and long-term functionalities to meet the follow-up programme's requirements.

6.2 Rehabilitation Follow-Up Programme Design

In general, there is no standard hip fracture rehabilitation follow-up protocol. However, as perceived from the critical literature review analysis and based on our proposed programme illustrated in Chapter 4 under section 4.2, a more structured hip fracture rehabilitation program can be designed. This is portrayed in Figure 6.1, which highlights the key stages of care, the follow-up duration, achievable goals during a particular duration and the activity movement of interest across all stages of care. In the figure, the green-coloured text refers to the activity movements our IoT system model (discussed in section 6.3) can recognise, while the orange text indicates the activity that can be recognised with an additional sensor attached to the body. However, other activities could be added to the automated solution capabilities as part of future work, which may require additional information from other sensing types and the on-body location of interest. Following that the surgery patients are mobilised either on a similar day or a day following the surgery where the hospital-based rehabilitation takes place. This is part of stage 1 of the rehabilitation

Stages of Care	Follow-Up Time	Achievable Goals	Activity Movements
Surgical Operation Stage 0	0 week	Hip fractured bone stabilization, ability to move around sooner, weakness and pressure injuries prevention	After surgical operation patient mobilization starts on a similar day or the day following operation
Hospital Rehabilitation Stage 1	0-3 week	Leg movement in and out of bed, able to walk with a walking aid or crutches, sit and stand from chair and bed.	1. Heel slide, knee straightening, hip bend, leg slide out, lower buttock squeeze while lying and sitting (Repeat 6-8 times, once a day 2. Hip, hamstring, calf stretches and hip lift (repeat 8-15 times, 3 times a week) 3. Sit-to-stand and stand-to-sit (repeat 5-10 times and Walking with aid or assistance (5-10 min)
Home Rehabilitation Stage 2A	3-6 week	Capable of walking several blocks, Riding on a stationary bike, Able to bend hip 90 degree, straighten hip to 0 degree and slide leg out to 25 degree	1. Core bent knee turn out (repeat 6 – 8 times, 3 times a day) 2. Thigh lift , heel squeeze, hip bend sideways along wall and back against wall, hip side lift against wall, half bridge (repeat 8 – 15 times, 3 times a week) 3. Leg movement (repeat 10-20 times, 3 times a week) 4. Exercycle (2 times a week, 10-20 min)
Home Rehabilitation Stage 2B	6-9 week	Walk longer distances, Sit-to-stand and stand-to-sit without help, balance for a short duration on the operated leg, climbing up and downstairs with alternate feet	1. Bent knee pull out, leg push against wall, Balance on one leg, heel rises and sit-to-stand and mini squats (repeat 8 – 15 times, 3 times a week). 2. Stationary exercise while lying on the back and stomach, swinging leg to a side, lifting thigh upwards (repeat 10-20 times, 3 times a week).
Outdoor Rehabilitation Stage 3	9-12 week	Walk without a limp, sit and stand from a normal height climbing up and down stairs with little or no railing support, return to driving with advice from physio and surgeon, progress home exercises and able to train in community fitness centers	1 .Leg lift on belly and straight leg lift, split squat, step up and down forward and sideways (Repeat 8 – 15 times, 3 times a week) 2. Walking independently ,balance board forward and backward and side to side 3. Leg movement , lifting thigh upwards, lying on back and stomach, swinging leg to a side (Repeat 10 – 20 times, 3 times a week).

Figure 6.1: Post-operative hip fracture rehabilitation follow-up stages, duration, achievable goals, and activity movement of interest across all stages of care (hospital, home and outdoor)

process. Findings shows that the hospitalisation period is normally around four weeks (0-3 weeks as illustrated in Figure 6.1). However, the time frame varies, depending on the functional status of a patient and how well one is recovering. During the hospitalisation period and based on the activity movements/exercises listed in proposed Figure 6.1, it is advised that a maximum of two hours of physiotherapy is essential each week. Following the four week duration or earlier, depending on the patient status, a discharge assessment takes place to ascertain whether the patient is ready to be discharged home in a safe environment. The examination test is based on six functions: (1) Cognitive function; (2) grip strength; (3) walking speed (10-min walking test); (4) walking endurance (6-min walking test); (5) balance ability (one leg standing test) and (6) ADL (functional independence measure). However, as discussed in the literature review, other assessment criteria involve a score-based monitoring approach in assessing the discharge criteria such as CAS, NMS, Barthel index and VRS. The solution available movement may offer these functional assessment indicators information by incorporating an algorithmic model. Whereas, in the case of the score-based assessment, it may require additional input from other types of sensing, a clinician, or a health carer. After examining the patient's functionality levels, a team of healthcare professionals along with family members accord on the achievable goals and for a secure discharge. However, in scenarios where patients do not meet the discharging criteria, they are placed in a rehabilitation home where activities are performed under a physiotherapist's supervision. This helps improve the patient's mobility and recovery requirements at the earliest time and in a safe ambulatory environment. The crucial period of the rehabilitation process starts when the patient is discharged home and living independently (i.e., 3-9 weeks period). This is because the focus is on strengthening the hip fractured bone muscle, mobility and physical functionality provided with a varied set of activities to be performed daily and as part of daily life's routine. The primary focus while the patient is performing activities at home relies on three indicators i.e., (1) The type of activity movement the patient has performed; (2) How many repetitions the patient has performed for a particular type of activity and (3) how many times a particular type has been performed. The indicators would help the physiotherapist to observe patient progression levels either on a day-to-day, weekly, or monthly basis. Moreover, the findings will aid in analysing the recovery progression levels and stages the patient is at for that moment. During this period, if the patient is progressing well in accordance with the programme and recovery requirements, patients move onto the final stage i.e., outdoor-based rehabilitation (i.e., 9-12 weeks). This phase is combined with home-based exercises along with outdoor exercise (fitness centres, activity movements and walking). Therefore, along with recognition of the activity movements involved at each stage, the aforementioned indicators play a significant role in deciding patient progression and improvement levels. From 12 weeks (i.e., three months) till one year period, the patient is advised to train two days a week to maintain their current strength, three days to increase the strength with the emphasis more on resistance training, and avoid training the same muscle four days a week.

6.3 IoT Based Real-Time Monitoring System

As discussed previously in Chapter 5, IoT-enabled with wearable could play a significant role in the development of a rehabilitation movement monitoring system. This is accomplished by distributing the functionalities at different levels to meet the rehabilitation programme's requirements. Considering our proposed movement monitoring architectural solution (refer Chapter 5 under section 5.7) and the clearly-defined structured rehabilitation programme (refer to section 6.1) in mind, an overall IoT-enabled with wearable rehabilitation care follow-up solution is designed. The design as presented in Figure 6.2 reflects the functionalities discussed in our previous solution, along with what is required to be done as part of the future work to meet the overall rehabilitation programme requirements. At the wearable tracker level, the triaxial accelerometer has been used for gathering activity movement data and has shown the potential for recognising most of the proposed activities. However, from the literature analysis in Chapter 2, findings have shown how a combination of sensors could be effective in providing additional information about the movement behaviour. As a result, understanding the role of sensor fusion (accelerometer, gyroscope and magnetometer) in covering all of the key activity movements that are part of the follow-up programme could provide key activity sensing parametric indicators, essential for precise movement recognition. Another major factor is that of on-body sensor localisation. In our proposed approach, the ankle joint location is the favourable location of choice. This location covers most of the proposed activities. However, our preliminary results indicated the significance of other locations in recognising activities with good precision. As a result, it would be significant to analyse the combination of other on-body locations along with sensor fusion to see how it can contribute to covering all the activity movements with higher precision. With respect to the selection of sensor and its on-body location, the sampling rate at which data is collected and the time duration for activity recognition is crucial. In our previous approach, a sampling rate of 128 samples per second have been used with a time duration of every four seconds. However, this approach proved feasible for most of the activities involved in the programme. Consideration of a different sampling frequency and an analysis of how it could be made adaptive-relevant to each movement type is critical. The movement recognition approach is based on frequency-based signal processing. However, considering variant types of techniques used in movement recognition (discussed in Chapter 2) requires further exploration to cover and recognise the majority of the activities part of the programme. Whereas at the gateway level, our proposed approach highlighted the

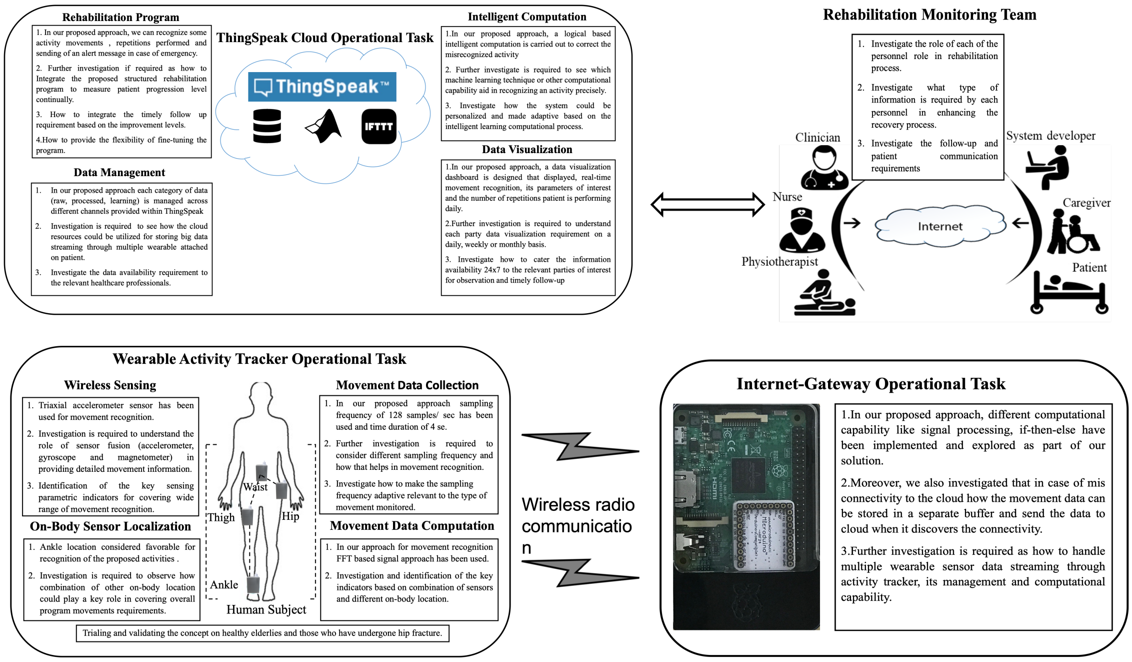


Figure 6.2: Overall IoT-enabled with wearable rehabilitation follow up movement monitoring system design attributes)

significance of edge computing and how it facilitated powerful computation such as digital signal processing and storage for a smooth and robust operation. However, if the system involves multiple embedded sensors within the wearable tracker and is attached at multiple locations, further analysis of handling such a scenario is essential from the data storage, its management and computational capability. This approach would help in covering the monitoring of a number of patients such as those at rehabilitation homes or hospital-based monitoring. Lastly, at the cloud level, four areas play a key role in delivering the overall solution outcomes. This includes rehabilitation programme, data management, intelligent computation and data visualisation. In our proposed approach, each category of data (raw, processed and learning) is managed and stored across different channels provided within ThingSpeak. For storing big data streaming through multiple wearable trackers and from multiple patients, it requires further investigation to observe how the cloud resources could be utilised to their maximum potential without affecting the efficiency of the overall system. Furthermore, in our proposed rehabilitation programme, we can recognise some activity movements, along with the repetitions performed. However, with the proposed follow-up programme, further investigation is required to see how the programme could be integrated at the cloud level to measure patient progression levels continually. This also involves the integration of timely follow-up requirements based on the improvement level and providing healthcare professionals more flexibility in fine-tuning the programme according to individual recovery needs. This also involves a personalisation of the system for each individual and an adaption based on intelligent computational purposes. The most important aspect is to display meaningful information from the outcome. In our previous approach, the data visualisation dashboard was designed that displayed real-time movement recognition, its parameters of interest and the number of repetitions the patient was performing daily. However, based on the healthcare professional's and hospital's requirements, catering the information availability 24x7 for observation and timely follow-up on a regular, weekly or monthly basis would help the user and healthcare professional interaction. This timely continual monitoring and information display would lead to enhancing the recovery process along with the follow-up in case of emergency.

6.4 Significance of Cloud Level

This section highlights the significance of the cloud concerning the rehabilitation follow-up programme. As activity movements play an important part in the recovery process, it is essential that a movement implementation is correct. As a result, providing the activity movement animation video at the cloud level would help the patient implement and perform the movement correctly especially in an unsupervised environment. A sample representation of the swinging leg to a side and lifting thigh upward activity movement animation is represented in Figure 6.3. However, other activities could be represented in

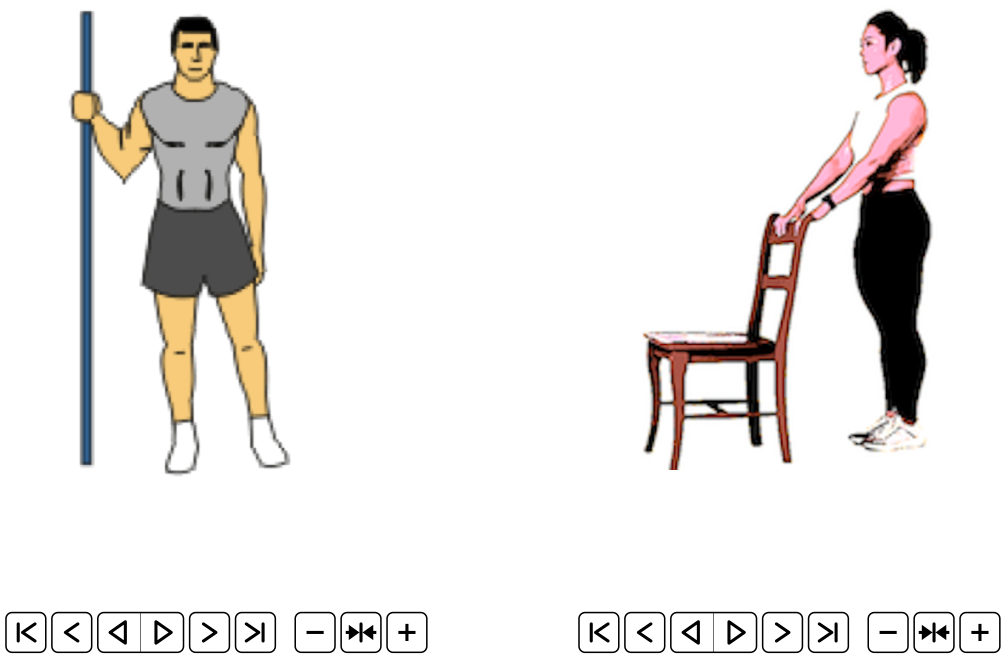


Figure 6.3: Swinging leg to a side and lifting thigh upward activity movement animation

a similar way. The controls button is provided below each figure that allows patients to either fast-forward, rewind and/or pause the animation illustrating a particular movement. The sample representation of the particular activity movement performed during the day has been represented in Chapter 5 under Figure 5.40. However, there might be situations, especially at the premature stage, when the patient struggles to perform the movement correctly or forgot or find it lazy to perform the movement as part of the programme. In such scenarios, the system would offer necessary feedback. For instance; (1) whether the activity has been performed correctly or not; (2) sending an alert warning on avoiding certain movements at a particular stage and (3) emphasising the activity movements that lack an exercise performance. All these warnings could be integrated within the ThingSpeak cloud platform using IFTTT, as discussed in Chapter 5 under subsection 5.7.3. A sample illustration where the system sends necessary feedback (via automated email) to the patient based on the aforementioned instances is represented in Figure 6.4. Furthermore, it is essential for a physiotherapist along with the patient to know what stage they are in and how well they are progressing and all the movements they lack performance during the recovery process. Considering such a scenario, Figure 6.5 reflects a sample illustration of the possible maturity of the stage.

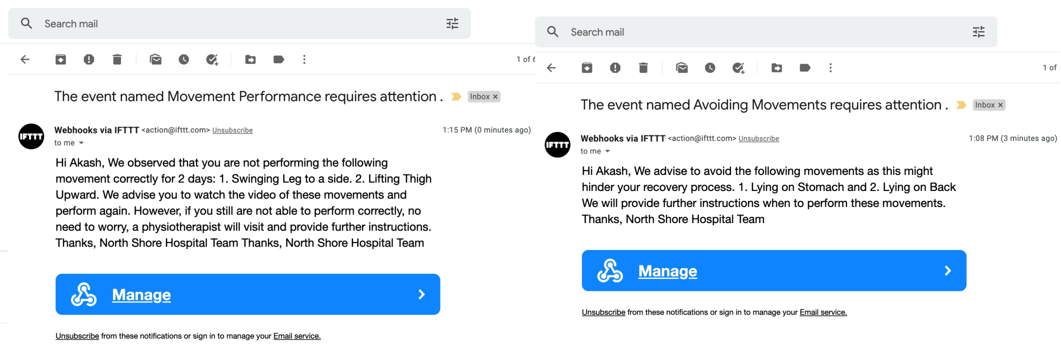


Figure 6.4: Rehabilitation monitoring system feedback alerts using IFTTT

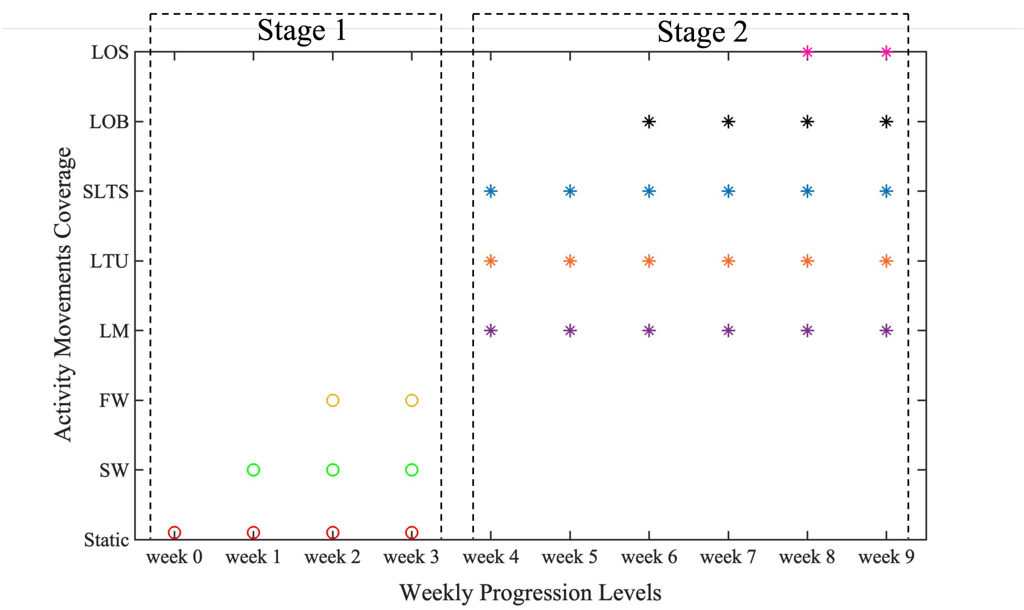


Figure 6.5: Weekly based rehabilitation stage movement progression level

The figure shows that the patient has completed stage 1 of the rehabilitation process by performing all the activity movement part of the programme and has been discharged home after meeting the discharging criteria requirements. In rehabilitation stage 2, Figure 6.5 depicts the following; (1) during weeks 4 and 5, the patient did not perform lying on back and stomach activities ; (2) during weeks 6 and 7, the patient did not perform lying on stomach activity; and (3) patient performed all the activity movements. This overall summary of stages indicates how well the patient is progressing. In the case of weeks 4-7, some activities were not performed and sending an alert warning through email or text message as depicted in Figure 6.4 allows the patient to be focused and perform the movement that was missed during the process.

6.5 Conclusion

This chapter proposed and suggested a more clearly-defined structured rehabilitation follow-up programme for monitoring the hip fractured patient following the surgery. Based on the follow-up programme requirements and the customised solution part of this study, a detailed IoT-based real-time monitoring system was illustrated. The system discussed how the overall system approach could aid in the development of a more robust online rehabilitation monitoring system.

Chapter 7

Conclusion and Future Directions

7.1 Introduction

The chapter principal objective is to offer the thesis findings, concluding statement, and future work requirements to enhance the research work outcomes moving forward. The chapter is divided into the two following sections. Section 7.2 concludes the overall thesis research work while Section 7.3 discusses the future directions.

7.2 Conclusion

This thesis provided the motivational background behind the hip fracture rehabilitation problem that healthcare professionals and hospitals are facing, due to the ageing population and increasing demands of healthcare services. Considering the problem domain, an examination of the crucial components involved in constructing a remote post-operative hip fracture rehabilitation movement monitoring system is critically discussed and focused on two major segments. The first segment relates to the post-operative hip fracture rehabilitation programme, the key movements involved and their recognition, the intuitive intelligence in grouping personalisation, the degree of fuzzy overlap and filtering of the possible occasional recognition errors that reflect illogical recognition when looking at the nature of the sequence of movements.

From the analysis observation, with incremental knowledge of existing health practice rules and programmes, this thesis proposed and suggested a generic model for the post-operative hip fracture rehabilitation process. In the proposed model, key involved activities along with measuring indicators such as daily frequency practise, repetition and activity duration at different stages of the rehabilitation programme are discussed. The physiological interaction between the rehabilitation process and the affected muscles are also highlighted. It then relates the external physical or motor activities with the possible recovery of these affected muscles. While the programme has emerged out of an analysis of existing recommendations within the science and practise of the hip fracture rehabilitation process, the defined movement and rehabilitation schedule offers grounds for automating the process and allows for effective utilisation of the modern digital environment. This should help evolve the solution as further implementation data becomes available. The ultimate target is the online rehabilitation program implementation that contains the key components to all detailed and abstracted data [9]. As a result, these should facilitate the environment for various personnel who work and interact with patient movement history and progress towards ultimate health. The movement recognition algorithm based on frequency-based signal processing is proposed to categorize the key activities involved in the programme. The COVID-19 pandemic and the restrictions it has caused in interacting with the elderly, along with the delay in issuing an ethical approval led to the consideration of data collection from healthy young individuals. Experimental results using the data collected from ten healthy young individuals showed that the proposed activity recognition model proved to be feasible and effective at recognizing most of the proposed activities. Furthermore, ankle location is considered the best location and a data collection time of four seconds is considered suitable for categorising the majority of the monitored activities [12]. The data analysis outcomes reflected the significance and impact of personalisation and logical analysis of movement dynamics on the alignment with reality.

The second segment relates to the technology used to support the rehabilitation model requirements and in structuring the IoT system. This thesis proposed an IoT-enabled wearable movement monitoring system architecture where edge computing plays a significant factor in easing out the communication, reducing the size of data at the cloud, and reducing the latency in tracking the patient movements. It is a three-level-based architecture, involving the wearable activity tracker, Internet gateway and cloud computing levels. The architecture reflects the key operational functionalities required to monitor patients in real time and throughout the rehabilitation process [3]. The architectural design is driven towards a modular structure that allows both hardware and software modules to be tested and can be applied to a wide range of healthcare applications [34]. In addition, the way the single accelerometer sensor has been employed to deliver the data that holds the necessary movement behaviour information also allows the approach in distributing the role among the three levels in supporting an efficient operation. This also includes convenience, life-time, the wearability of the wearable device, the potential of the gateway to facilitate the more powerful processing and storage for absorbing any latency in communication, and the ability of the cloud-based resources in offering more involved analysis and user interaction.

While the custom-based solution has proved its workability, it is worthwhile to explore a future work role. This is discussed in the next section.

7.3 Future Directions

The contribution accomplished in this study require some future work to further enhance and fulfil the overall conceptual ideology functionality. From all the key activities involved in the proposed rehabilitation model, only a few activity movements have been implemented and tested as part of the proposed approach. This approach needs to be tested across all the activities proposed in the programme. Moreover, it would be useful to explore how much movement recognition can be gained with the utilisation of Artificial Intelligence (AI) and adaptivity in dealing with the demands of various activities for the sampling duration, recognition precision as well as the variances in the manifestation of activities for different subjects [12]. Moreover, the recognition results were obtained using the accelerometer sensor. However, to cover all the activities part of the rehabilitation follow-up programme, further analysis is required to observe the role and integration of multiple sensors fusion. This also involves the analysis of using a combination of sensor locations. Such analysis could be of great significance in providing useful information about a particular activity movement, its indicative parameters and recognition precision. In this research, the movement data has been collected from healthy young individuals who were active and did not have any type of injuries. While this offered encouraging validation results outcomes of our proposed approach, future work is required to cover the data collection, test and validate the methodology used on elderly patients and hospitalised people who have undergone hip fracture surgery. This will offer more insights into key data and variance of the subject on long-term data collection and analysis of the elderly patients. In doing so, this will also allow extension within the proposed concept for offering communal elderly home care monitoring. Investigate how to further enhance the proposed IoT-enabled with wearable post-operative hip fracture rehabilitation monitoring so that system can be implemented on large scale like hospitals and rehabilitation homes [34]. This will include exploring the mobile phone and wearable electronics in offering a commercially viable solution, the establishment of multiple wireless sensor connectivity, multiple sensors sending movement data to a nearby gateway and the cloud. In addition, packet loss, data drop rate analysis when multiple sensors are involved, investigation of suitable number of sensors that can accommodate a single gateway in establishing secure connectivity and data transmission and reception, analyse how to optimise data traffic and process and the overall system performance [34]. This also involves looking into system compliance with Industry 4.0 direction and with a software-defined infrastructure [34].

Appendix A

Appendices

A.1 List of Publications

1. A. Gupta, A. Al-Anbuky, and P. McNair, ”Activity Classification Feasibility Using Wearables: Considerations for Hip Fracture,” Journal of Sensor and Actuator Networks, vol. 7, no. 4, p. 54, 2018.

2. A. Gupta, A. Al-Anbuky, and K. Al-Naime, ”IoT Based Testbed for Human Movement Activity Monitoring and Presentation,” in 6th International Conference on Information and Communication Technologies for Ageing Well and e-health, 3-5 May, 2020, Prague, Czech Republic, pp. 61-68, doi: 10.5220/0009347800610068.

3. Gupta, A., Al-Anbuky, A. and McNair, P., 2021. Postoperative Hip Fracture Rehabilitation Model. In Advances in Computer Vision and Computational Biology (pp. 319-330). Springer, Cham.

4. Gupta, A., Al-Naime, K., and Al-Anbuky, A. (2021). IoT Environment for Monitoring Human Movements: Hip Fracture Rehabilitation Case. In Information and Communication Technologies for Ageing Well and e-Health: 6th International Conference, ICT4AWE 2020, Prague, Czech Republic, May 3–5, 2020, Revised Selected Papers 6 (pp. 44-63). Springer International Publishing.

5. Gupta, A. and Al-Anbuky, A., 2021. IoT-Based Patient Movement Monitoring: The Post-Operative Hip Fracture Rehabilitation Model. Future Internet, 13(8), p.195.

A.2 Mathematical Equations Used in Feature Extraction

The mathematical equations used in feature extraction and as extracted from different literature analysis are as follows:

$$Mean(\mu) = \frac{1}{n}\sum_{k=0}^{k=n} S_i \tag{A.1}$$

$$Median = median(S_1, S_2, S_3...., S_n) \tag{A.2}$$

$$CoefficientofVariation = \frac{\mu}{\sigma} \times 100 \tag{A.3}$$

$$Maximum = max(S_1, S_2, S_3...., S_n) \tag{A.4}$$

$$Minimum = min(S_1, S_2, S_3...., S_n) \tag{A.5}$$

$$PeaktoPeakAmplitude = max(S) - min(S) \tag{A.6}$$

$$StandardDeviation(\sigma) = \sqrt{\frac{\sum_{k=0}^{k=n}(S_i - S)^2}{(n-1)}} \tag{A.7}$$

$$RootMeanSquare(RMS) = \sqrt{\frac{1}{n} \times \sum_{1}^{n} S_i} \tag{A.8}$$

$$IQR = Q3 - Q1 \tag{A.9}$$

A.3 Approved Ethics Application

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

15 October 2019

Adnan Al-Anbuky
Faculty of Design and Creative Technologies

Dear Adnan

Re Ethics Application: **19/96 Post operation elderly activity monitoring: The hip fracture case**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved in stages for three years until 15 October 2022.

This approval is for the first sages of the research only. Full information about future stages this research needs to be provided to an and approved by AUTEC before data collection for those stages commences.

Non-Standard Conditions of Approval

1. On the Consent Form (healthy participants only) please make the statement regarding being contacted for future research optional

Non-standard conditions must be completed before commencing your study. Non-standard conditions do not need to be submitted to or reviewed by AUTEC before commencing your study.

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 in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted. When the research is undertaken outside New Zealand, you need to meet all ethical, legal, and locality obligations or requirements for those jurisdictions.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

Yours sincerely,

Kate O'Connor
Executive Manager
Auckland University of Technology Ethics Committee

Cc: akashrocksc63@gmail.com; Peter McNair

Figure A.1: Post operation elderly activity monitoring: The hip fracture case approved ethics letter

A.4 Participant Information Sheet

AUT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Participation Information Sheet 1 and 2

Date Information Sheet Produced:

23 March 2019

Updated with required amendments on:

13th Oct 2019

Project Title

Post-Operation Elderly Activity Monitoring: The Hip Fracture Case

An Invitation

My name is Akash Gupta, and I am a Phd candidate in the School of Engineering, Computer and Mathematical Sciences at AUT University. I would like to invite you to take part in our research project called '*Post-Operation Elderly Activity Monitoring: The Hip Fracture Case.* Here the term elderly refers to the people aged 60 and above Your participation in this project is voluntary and you may withdraw at any time prior to the completion of data collection.

What is the purpose of this research?

The purpose of this research is to design a sensor that can monitor physical activity (exercise and walking). This device will ultimately be used to assess such activity in people recently discharged from hospital for a hip fracture. The first phase of developing this sensor is to recognise variant different types of activities/exercises involved during the post-operative hip fracture rehabilitation period. The recognition will be based on the real-time data collected from the sensor. Following phases will concern the transmission of signals to the internet and the subsequent presentation of the data in software.

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

You will have responded to an advertisement about the study. There are two testing phases of data collection. In these phases, participants should be healthy with no knee or lower limb injury, whereas during the third phase, participants who have had a hip fracture will be assessed. For phases one and two, you may be excluded from participating if you have had a notable previous knee injury, surgery or current cardiovascular, neurological or musculoskeletal conditions, or are unable to communicate or understand English.

How do I agree to participate in this research?

You will receive the full information sheet concerning the study from the research candidate and involved directly with you if you wish to participate. You will be required to complete a written consent form prior to participating in this study.

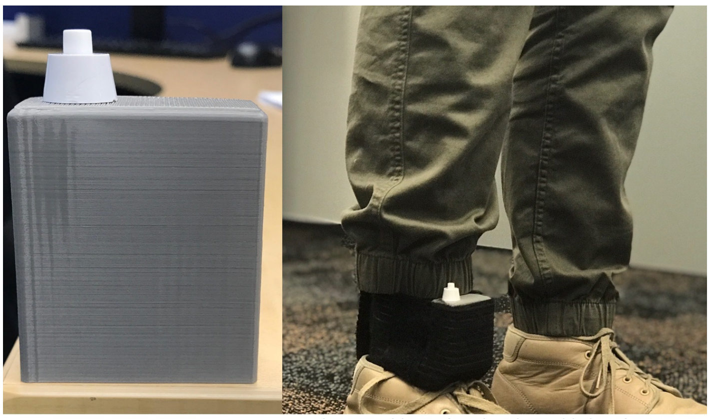
Your participation in this research is voluntary (it is your choice), and whether or not you choose to participate will neither advantage nor disadvantage you. You are able to withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having 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?

If you participate in phase 1 of this project, you will be asked to attend a data collection session at either of two locations: the North Shore AUT campus on Akoranga Drive, OR: the AUT Auckland city campus. During these sessions you will be required to wear the monitoring device (shown in figure 1(a)) at the ankle joint location (shown in figure 1(b)). The device can be worn at any side of the foot depending on your comfortability. The activities that are of interest to hip fracture rehabilitation activities and you would be performing as part of study are:

1. The transitions, like lying to sitting and sitting to standing.
2. The ambulatory activities, like slow and fast walking.
3. Minimizing impairments, like walking with weights, exercycle, and stretching routines.
4. Stationary exercise while lying on the back and stomach.
5. Stationary exercise while sitting, i.e., straightening the knee from 90-degree flexion to fully extended and then returning to flexed.
6. Stationary exercise while standing, like lifting the thigh upwards in front of the body, swinging a leg side to side, stepping up, and squats.

The exercises are performed at a low to medium level of exertion and you will get rest breaks as you need them. Overall, the tests should not take longer than 1-2 hours.

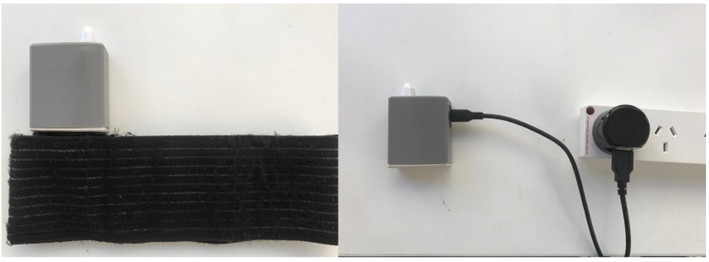


(a) Wearable Device (b) Wearable Device placed at ankle location

Figure 1 (a) Wearable Device and (b) its placement at ankle location

You will be asked if you wish to participate in phase 2 of the research. This involves wearing the device (shown in figure 1(a)) at ankle location (shown in figure 1(b)) at home for 2 weeks. You can wear the device in any position and at any side of the foot depending on your comfortability.

The device will be worn by you continuously for the whole day except while showering and in the night before going to bed. After taking off the device from the wearable strip (shown in figure 2 (a) below), you just need to put the device on charge with the USB charging cable (shown in figure 2 (b) below) similar to the way we do for any mobile devices. In the morning, when awake, you will remove the device from charging and wear it again.



(a) Wearable Device removed from the strip (b) Charging the werable device using a USB cable

Figure 2(a) Wearable Device removed from strip and (b) charged using a USB cable

In this phase, you will perform the same sets of exercises undertaken in the lab (in phase 1) over a two-week time period. However, you would need to record the key activities performed in the diary provided during participation. You would need to fill the start and finish time and the type of activities performed by you at a particular day with date. An example of written requirement of the daily activity log is shown in figure 3 below.

Hip Fracture Rehabilitation Activities Monitoring Log Sheet Diary				
Daily Activity Log				
Complete the activity log below to record your hip fracture related rehabilitation activities. You would require to record the start time (third column) when you would be commencing the exercise and the finish time (fourth column) when you would be finishing off the exercise. Along with the time, record the activity performed (last column) during that particular time.				
Date	**Day**	**Start Time**	**Finish Time**	**Activity Performed**
06/10 /2019	**Monday**	7 am	7:20 am	Leg Movement
		8 am	8:30 am	Walking

Figure 3 Activity Diary Sample and written requirement example

The data concerning your activity is transmitted via the internet to software that allows us to monitor your activity levels. This will also allow us to assess the sensors ability to detect and transmit the data to the software.

What are the discomforts and risks?

There are no major risks associated with this testing, as it is non- invasive and safe. Tests are designed to mimic normal activities of daily living (e.g. walking, stairs, squatting and sit to stand) so are unlikely to cause any discomfort. You might feel some discomfort from the device and this would normally be a skin irritation. In phase 1 in the lab, we will ask you often how the sensor feels. In phase 2, using it while at home, we will call you every couple of days to ask whether the device is comfortable or otherwise.

How will these discomforts and risks be alleviated?

If you consider any of the movements excessively painful, you can stop at any time or ask for our help. Similar tests have previously been done without any adverse effects, however a physiotherapist who has the appropriate knowledge and skills in dealing with injury will be involved in the different phases, and therefore can provide you with advice if required. If your skin is affected by wearing the sensor, you will be able to remove it.

What are the benefits?

You will not receive direct benefit from participating in this research. The project outcomes will provide us with more information about the relationships between activity recognition, accuracy and functional mobility associated with activities undertaken in rehabilitation after hip fracture surgery. If successful, the sensor will help provide better information for the safe return to normal daily living routine activities, preventing the risk of re-injury or longer term chronic conditions. Overall, these findings could lead to new and improved monitoring of exercise treatment following the hip fracture and will help in completion of a PhD research degree.

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 (ACC), providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

You will be given a code upon entry to the study and your name will not be used. The consent form, which will contain both your name and code, will be stored in a locked filing cabinet and kept separate from the study. No individual results will be identifiable in the study.

What are the costs of participating in this research?

The cost of participating in this project will be your time. In phase 1, the data collection time is expected to last approximately 1-2 hours. In phase 2, you will wear the sensor continuously for 2 weeks.

What opportunity do I have to consider this invitation?

You will have as long as you like to consider this invitation after receiving the information sheet. We will call you after 7 days to see if you would like to participate. If you need more time than this to decide, just let us know.

How do I agree to participate in this research?

You will need to complete a consent form at the beginning of the data collection session. This session will be scheduled after you have told us that you would like to participate.

Will I receive feedback on the results of this research?

A one-page summary of the study results will be sent upon completion of the project. There will be a section in the Consent Form to indicate if you would like to receive this information.

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, Peter McNair, *peter.mcnair@aut.ac.nz* , +64 9 921 9999 ext 7143 or Adnan-Al-Anbuky, *adnan.anbuky@aut.ac.nz*, +64 9 921 9999 ext 9836

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, Kate O'Connor, *ethics@aut.ac.nz* , 921 9999 ext 6038.

Whom do I contact for further information about this research?

Researcher Contact Details:

Akash Gupta, AUT University City Campus
Ph: 0275274024
Email: akashrocksc63@gmail.com

Project Supervisor Contact Details:

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Ph: +64 9 921 9999 ext 7143
Email: peter.mcnair@aut.ac.nz

Professor Adnan-Al-Anbuky, AUT University City Campus
Ph: +64 9 921 999 ext 9836
Email: adnan.anbuky@aut.ac.nz

A.5 Consent Form

AUT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Consent Form

Project title: ***Post-Operation Elderly Activity Monitoring: The Hip Fracture Case***

Project Supervisor: ***Professor Adnan-Al-Anbuky and Professor Peter McNair***

Researcher: ***Akash Gupta***

○ I have read and understood the information provided about this research project in the Information Sheet dated 13th October 2019.

○ 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 that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, removal of my data may not be possible.

○ I do not suffer from previous neurological or a musculoskeletal condition affecting my knee and lower limb. I have never had surgery on my knees. If I am in the pain free control group, I am currently pain free and have not experienced constant pain for 3 months or more at any time in my life.

○ I agree to take part in this research.

○ I am happy to be contacted should another study related to hip fracture rehabilitation be undertaken in the future.

○ I wish to receive a summary of the findings of my data (please tick one): Yes○ No○

○ I would to receive a summary of the overall research findings (please tick one): Yes ○ No ○

Participant's signature: ....

Participant's name: ....

Participant's Contact Details (if appropriate):

....

....

....

....

Date:

April 2018 page 1 of 1 This version was last edited in April 2018

Figure A.2: Participant Consent Form

A.6 Data Acquisition and Processing Method

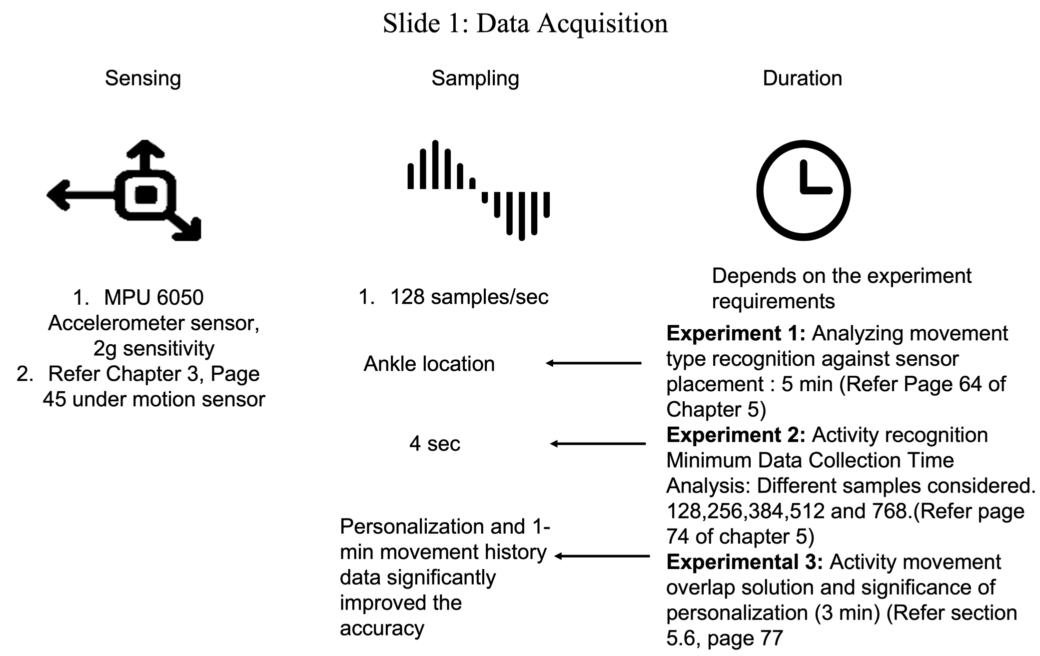

Figure A.3: Data Acquisition Method

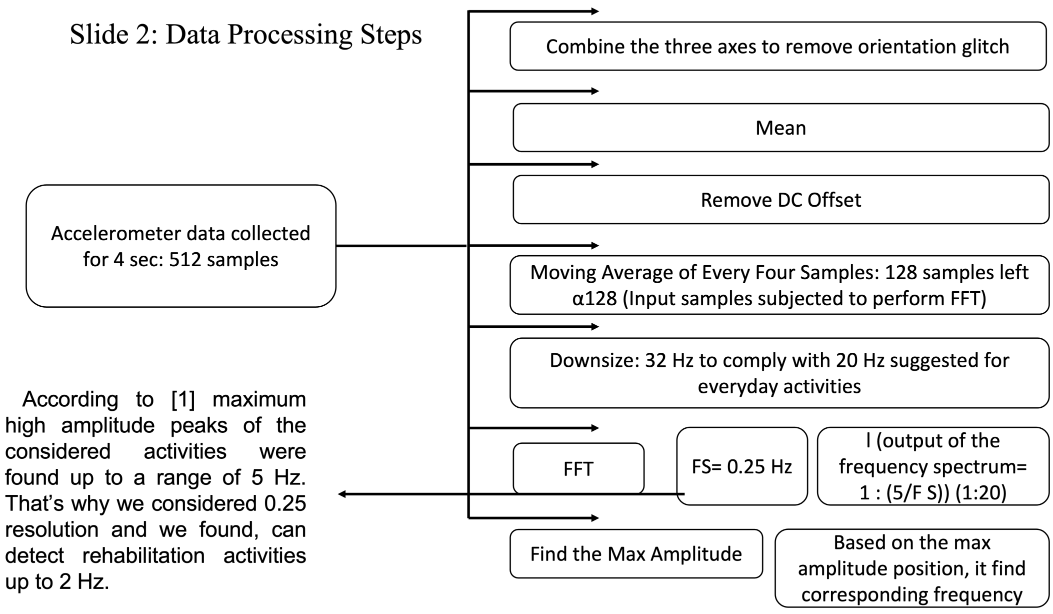

Figure A.4: Data Processing Method

A.7 Recognition Algorithm Threshold Feasibility

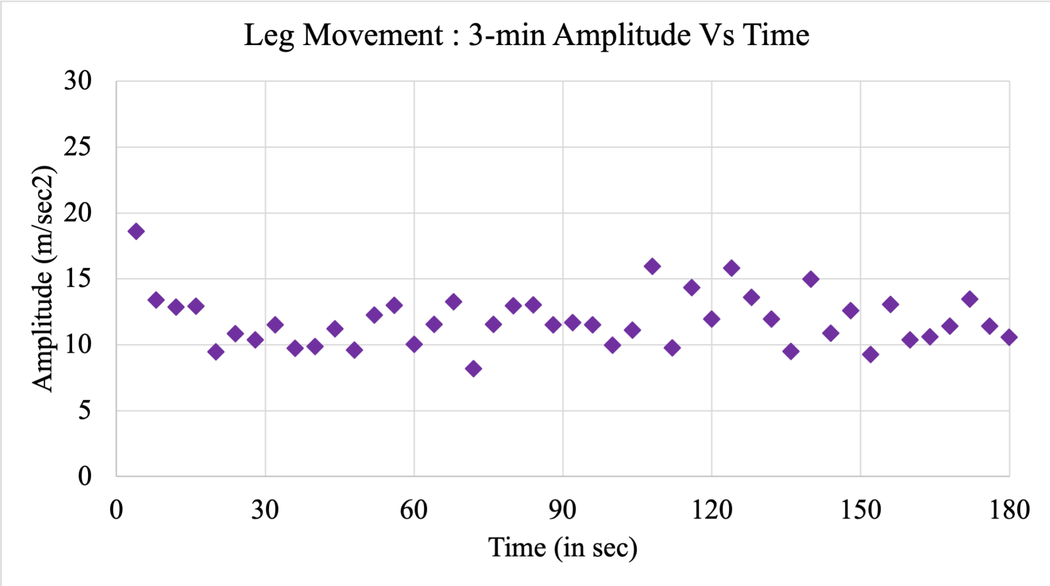

Figure A.5: Leg Movement:3-min Amplitude

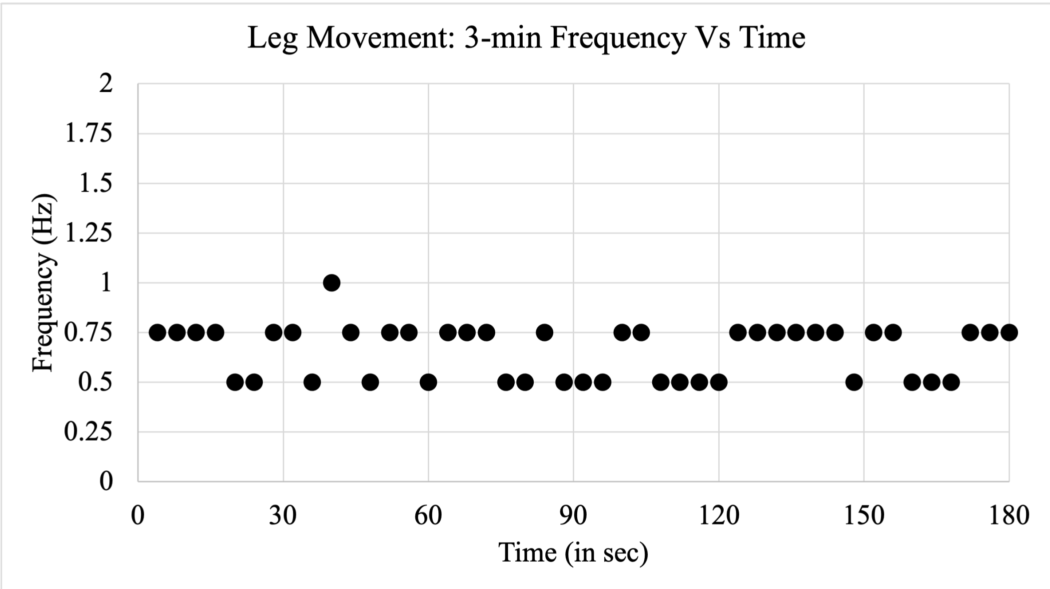

Figure A.6: Leg Movement:3-min Frequency

A.8 Recognition Algorithm Threshold Feasibility

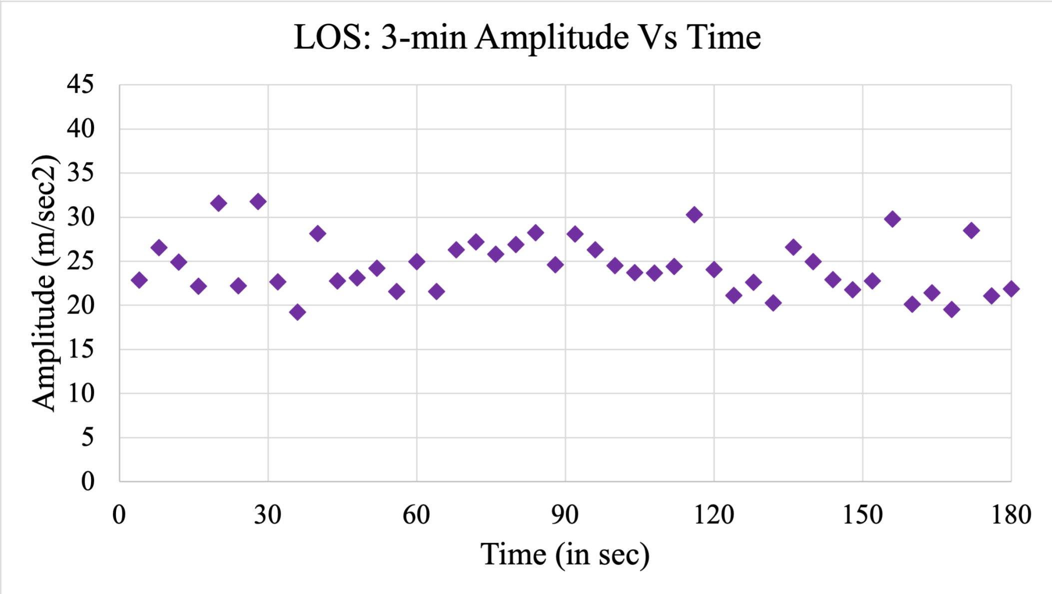

Figure A.7: Lying on Stomach:3-min Amplitude

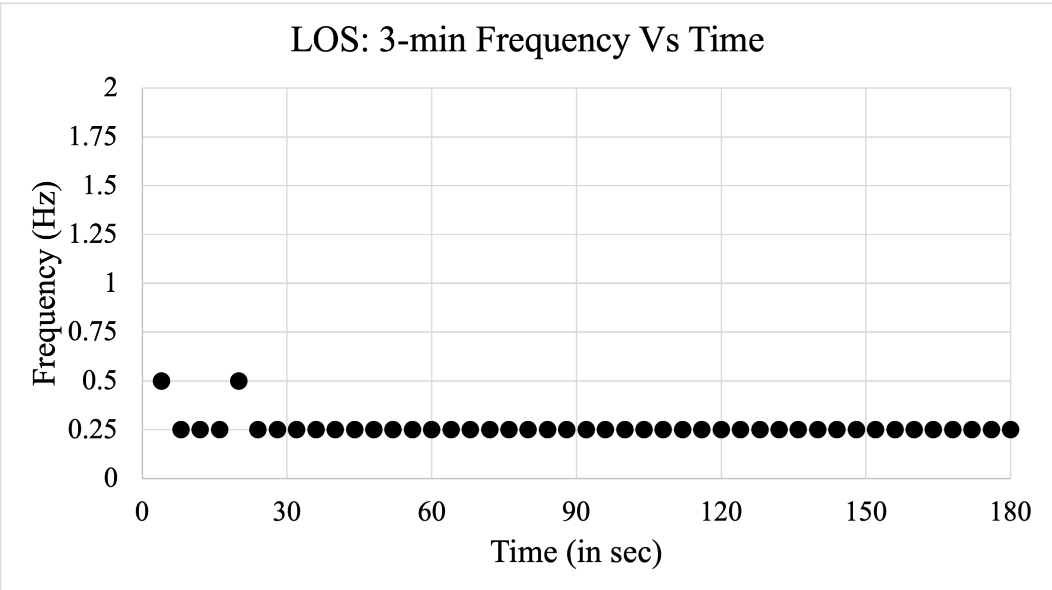

Figure A.8: Lying on Stomach:3-min Frequency

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