An Experimental EACI-Based Localization Framework Using LQI and CNN for Consumer IoT

Tanveer Ahmad, Muhammad Usman Hadi, Xue Jun Li, Asim Anwar, Mandour Mohamed Ibrahim, Shakir Khan

***Abstract*—Precise indoor localization remains a challenge in wireless sensor networks (WSNs) due to multipath fading, interference, and signal fluctuations in different environments. Traditional methods depend on Received Signal Strength (RSS) also often struggle with accuracy in indoor scenario. This study presents an experimental localization framework that utilizes Link Quality Indicator (LQI) values and Convolutional Neural Networks (CNNs) within an Edge Computing-Assisted Consumer IoT (EACI) model. The proposed approach segments the network using a pyramid-loop algorithm and employs LQI-based measurements for more stable and accurate distance estimation. A CNN classifier is trained on normalized LQI data, including statistical features such as kurtosis, to predict node locations. The system is authenticated by a real-world testbed using Zigbee XB24C nodes. The experimental results show an overall localization error of 0.12m at zone 1 with a standard deviation of 0.89m. This reflects an improved localization accuracy and reduced error compared to RSS-based and existing CNN-based methods. The proposed technique effectiveness is observed for indoor localization in consumer IoT environments.**

***Index Terms*—Localization, Edge Computing-Assisted Consumer IoT (EACI), Zigbee, LQI, CNN**

I. Introduction

Wireless sensor networks (WSNs) have gained global recognition as a fundamental infrastructure for ubiquitous computing systems. They represent an intelligent information backbone, offering user-centric data and knowledge services at any time and in any context. The IEEE 1451 standard plays a pivotal role in this space by providing a unified interface for smart wireless sensors, facilitating their seamless integration into networks and systems. This standard simplifies the task for manufacturers to design smart IoT devices that can easily interface with loop-back systems, instruments, and broader network architectures [1]. Edge computing-assisted consumer devices and IoT (EACI) are becoming a major solution to the limitations faced by traditional WSNs in real-world settings. EACI shifts computational processing closer to the devices, reducing latency, cutting energy consumption, and enabling real-time operation. As localization becomes essential for consumer IoT applications such as smart homes, healthcare, and retail, systems need to be accurate, fast, scalable, and lightweight enough for constrained hardware. EACI addresses these needs by enhancing the positioning capabilities of consumer devices, particularly indoors, where high precision is challenging [2], [3].

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This paper was produced by the IEEE Publication Technology Group. They are in Piscataway, NJ.

Manuscript received April 19, 2021; revised August 16, 2021.

Localization is typically achieved by measuring the signal strength, time of arrival (ToA), or angle of arrival (AoA) between the reference anchor and target nodes. The estimated values of RSSI and LQI, may fluctuate due to varying distance and mobility constraints [4]. The estimated values obtained from the measurements are utilized to calculate the sensor node's location using triangulation or centroid-based methods. The location estimation approach utilizes the computed values to determine the position of the sensor node within the network. However, these techniques are challenging to implement in indoor environments due to signal attenuation, multipath fading, and noisy signal distortion caused by objects, walls, furniture, doors, and other indoor appliances [5].

A. Motivation

Indoor environments are complex, making it challenging to create a reliable and precise localization system. Traditional RSSI-based methods often struggle indoors due to multipath fading, signal loss, and interference from walls, furniture, and electronic devices, resulting in unreliable measurements and lower accuracy. Moreover, current solutions tend to rely heavily on simulations, lack flexibility in response to changing indoor conditions, or require high computational power, making them unsuitable for low-resource consumer devices. To overcome these issues, a robust, edge-assisted localization system is needed, one that can utilize more stable channel metrics, adapt to noisy environments, and operate efficiently on low-power hardware without sacrificing accuracy.

B. Contribution

This paper introduces a practical indoor localization method based on EACI, which utilizes LQI instead of RSSI to enhance signal stability. LQI readings from multiple reference anchors are classified by a Convolutional Neural Network (CNN), incorporated within a pyramid-shaped, looped structure. CNNs are highly effective at automatically identifying spatial patterns

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in complex data and are well-suited for analyzing LQI variations in noisy indoor environments. A key aspect of our work is its validation in real-world settings. Unlike studies that rely solely on simulations, we deploy the system on a physical Zigbee Chipcon XB24C testbed and set it up with the X-CTU platform. This experimental configuration demonstrates how the EACI model enables low-latency, efficient, and scalable localization by utilizing edge-assisted CNN processing on consumer IoT devices [6]. The findings verify that EACI enhances localization accuracy while maintaining a lightweight and flexible system, making it well-suited for integration into future consumer IoT environments.

The rest of the paper is organized as follows: Section II presents the related work. Sections III and IV describe the proposed technique and the experimental model, respectively. Finally, the conclusion is provided in Section V.

II. Related Work

Traditional indoor localization methods, such as triangulation and centroid, often suffer from low accuracy due to weak signals and multipath fading. To overcome this, LQI-based techniques have been explored for more reliable distance estimation and improved performance.

In [7], the author presents an indoor localization system, "DuLoc that gains channel state information (CSI) by using a dual-channel CNN model. By exploiting the unique characteristics of CSI, DuLoc achieves accurate localization in indoor environments. It combines the power of CNNs with CSI data to increase the accuracy and reliability of indoor localization systems. The KD-CNN approach is a fast and efficient indoor positioning method presented in which utilizes a knowledge-distilled CNN model. By transferring knowledge from a larger pre-trained network to a smaller network, KD-CNN achieves comparable performance with reduced computational complexity. This technique enables real-time indoor positioning by leveraging the power of CNNs while maintaining computational efficiency. It provides an effective solution for accurate and rapid indoor positioning in various applications. In [9], the author presents a CNN model for a hierarchical appearance-based localization system. The CNN is trained to learn hierarchical features from visual data, allowing for accurate localization in complex environments. By applying the power of deep learning, this approach enables robust and efficient localization based on visual appearance. The hierarchical structure of the CNN enhances the discriminative power, contributing to improved localization performance in various scenarios.

Authors in [10] propose a privacy-preserving location information fusion framework for secure localization in Cyber-Physical Social Systems (CPSS). It focuses on enhancing consumer trust by utilizing personalized recommendations without compromising sensitive location data. The approach strikes a balance between localization accuracy and privacy and data security. In [11], the author presents an experimental evaluation of indoor localization for WSN. The performance of various localization techniques, including RSSI-based methods and trilateration algorithms, is evaluated in a controlled indoor environment. The findings offer insights into the strengths and limitations of the tested approaches, contributing to a deeper understanding of indoor localization performance in wireless sensor networks. The use of RSS and a smaller number of anchor nodes degrades the accuracy of the proposed scheme. In our proposed system, we also address this issue by deploying anchor nodes at the network's boundary. Furthermore, the adoption of LQI values also provides superior accuracy with less computation. Similarly, in [12], the author focuses on fusing of CNN model with geometric constraints for mapping and image-based indoor localization. By combining the visual features extracted by the CNN with geometric information, such as key points and object boundaries, a more robust and accurate indoor localization system is developed. Experimental evaluations are directed to assess the accuracy of the proposed fusion approach, demonstrating its efficiency in attaining precise and reliable indoor localization using image-based data. he system's accuracy drops with changing node numbers and lacks a mechanism for node failures. The proposed approach allows flexible deployment of nodes with sufficient anchors for reliable localization. In [13], a novel localization algorithm is proposed for indoor environments that combines RSSI measurements with multilateration techniques. The RSSI values are obtained from multiple reference nodes, and the algorithm estimates the position of the target node using geometric calculations. Experimental evaluations are conducted to assess the performance of the proposed algorithm, demonstrating its effectiveness in achieving accurate and reliable indoor localization.

III. Proposed Localization Scheme

This section presents the proposed localization algorithm, highlighting its core components, the adoption of LQI values, CNN-based classification of LQI patterns, and distance estimation among consumer devices. We begin with the motivation for choosing LQI and CNN, followed by an overview of the system model and a step-by-step explanation of the algorithm tailored for accurate sensor localization.

A. Justification for LQI as a Localization Metric

Indoor localization has been an active research area, but so far, there is no agreed-upon solution for indoor environments. RSSI may be a solution but is not ideal for indoor localization due to (1) RSSI measurements are highly susceptible to signal interference and attenuation caused by various indoor obstacles such as walls, doors, furniture, and electronic appliances, leading to inaccurate RSSI readings and unreliable localization results, (2) RSSI does not provide sufficient information about the quality and characteristics of the wireless channel. It solely measures the signal strength, ignoring important factors like packet error rate, noise level, and interference. Due to RSSI's instability even in static environments, we adopt LQI in our technique, which provides a more consistent and comprehensive measure of link quality. Furthermore, existing algorithms neglect noisy channel effects, channel estimation, and full network coverage. To overcome this, we propose a novel solution that segments the network into pyramids and uses a Loop algorithm to transfer control based on gradient flow. Unlike RSSI, LQI reflects broader link characteristics, including packet error rates, noise, and interference.

B. System Model

The system model has two phases. The first involves collecting and preprocessing RSSI data for the LQI classification CNN model. The second uses LQI values in a pyramid loop algorithm to estimate distance for localization. This technique addresses overlapping triangles issues found in methods like Apoint in triangulation (APIT) [14]. APIT estimates an object's position by measuring distances from reference points using geometric calculations and triangulation, used in trilateration or multilateration.

Let us consider a network of N nodes that possess ranging capabilities i.e., $\mathbb{N} = 1, ..., N$, along with ζ_i denotes the exact position of node i and n number of Cartesian coordinates, where $n = 2$ for 2D localization and $n = 3$ for 3D localization. We consider a network of A anchor nodes and N target nodes. As we have a non-overlapped network of anchor and sensor nodes, where all the anchors are deployed at the outermost boundary of the network. Let $\mathbb{N}_i$ is a neighbor node of i where an estimate $\mathcal{R}_{i,j}, j \in \mathbb{N}_i$ for Euclidean distance $d_{i,j} = \parallel \zeta_i - \zeta_j \parallel$, which exist on both side of the link. The estimate $\mathcal{R}_{i,j}$ is a noisy measurement. Furthermore, the anchor nodes $i \in A$ have an exact position i.e., $\zeta_i = \wp_i$. In this context, it is assumed that the nodes possess perfectly synchronized clocks unless specified otherwise. Additionally, the nodes are equipped with one or more radio technologies, with one technology dedicated to measuring distance (range) and potentially another technology for communication purposes.

C. Algorithm Design

This section explains algorithm design steps. We used symbolic localization for position estimation [15]. Location systems give physical (via GPS) or symbolic info. Symbolic indicates abstract locations, such as 'Kitchen' or 'next to the mailbox'. Sometimes, physical locations must be converted into symbolic ones to improve context awareness and user experience, making location info more intuitive.

1) LQI measurement: The measurement of link qualities in sensor networks involves evaluating the performance and reliability of communication links between nodes. Performance metrics, such as RSS, signal-to-noise ratio (SNR), packet loss, and bit error rate (BER), are used to assess wireless connection quality. These measurements facilitate the optimization of network performance and enable effective decision-making in areas such as routing and resource allocation.

Conventional radio transceivers utilize RSSI as a metric for assessing link quality. However, modern transceivers, such as vendor-specific Chipcon's XB24C Zigbee transceivers, offer a few extra performance metrics known as the link quality indicator (LQI). That is why we used to adopt LQI to estimate the link quality of unknown target nodes. The XTCU software is used for LQI measurement and gathering between the target node T and the reference anchor nodes R as shown in Figure 1. The target node T, transmits a beacon data packet to all the reference anchor nodes. Subsequently, each reference anchor node acquires an LQI value associated with the base station for LQI classification and localization purposes.

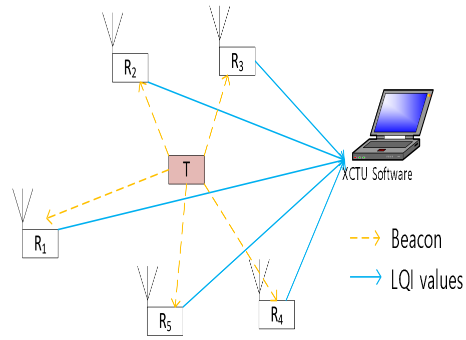


Fig. 1: LQI measurement through XCTU Software.

2) Data Collection: The reference anchor nodes receive data packets from the target nodes, estimate the power of the beacon, and then periodically transmit an LQI value to the receiver. Additionally, the LQI is converted into distance measurements, which can be utilized in theoretical or empirical models. The beacon packet contains relevant information about the target node's identity and position. The reference anchor nodes receive the data packet and measure the LQI value, which indicates the quality of the received signal. This LQI value is then used for classification and localization purposes. By analyzing the LQI values from different reference anchor nodes, the system can estimate the target node's position relative to the anchor nodes, facilitating accurate localization in the network.

3) CNN-model for LQI Classification: To classify the LQI pattern from a set of multiple LQI's we adopted a CNN classifier. LQI values received from k^{th} reference anchor nodes were measured at different instants. To standardize the LQI measurement, a normalization process was performed, ensuring that all LQI values fell within the range of [0, 1]. This normalization step enables consistent comparisons and avoids any bias introduced by varying LQI scales. By scaling the LQI values to a common range, subsequent analysis and modeling can be performed accurately and effectively. The RSSI matrix served as the 2D representation of the radio tensor. To enhance localization accuracy, the "kurtosis" parameter was calculated and incorporated as the third dimension. Various CNN architectures were implemented and tested after organizing the inputs to ensure accurate LQI normalization.

Preprocessing of LQI data: LQI data preprocessing involves transforming the input data before feeding it into the CNN model.

The LQIs are received from the k^{th} reference points of the target node T at each training point. For each training phase, Y LQI datasets, known as realizations, are constructed as shown in Figure 2, where T denotes the number of LQI estimations from each reference anchor node, and N is the total number of realizations from k reference points. For accurate CNN realization, the system needed to know how much and how relevant the data is available for training purposes.

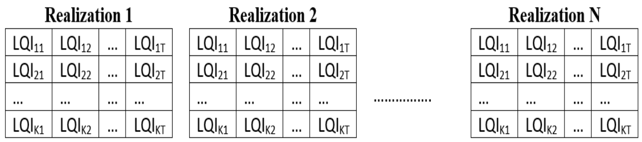


Fig. 2: LQI realization construction at each training point.

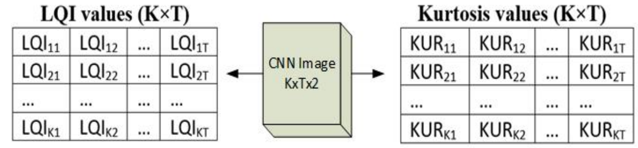


Fig. 3: LQI image construction.

Kurtosis Calculation: To provide an efficient method for LQI classification, we consider kurtosis as an additional dimension in our tensor to introduce novel information to the network. This is later used to provide statistical information from LQI values, which hold useful information for the accurate positioning in the pyramid loop algorithm. Kurtosis introduces valuable nonlinear information that complements the linear operations performed by a neural network, making it useful and non-redundant. Considering LQI value l_{kt}, received from reference anchor at time t where $k = 1, 2, .., K$, and $t = 1, 2, ..., T$ as defined by Karl Pearson [16]. Hence, the "kurtosis" is calculated for each sensor node we get.

$$kur_{kt} = \frac{1}{T} \times \sum_{t=1}^{T} (\frac{l_{kt} - \mu_k}{\sigma_k})^4 \tag{1}$$

$$where \quad \mu_k = \frac{\sum_{k=1}^{K} l_{kt}}{K} \tag{2}$$

$$and \quad \sigma_k = \frac{\sum_{k=1}^{K} l_{kt}^2}{K} \tag{3}$$

The Mean Absolute Deviation (MAD) of LQI is used for average deviation from the mean LQI, capturing signal fluctuation over time.

$$\mathrm{MAD}_k = \frac{1}{T} \sum_{t=1}^{T} |l_{kt} - \mu_k| \tag{4}$$

The skewness quantifies asymmetry in LQI values, which shows whether the distribution is skewed due to link instability.

$$\mathrm{Skew}_k = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{l_{kt} - \mu_k}{\sigma_k} \right)^3 \tag{5}$$

The LQI Entropy-Based Feature is estimated binned probability p_b, reflecting randomness in link quality.

$$H_k = - \sum_{b=1}^{B} p_b \log_2 p_b \tag{6}$$

LQI Image construction: Following the collection of LQI values and computation of corresponding kurtosis values, a radio tensor was formed at each realization. Subsequently, 3D radio images were generated by organizing the LQI and kurtosis data within the tensor. In the first two dimensions of the matrix, T measured LQIs and K reference points are stored, whereas in a third dimension, the corresponding "Kurtosis" values are stored, which makes realization size $(K \times T \times 2)$ as shown in Figure 3. LQI values are preprocessed into radio images matching the training format, then fed into the model to predict the sensor's region and estimate distance.

4) Pyramid Loop Algorithm for Localization: Assuming a set of anchor nodes $A = a_1, a_2, ..., a_m$, where $m \geq 3$. To compute node position using the Loop algorithm, the first step is to measure a midpoint in the network. The computation of the midpoint in our proposed technique differs slightly. Let A_1 be the reference anchor node as shown in Figure 4. The distance from the reference anchor node to all other nodes will be computed using the Euclidean distance formula. For midpoint computation, we then take the average of the sum of the distances from the reference anchor node to the node farther away from it, which also solves the problem of overlapping.

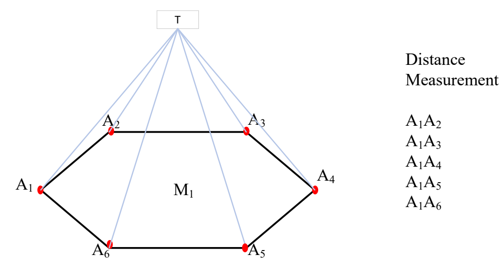


Fig. 4: Midpoint computation in pyramid-looping.

Therefore, the midpoint can be computed as:

$$M = \frac{1}{2}(A_1 + \chi) \tag{7}$$

where χ is the coordinates of the node, larger in distance from the A_1. In the next phase, we can shrink the network through the well-known parametric equation adopted by [17].

$$P_i = \frac{3}{8}(M + A_m) + \frac{1}{8}(A_{m-1} + A_{m+1}) \tag{8}$$

First, the LQI from each target node is calculated and normalized using the CNN model. To find the target's position, we use a maximum-likelihood method that minimizes the difference between measured and estimated distances with an MMSE approach [18]. This helps accurately locate the target even with some data errors. For 3D positioning, at least three sensor nodes (EACI consumer devices) are needed. The process starts with the anchor node gathering data from the sensors, then calculating the difference between measured and estimated distances.

$$f_i(x_0, y_0, z_0) = d_i - \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2} \tag{9}$$

where, (x_0, y_0, z_0) is the target unknown positions, and d_i shown the distance between the target node and refernece anchor i.

This article has been accepted for publication in IEEE Transactions on Consumer Electronics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TCE.2025.3631740

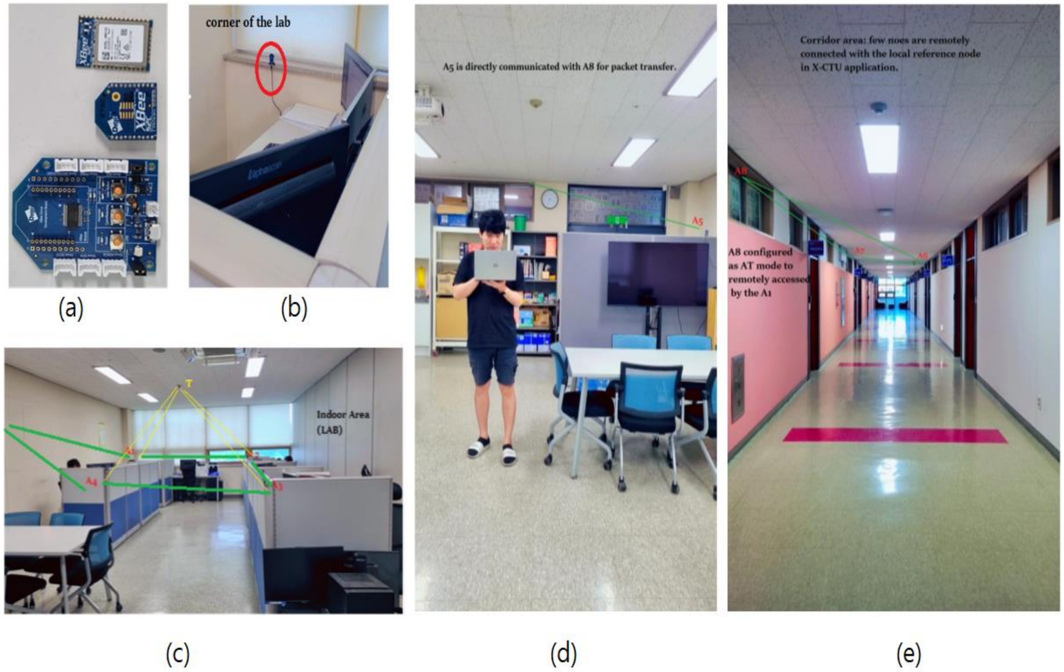


Fig. 5: (a) Zigbee sensor node with Chipcon's XB24C, (b) Reference Anchor node configured in API-1 mode directly connected with the system via COM3, (c) the reference anchor A_n and one target node T in pyramid form, (d) author collecting LQI values at each node, A_5 is deployed on the top of the obstacle, directly sending the packet to A_8 in the corridor, and (e) corridor area, few nodes configured in AT mode are remotely connected with the local reference node.

The unknown target position is computed by minimum mean square error (MMSE) in 3D form, i.e., (x_0, y_0, z_0). Substituting $f_i = 0$, Equation 9 becomes:

$$-x_i^2-y_i^2-z_i^2+d_i^2 = (x_0^2+y_0^2+z_0^2)+x_0(-2x_i)+y_0(-2y_y)+z_0(-2z_i) \tag{10}$$

$$\begin{aligned} &-x_i^2 - y_i^2 - z_i^2 + d_i^2 - (-x_k^2 - y_k^2 - z_k^2 + d_k^2) \\ &= 2x_0(x_k - x_i) + 2y_0(y_k - y_i) + 2z_0(z_k - z_i) \end{aligned} \tag{11}$$

which can be rewritten in matrix form

$$y = Xb \tag{12}$$

$$b = (X^T X)^{-1} X^T y \tag{13}$$

$$X = \begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) & 2(z_k - z_1) \\ . & . & . \\ . & . & . \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) & 2(z_k - z_{k-1}) \end{bmatrix} \tag{14}$$

$$y = \begin{bmatrix} -x_1^2 - y_1^2 - z_1^2 + d_1^2 - (-x_k^2 - y_k^2 - z_k^2 + d_k^2 \\ . \\ . \\ -x_{k-1}^2 - y_{k-1}^2 - z_{k-1}^2 + d_{k-1}^2 - (-x_k^2 - y_k^2 - z_k^2 + d_k^2) \end{bmatrix} \tag{15}$$

$$b = \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} \tag{16}$$

Our approach decreases data collection by having sensor nodes transmit data depending on neighbor density and their distance to the target. CNN classification helps to minimize data size while still providing LQI information values.

IV. Experiments and Results

In this section, we will describe the experimental setup and present our results on localization in an indoor environment.

A. Experimental Environment

Figure 5 shows the experimental setup of our ubiquitous test bed performed in the lab of Chungnam National University, South Korea, and the actual Zibee Chipcon used in the experiment. As shown in the figure, the test bed consists of two areas: one located inside the lab and the other in the corridor area. Four reference anchors are deployed in the lab, whereas one node is on top of the separator. The local reference node, configured in API-1 mode, is directly connected to the computer via the COM3 port and has remote communication with the nodes deployed in the corridor area, which are configured in AT mode.

1) Training of LQI Patterns: For simulation and experiments, we deploy 5 anchor nodes inside the lab and 3 in the corridor, covering an area of approximately $(30m \times 30m)$. Initially, 1 target node is inside the lab and 2 are in the corridor. Sensor nodes are equipped with XB24C Zigbee radio transceivers, serving as wireless sensors collecting environmental data. The base station, running on a Windows laptop, utilizes the X-CTU application and MATLAB for CNN simulation, using the experimental localization classifier. To capture various signal propagation scenarios on the communication channel, the tested area was divided into two zones, the lab (zone 1) and the corridor (zone 2), as illustrated in Figure 5. This division enabled the assessment of various situations, including line-of-sight (LOS) and non-line-of-sight (NLOS) conditions. In the first zone (lab), the local reference anchor node A_1 is in NLOS to all other reference anchor nodes. While the A_2, A_3, and A_4 are in the LOS state. Similarly, node A_5 is in NLOS state to all the nodes in the indoor lab.

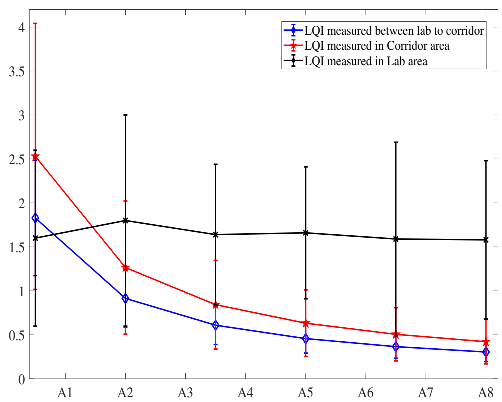


Fig. 6: LQI patterns measured at zone1 (black line), zone2 (red line), zone1 to zone 2 (blue line).

To train and test the localization classifier for CNN, it was necessary to measure the LQI values between the reference anchor A_n and target node T for each zone in an experimental environment. The LQI values were collected by traversing each location in a spiral trajectory, starting from the center and moving toward the border. We collected 200 LQI tuples per zone, totaling 1600 across 8 sensor nodes, to train the localization model. To prevent overfitting, we used dropout after each fully connected layer. We also expanded the dataset through simulations and throughput analysis to enhance generalization and provide the model with a broader understanding of diverse scenarios. Figure 6 provides a visual representation of the LQI value patterns observed in the three zoning locations of the test bed: "zone 1, zone 2, and zone 1 to zone 2. The simulation diagram, created from LQI tuples in the X-CTU application, displays noise levels against LQI values. Following CNN classification, LQI tuples at each point exhibit clear, distinct patterns even though they initially overlapped.

The distinguishable patterns in the LQI value tuples suggest that the LQI values can serve as effective indicators for differentiating between the "zone 1," "zone 2," and "zone 1-zone 2" locations. By analyzing location-specific LQI patterns, we can achieve robust localization by identifying unique wireless channel features, which enable precise positioning of sensor nodes using their LQI measurements.

2) Hyperparameter adjustment: Hyperparameter tuning plays a key role in LQI classification using CNN. Since model performance depends heavily on architecture and parameter selection, we experimented with various convolutional and fully connected layer setups. To speed up training and reduce noise, we used mini-batches of LQI data instead of full RSS inputs. Choosing the right batch size was essential; larger batches helped with convergence, but overly large ones negatively impacted generalization. Our goal was to strike a balance between training efficiency and model accuracy.

$$\xi = \frac{l_{kt}}{\rho} \times \psi \tag{17}$$

where ξ is the number of iterations, ρ shows the mini-batch size, which refers to the number of training examples or samples that are processed together in one iteration during the training phase. Instead of updating the network weights after each sample, mini-batch training allows for more efficient computations by processing a small batch of samples simultaneously.

The mini-batch size is typically set to a value between 1 and the total number of training samples. It is a crucial hyper-parameter that can significantly impact the training process, memory usage, and convergence speed of the CNN model. ψ represents the epochs, which refers to the number of times the entire training dataset is passed forward and backward through the network during the training process. Each epoch consists of a full iteration over the training data, where the network updates its weights and adjusts its parameters based on the computed gradients. Increasing the number of epochs allows the network to learn and refine its representations over multiple passes through the data. It is essential to strike the right balance of epochs to prevent underfitting (insufficient learning) or overfitting (excessive learning), thereby achieving optimal performance.

B. *Positioning Results*

After classifying the LQI values, the pyramid localization techniques are formed to compute the error distance.

1) Localization Error: The LQI classified values are used to measure the distance between the target and reference anchor nodes. In zone 1, the target node T is ideally located in the middle of the pyramid, hence providing very low localization error and gaining full network coverage. From the node A_5, the target node is in NLOS of state, leading to a high localization error. Let the true position be $\mathbf{p}_i = (x_i, y_i, z_i)$ and the MMSE estimate from Eq. (9)-(16) be $\hat{\mathbf{p}}_i = (\hat{x}_i, \hat{y}_i, \hat{z}_i)$. The localization error for the sample i is the Euclidean distance.

$$e_i = \|\hat{\mathbf{p}}_i - \mathbf{p}_i\|_2 = \sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2} \tag{18}$$

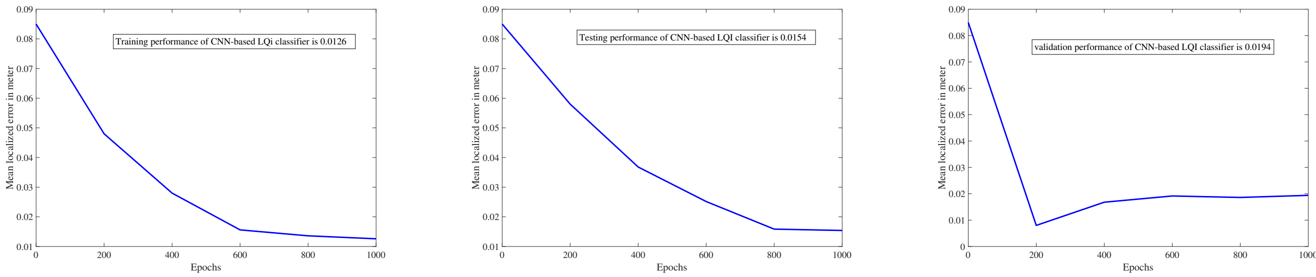
Over N samples, report the mean localization error $\bar{e} = \frac{1}{N}\sum_{i=1}^{N} e_i$ and the MSE/RMSE:

$$\bar{e} = \frac{1}{N}\sum_{i=1}^{N} e_i \tag{19}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} e_i^2, \qquad \mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{20}$$

The standard deviation of the error is

$$\sigma_e = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (e_i - \bar{e})^2} \tag{21}$$



(a) (b) (c)

Fig. 7: CNN performance for (a) training dataset for LQI tuples, (b) testing, and (c) validation of data after realization.

Test data	**Correct**	**Non classified**	**Incorrect**	**Accuracy**
Zone1 5x300=1500 tuples LAB	1477	12	11	98.6%
Zone2 3x300=900 tuples Corridor	802	32	66	89.11%
Zone1-Zone2 4x300=1200 tuples Lab-Corridor	1027	68	105	85.58%

TABLE I: Misclassification LQI pattern at border area

On the other hand, the target nodes towards A_5, may provide inaccurate LQI tuples. To overcome this, we need another anchor node located close to or opposite to A_5. To verify the authenticity of the proposed technique, we collected an additional 100 tuples from each reference location, resulting in a total of 2,400 tuples for all eight locations. These tuples were collected from randomly selected positions within each location to evaluate the classifier's performance. We observed that an overall localization accuracy of 91.4% is achieved. It is worth noting that in real-world application scenarios, where the movements of the target node are primarily concentrated in the central regions of each location, the overall accuracy would likely improve due to reduced misclassifications at the border areas, which is also a main consideration in our proposed pyramid loop algorithm, where enough reference anchors are deployed at the network boundary.

The localization error was examined at different zones in the form of LQI patterns and Epochs. The misclassification LQIs are shown in Table I. At zone 1, a total of 1500 tuples were recorded, of which 23 were discarded due to multipath fading and SNR ratio. However, with sufficient reference anchors in the border area, an overall accuracy of 98.6% was achieved. The localization performance of the CNN can be assessed using Mean Squared Errors (MSEs). Among the evaluated epochs, the CNN achieved its best MSE values at 1000 epochs, with 0.0126 for training, 0.0154 for testing, and 0.01942 for validation. These MSE values serve as indicators of the accuracy and effectiveness of the CNN model in the localization task. The CNN performance against location error is shown in Figure 7. The throughput functions of the Zigbee networks are established by employing a throughput model through X-CTU after 100 sample reads. This model enables the calculation of the maximum achievable throughput for different distances across all IEEE 802.15.4 modulation schemes. The resulting curve, depicted in Figure 8, provides a characterization of the Zigbee throughput against each channel.

The localization results are also obtained using the pyramid and centroid-based method with the dataset utilized for testing the localization classifier presented in Table II. For each tuple in the test dataset, we selected the three highest LQI values and determined the corresponding locations of the reference nodes that recorded those values. The additional localization results demonstrate that the presence of walls and the division of the zones in the test bed significantly impacted the accuracy of the triangulation method. This discrepancy arises because the triangulation method relies on the assumption that the measured link quality values decrease with the distance between the target node and the reference nodes. Consequently, achieving accurate localization becomes challenging in indoor environments with obstacles such as walls in the test bed. The set of highest LQI values also leads to anomalies in data elements and may not provide even full network coverage. This also proves that the CNN-based model proposed in this paper provides superior accuracy.

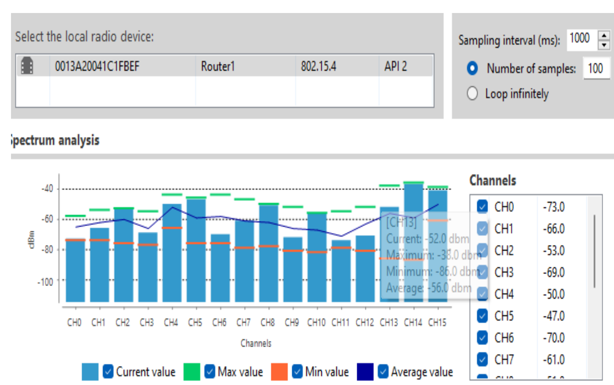


Fig. 8: Throughput analysis against each channel after 100 sample reads.

C. Comparison of the Indoor Localization Accuracy of Different Approaches

The evaluation and comparison of the proposed indoor localization method, which utilizes CNN-based LQI values, were conducted. A novel idea is proposed to utilize these CNN-based LQI values in a pyramid-looped algorithm.

Test data	Correct	Incorrect	Accuracy
Zone1 **5x300=1500 tuples** **LAB**	827	673	55.1%
Zone2 **3x300=900 tuples** **Corridor**	541	359	60.11%
Zone1-Zone2 **4x300=1200 tuples** **Lab-Corridor**	589	611	49.08%

TABLE II: Localization accuracy without CNN classification

To evaluate the authenticity of the proposed scheme, the system has been tested and compared with state-of-the-art techniques, such as KD-CNN [8], H-CNN [9], and an experimental indoor localization scheme presented in [10], as shown in Figure 9. The H-CNN model achieves very low accuracy with a localization error of 1.9m due to insufficient training data and Epochs. KD-CNN, have the average localization error of 1.57m in better conditions. The experimental localization algorithm proposed for the indoor environment has an average localization error of 0.56m. In an overall comparison, we observed that the proposed localization scheme has an average error of 0.12m, which can be further reduced by deploying one additional reference node in zone 1.

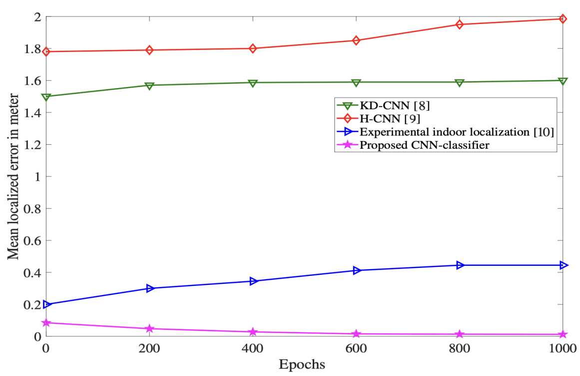


Fig. 9: Comparison of proposed solution with state-of-the-art.

V. Conclusion

This study presents an efficient indoor localization method for Zigbee sensor networks. Instead of relying on RSS or arrival time calculations, the proposed approach employs classification of link quality patterns between reference nodes and a target node in a specific location. An artificial neural network (ANN) localization classifier was implemented using WEKA and Java to classify these patterns. Experimental localization tests were conducted in a real-world Zigbee sensor network deployed in a home test bed. The proposed algorithm achieves an overall localization error of 0.12m in Zone 1 because it has enough anchor nodes in this area. Additionally, most of the computation is performed at the edge nodes, which also saves energy and extends the lifespan of the sensor nodes. This makes the proposed technique superior in real-time deployments. Future research aims to explore indoor human location tracking and behavior recognition by combining the proposed localization method with temporal pattern recognition techniques, such as hidden Markov models (HMMs).

VI. Funding Statement

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP-RP25).

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