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RESEARCH ARTICLE - ENGINEERING

Children Tracking System Based on ZigBee Wireless Network and Neural Network

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Article Info.	**Abstract**
Article history: Received 09 August 2022 Accepted 17 October 2022 Publishing 31 March 2023	The safety of children is one of the fundamental concerns of parents. Recently, child kidnapping has increased by a large percentage, some children have been found, and some children have not found yet. This paper proposes an indoor localization system based on ZigBee wireless sensor network (WSN) and Backpropagation Artificial Neural Network (BP-ANN) to locate the child in an indoor environment. Several ANN topologies were investigated to select the best one with minimum tracking or localization error. The Received Signal Strength Indicator (RSSI) was collected from four ZigBee XBee S2C anchor nodes by the mobile node carried by the child in an indoor area of 32m × 32m. The RSSI was collected from 127 test points inside the tested area. The measured RSSI was used to train, test, and validate the performance of BP-ANN to determine the two dimensions (2D) of the target child's location. Different topologies of ANN have been examined for training, testing, and validation which are 5-5, 10-10, 15-15, and 20-20 neurons in the hidden layer. The findings indicate that the 20-20 ANN topology can achieve higher accuracy than other topologies. Additionally, 20-20 topology localization errors were 1.0, 1.157, and 1.356 m for training, testing, and validating ANN performance.

Publisher : Middle Technical University

Keywords: Indoor Environment; Neural Network; RSSI; Tracking; ZigBee.

1. Introduction

Many children are reported missing from their parents, especially in public areas. In the USA, 800,000 children are missing from their parents yearly [1]. Tracking systems can be developed for outdoor and indoor environments. Indoor tracking technologies attract the interest of many researchers because they are used in many applications for tracking and monitoring children [2, 3]. The design and implementation of a tracking system for determining the location and getting a coordinated location in an indoor environment is the main challenge because of the harsh nature of the indoor wireless channel, such as object reflection, diffraction, and scattering can cause signal with multipath, in addition, to signal interference with noise. So, the radio signal can suffer high attenuation when the elements are located in different rooms, and it will be Non-Line of Sight (NLoS) with the tracked child [4]. Finally, indoor tracking systems deployment scenarios can change, so using an accurate model to characterize multipath and attenuation effects is impossible [5, 6]. On the other hand, some techniques are mainly designed to supplement satellite navigation technologies like the Global Positioning System (GPS), which has outdoor tracking accuracies of 1–10 m [7]. However, they cannot track people indoors for several reasons. First, people inside buildings are NLoS with the satellite constellation, whereas GPS requires a Line of Sight (LOS) connection to determine their positions [8]. Second, the weather situations like cloudy or rainy weather directly impact the tracking process for outside tracking, making indoor tracking impossible. Third, the GPS is a high cost to use in indoor tracking. Finally, there is no GPS signal inside the high buildings. Range-free and range-based systems are localization algorithms [9]. Range-free localization algorithms estimate node positions using a communication link between mobile nodes and beacon nodes in the network. However, they do not offer information regarding angle or distance [10, 11]. Furthermore, it is directly related to the quality of RSSI, which changes over time due to environmental variables such as channel reflection, fading, scattering, refraction, diffraction, multipath, and so on [12]. This approach is less accurate than a range-based method. On the other hand, range-based techniques are more precise and effective than range-free localization methods [13]. The angles and distances between nodes in Wireless Sensor Network (WSN) are calculated using Time of Arrival (ToA) range-based algorithms [14], Angle of Arrival (AoA) [15], Time Difference of Arrival (TDoA) [16], acoustic energy [17], and RSSI [18]. All receiving nodes that detect the target signal's location must be synchronized using the TDoA and ToA procedures. TDoA has a low localization error but uses much power and requires additional hardware. The precision of the antenna direction is essential to the AoA approach; adding an extra antenna array increases the cost and adds more hardware. However, while GPS is the most straightforward approach and is commonly used in outdoor localization, a reliable location based on GPS is not achievable in an inside setting due to the barrier between the GPS device and the satellite. Furthermore, GPS uses more energy than other systems. Acoustic energy faces some limitations (for example, bandwidth constraints that limit the amount of data transmitted in the network and limited node processing capability) that prevent it from performing complex and sophisticated processes; additionally, the audio in the network is not synchronized because each node operates independently. Because it does not require extra hardware, time synchronization, or an antenna array, the RSSI approach is cost-effective and

Nomenclature & Symbols			
WSN	Wireless Sensor Network	BP-ANN	Backpropagation Artificial Neural Network
RSSI	Received Signal Strength Indicator	NLoS	Non-Line of Sight
GPS	Global Positioning System	LOS	Line of Sight
ToA	Time of Arrival	AoA	Angle of Arrival
TDoA	Time Difference of Arrival	WiFi	Wireless Fidelity
RFID	Radio Frequency Identification	RSS	Received Signal Strength
MLE	Maximum Likelihood Estimator	BLE	Bluetooth Low Energy
IoT	Internet of Things	AP	Access Point
LMS	Least Mean Square	RF	Radio Frequency
DNN	Deep Neural Networks	SMS	Short Message Services
GSM	Global System for Mobiles	KNN-AVG	K-Nearest Neighbor Average
BPNN	Backpropagation Neural Network	WKNN	Weighted k-Closest Neighbor Technique
PSO-KF	Particle Swarm Optimization- Kalman Filter	KF	Kalman Filter
BA	Bat Algorithm	RBF	Radial Basis Functions
PTS	Personal Tracking System	CSI	Channel State Information
SVM	Support Vector Machines	CNN	Convolutional Neural Network
LSTM	Long-Short Term Memory	EETC	Electrical Engineering Technical College

minimizes power consumption. It also has a lower system complexity. While RSSI can be used to locate children and people in an indoor setting, this method has low localization accuracy due to the causes mentioned above. As a result, combining RSSI with a specific error minimization approach can reduce the localization error. Although ZigBee is mainly restricted to industrial and WSN, components depending on this technique consume substantially less energy than Wireless Fidelity (WiFi), Radio Frequency Identification (RFID), and Bluetooth [19]. Some indoor tracking systems based on Received Signal Strength (RSS), such as Maximum Likelihood Estimator (MLE)[20], Eco-tracking [21], and Mote Track [22], have been effectively evaluated and used for tracking people. Generally, the implementation and design of indoor tracking systems are limited to the main situations: 1) indoor scenario scalability, 2) constraints for the tracking people, and 3) the desired accuracy specification. The accuracy can be determined mainly by the density of nodes in the indoor tracking system. Therefore, if minimal accuracy is desired, the user can determine a minimum number of nodes. This paper proposes an indoor tracking system based on RSSI measurements of Zigbee technology to determine children's location, and the localization accuracy was improved using BP-ANN.

The contributions of this work are summarized as follows.

1. A prototype for children tacking was designed and practically implemented based on ZigBee wireless sensor network.
2. The localization error for children was improved by adopting a neural network in the indoor surrounding.
3. The proposed children tracking system was validated related to the previous articles regarding the localization error.

2. Related Work

In previous works, several techniques have been used for indoor tracking, like RFID [23], WiFi [24], ZigBee [1], and Bluetooth [25]. On the other hand, several algorithms are used to optimize locating accuracy with these techniques. One of these works is [2], where the authors proposed a tracking system for children in or out of the school bus. The system had been designed using the Internet of Things (IoT) by Bluetooth Low Energy (BLE), which is appropriate for RSSI. From the authors' viewpoint, the system decides if the child is in or out school bus by estimating the distance between the Access Point (AP) and the child's position while wearing a smartwatch. The least mean square (LMS) algorithm was used to set RSSI parameters to get high accuracy. By applying the system, the authors found that the RSSI inside the school bus (−68.2, −83.0 dBm) and RSSI outside the school bus (−40.6, −57.0 dBm). In [6], the author proposed an indoor system for tracking and locating movement people using the RSSI of Radio Frequency (RF) signal. They combined hardware with software for tracking a person in real-time by using a BLE beacon as a transmitter which the tracked person will carry, and Raspberry Pi and Bluetooth as receivers at a fixed point in the environment with the hardware to collect four databases. The software uses four models based on Deep Neural Networks (DNN) to analyze the four databases RSSI and determine a person's location. The average accuracy is 90.92% for the 0.5 m threshold. They can determine the main factors' effect on localization accuracy in cluttered environments: numbers and layout of RF receivers, location density of receiving RSSI, and person direction that carries the transmitter. In [26], the authors proposed location determination and fall detection for the elderly who live alone using WiFi and GPS. The proposed system is wearable hardware connected to WiFi and an accelerometer sensor to detect falls. In case of emergency, the WiFi module of the wearable device sends Short Message Services (SMS) by Global System for Mobiles (GSM) or an email. In the case of fall detection, the GPS coordinates the location from a Google map if there is no fall detection. While the authors in[27] design an indoor positioning system with Wireless sensor networks based on Zigbee, the proposed system consists of Zigbee sensor nodes which are used to measure RSSI values and send them to the database for processing. After that, the positioning accuracy by K-nearest neighbor average (KNN-AVG) was compared with the Backpropagation Neural Network (BPNN) and weighted k-closest neighbor technique (WKNN). The results show that the positioning accuracy by BPNN is higher than those achieved by the WKNN and KNN-AVG. The authors in [28] proposed Particle Swarm Optimization- Kalman Filter (PSO-KF) indoor fingerprint localization system. They used the PSO algorithm to select the optimum position of APs, enhance the system's accuracy, and analyze the position and number of APs on the performance of fingerprint localization. They used Kalman Filter (KF) to update the estimated location by PSO to track the user's mobile phone. The results of this work show that their proposed system improves performance in real-time and decreases computational, in addition to achieving high accuracy for tracking and localization with an estimated error equal to 1.5m. A fingerprint localization system based on Bluetooth RSS is designed by the authors in [29] using a Bat Algorithm (BA) to determine the location and improve the real-time localization accuracy. KF is used to reduce estimation error and update position, which is initially determined using the BA. The authors compare their tracking model's computational time and localization accuracy with other tracking models based on several algorithms such as PSO, WKNN, clustered Radial Basis Functions (RBF), and kernel. The experimental results show higher localization accuracy in real-time with lower computation complexity and error than other tracking models. Their tracing model obtained an accuracy equal to 89.50%. A personal Tracking System (PTS) is proposed in [30] by combining GPS and GSM for tracking and detecting a person's location in real-time. The hybrid system of Arduino, GSM Modem, and GPS receiver at the patient model and LCD, a smartphone with GSM module at the caretaker model. The GPS determines the patient's location and sends it by SMS using GSM to the caretaker, who uses Google Maps to know the location. They found that because of a bad connection, there are some locations GSM cannot determine, and the SMS may be a loss. Also, it has not been tracked accurately as GPS. Another indoor tracking system is proposed in [31] based on WiFi for tracking humans in indoor environments known as WI Locus. This system used the existing WiFi APs in the indoor environment to detect the direction of walking humans. These APs sense the changes in the Channel State Information (CSI) of RF signal, and then the multi-class Support Vector Machines (SVM) will classify moving behavior and tracking determination. The experimental results in three scenarios show that the show system achieves 95% accuracy for identifying moving behavior and 90%accuracy for determining the path. The authors in [32] combined Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) algorithms for fingerprinting localization. They measured CSI propagate from a single access point of WiFi in an indoor environment. The proposed algorithm estimates testing points that are not identical to the reference points. They analyzed the instability of CSI and demonstrated a mitigation solution using a comprehensive filter and normalization scheme. The authors practically investigated localization accuracy in the environment on hundreds of test points. The proposed system achieved an average localization error of 2.5 m. However, 80% of localization errors were under 4 m. In [33], the authors presented two-stages deep learning methods to improve accurate localization in indoor environments. Using actual data measurements to characterize the environment based on RF signatures. The CNN was employed in both stages to determine the type of indoor environment and to perform effective localization. The proposed method is tested in both stages using four scenarios: a lab, lobby, sports hall, and a narrow corridor. They observed that the suggested CNN localization model considerably improves localization accuracy to 51.3%. The results of the proposed two stages disclosed that the localization accuracy arrive to 31.8% compared to benchmark methods. In [34], an accurate magnetic indoor localization using the DNN algorithm is suggested in indoor localization. The localization was performed for a two-dimensional (2D) environment. The magnetic sequences are given features, and the DNN is utilized to identify the sequences based on patterns produced by surrounding magnetic features. The locations were determined in a corridor and atrium based on identified features. The results revealed that the localization error was 1 and 2.3 m for the corridor and atrium, respectively. The results indicate that magnetic positioning is possible using just a smartphone's sensors. As mentioned above, localization accuracy is one of the limitations that constrain indoor localization. The localization or distance estimation accuracy in most of the studies mentioned above is still insufficient because it has high localization errors due to its dependence on RSSI. The RSSI is fluctuated due to indoor environments, which leads to high localization error. Therefore, the BP-ANN was proposed to overcome this limitation. Thus, the localization accuracy was improved in the current work. Unlike previous works, this paper offers a practical, wearable, low-cost, and less complex child tracking system with higher localization accuracy based on applying BP-ANN with different topologies.

3. System Design

In this work, a child tracking system has been proposed to track children using Zigbee (XBee S2C). Electrical Engineering Technical College (EETC) was adopted as a practical scenario, specifically on the ground floor of the lab building where the target child moved in. The adopted indoor environment had 32 m×32 m dimensions, was constructed with concrete walls and included wood and metal doors, which highly affect signal propagation. Moreover, the adopted environment consisted of rooms with different dimensions and four corridors indicated as zones, each 32 m long. On the other hand, four anchor nodes are installed in these zones, known as Anchor Nodes (ANs), and they are located in a fixed position at the end of each corner in the adopted environment. The coordinators of AN1, AN2, AN3, and AN4 are (0,0), (0,31), (31,31) and (31,0), respectively. The fifth anchor node is mobile, known as the Mobile Node (MN), and the tracked child carries it. As shown in Fig. 1, zone1 includes 32 test points (TP1-TP31), zone2 includes 32 test points (TP32-TP63), zone3 includes test points (TP64-TP95), and finally, zone4 includes test points (TP96-TP127).

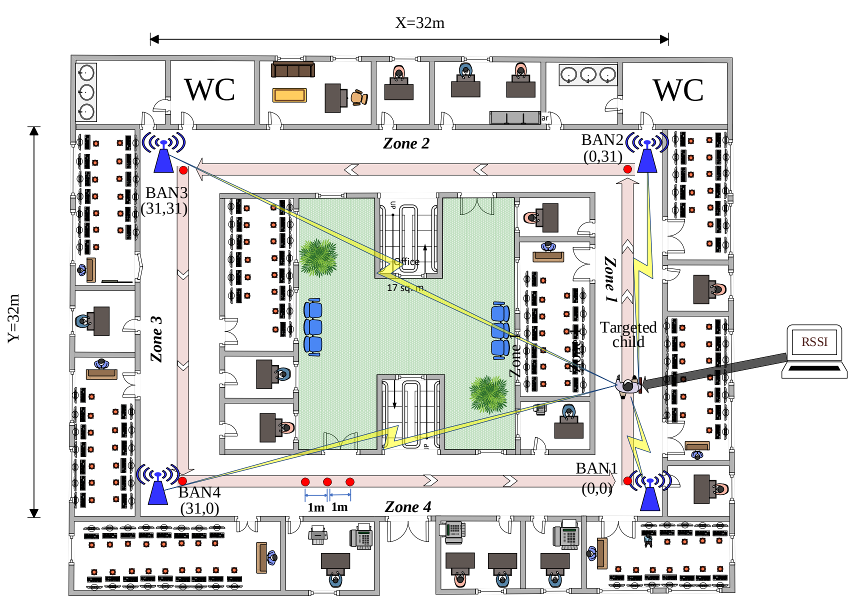
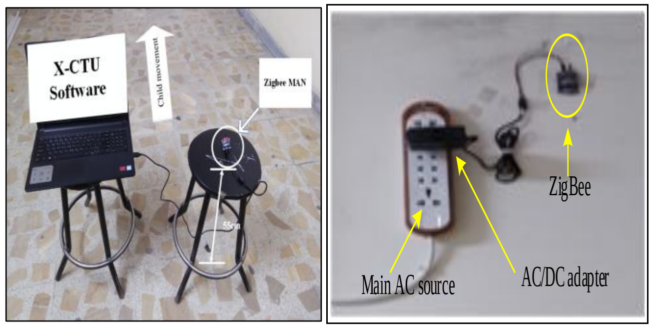


Fig. 1. Environment layout for children tracking system: RSSI= Received Signal Strength Indicator, BAN=Beacon Anchor Node, MAN= Mobile Anchor Node, m= meter

4. Experiment Configuration

In the adopted environment, the MAN is located 55cm high above the ground at the tracked child's waist to collect RSSI from BANs, as shown in Fig. 2a. While BANs are located at 1.5m high and have the electric power from their neighbours' labs, as shown in Fig. 2b. MAN is connected by USB to the laptop and powered by it. In contrast, in the actual application, the MAN must be powered by a battery when the tracked child is carrying it. The RSSI samples collected by MAN are recorded by X-CTU software. XCTU is free multi-platform software that allows designers to configure Digi radio frequency (RF) devices using a straightforward graphical interface. The software is compatible with embedded tools that make it simple to configure, set up, and evaluate Digi RF devices. This software sets the wireless connection's configuration between the MAN and BANs. As mentioned, 127 positions have been determined to collect RSSI in the zone representing the child's movement.



(a) (b)

Fig. 2. The hardware of the proposed system in the indoor environment: (a) BANs and (b) MAN. BAN= Beacon Anchor Nodes, MAN= Anchor Nodes Mobile, AC=Alternating current, DC=Direct current

5. Data Collection

In the adopted environment, 127 TNs have been determined to collect RSSI in the zones representing the child's movement in these zones. The separation distance between two positions is 1m. In each position, (120) RSSI samples are recorded from all BANs and (30) RSSI samples from each BAN. So, the total RSSI samples in all positions from all BANs are (3750), which are used for training, testing, and validating ANN's performance. As demonstrated in Fig. 3, RSSI samples are recorded at each TN in the zones when the MAN is moved in the zones. At the AN1, the samples from (1-1000) represented by TN1-TN31 in zone1 and the samples from (1001-2749) represented by TN32-TN63 in zone4 have an RSSI range from -40 dBm to -80 dBm because these TNs are LOS with AN1. While the rest of the TNs in zone 2 and 3 are NLOS and have an RSSI range between (-80- -90). Whereas at the AN2, RSSI range from -40 dBm to -80 received by the samples from (1-2000) represented by TN1-TN63 in zone1 and two because of LOS communication with AN2. While the TNs in zone3 and zone4 are NLOS and receive RSSI between (-80 to -90). Finally, AN3 covers the TNs in zone2 and 3, represented by samples from 1000 to 2750 that received RSSI between (-40 to -75) dBm since they are LOS with AN3. The other TNs in zone1 and zone4 receive RSSI (-75 to -90) dBm because of the NLOS communication between them and AN3. Despite some TNs in zone1 being NLOS with AN4, which are represented by samples (1-50), they have RSSI between (-60 to -80) dBm because of the small distance between them. The rest of the TNs in zones and all TNs in zone3 and four have RSSI less than -80 dBm. The TNs in zone2 receive RSSI between (-40 to -80) dBm.

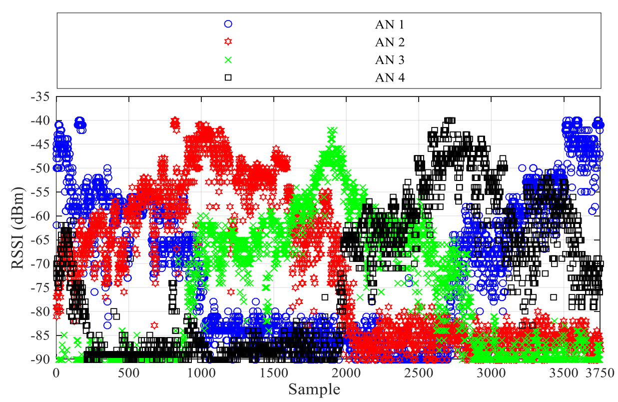


Fig. 3. BANs coverage in the adopted environment. RSSI= Received Signal Strength Indicator

6. ANN Algorithm

Neural networks provide practical computing approaches for information processing, machine learning, and user-generated information to estimate combined system output responses. Recently, ANNs have been used with great effectiveness, providing significant results. A biological neural network simulates the activity of the biological brain. Connections between neurons link neurons and transport information. Synapses can be enhanced during training. The BP training technique is one of several methods used to train an ANN. The calculation, BP of error, and a feed-forward input training pattern are all part of BP [35]. An input layer, an output layer, and one or more hidden layers make up the BP-ANN [36]. These layers are connected in a serial mode, starting with the input layer, continuing via the hidden layers, and finally to the output layer. The connections between layers are known as weights, and each layer contains one or more neurons [37, 38]. The main objective of this work's use of BP-ANN was to reduce comprehensive output errors during the learning process. The BP-ANN technique was divided into two stages: forward and backward. The Learning Rate (LR) and ANN topology were two essential criteria in the neural network's structure that influenced the proposed system's final performance [39]. The Matlab software (R2015b) was adopted in this study to train, test, and validate the ANN. The BP-ANN was designed and implemented in Matlab to achieve the goal of this research, which represents the enhanced child's location accuracy. The input layer of the BP-ANN structure includes four neurons: RSSI1, RSSI2, RSSI3, and RSSI4. Whereas two hidden layers in the structure with different topologies, these topologies have validated the number of neurons between 5 to 20 neurons. Finally, the output layer includes two neurons' location coordinators (X and Y), the tracked child's location in the adopted environment, as demonstrated in Fig. 4. The ANN flowchart can be seen in Fig. 5. It must initialize the parameters of ANN in terms of LR, number of hidden layers, and the number of neurons in each hidden layer before stating ANN training, testing, and validating processes. Two hidden layers are selected with a validated number of neurons in each hidden layer, whereas the LR has been selected between 0.1–1 with a step of 0.01 to get the minimum number of Mean Square Error (MSE) of ANN. After that, the ANN was run to calculate the Mean Absolute Error (MAE) of X and Y locations. The ANN run for 1000 iteration to get the optimum value of MAE, MSE, and Root Mean Square Error (RMSE). The best value of MSE was determined at 5 m. Also, whenever MSE is achieved 10^{-2} m which is considered the goal value in this work, the running of ANN will stop. Fig. 6 describes how MAE can change according to the changes in LR values. However, when MAE reaches the maximum value, the LR will equal 1.58m, while the MAE achieves the minimum value when the LR is 1m. The parameters of the proposed ANN model will be listed in Table 1.

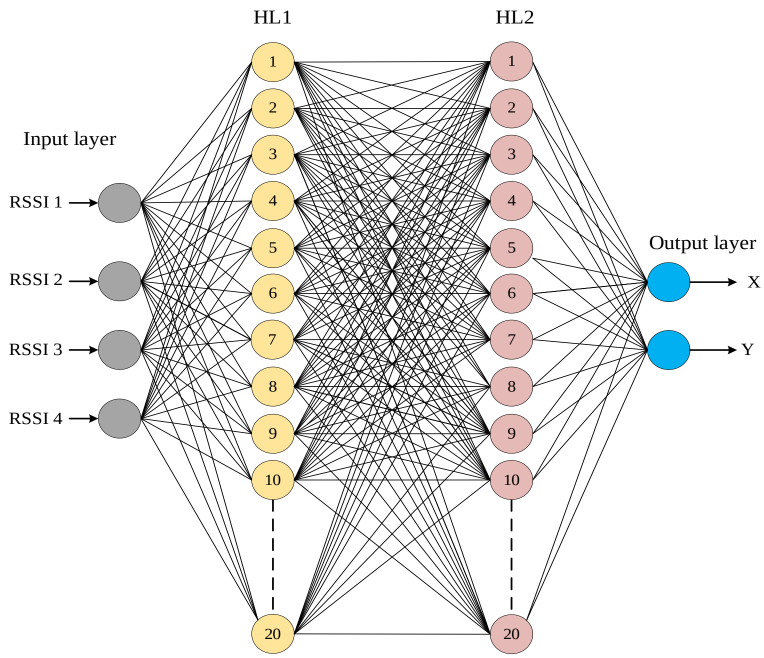


Fig. 4. ANN structure, RSSI= Received Signal Strength Indicator., HL=Hidden Layer

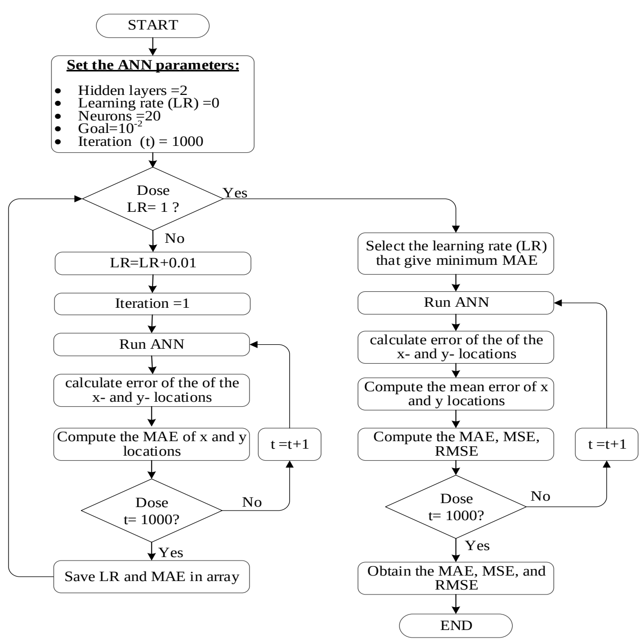


Fig. 5. ANN flow chart for the proposed system, LR=Learning Rate, ANN=Artificial Neural Network, MAE=Mean Absolute Error, MSE= Mean square Error, RMSE= Root Mean square Error.t= iteration number

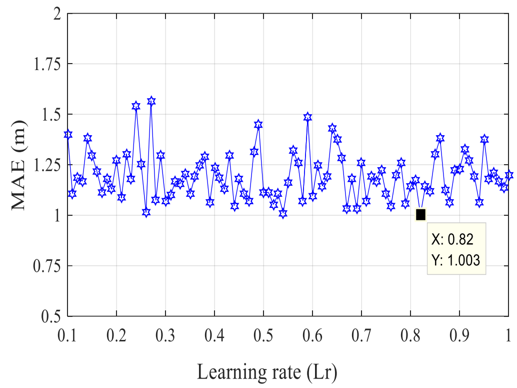


Fig. 6. LR VS MAE

Table 1. The hyperparameters of ANN

Parameters	Value	Type	Description
Network type	---------	Feed-forward backpropagation	---------
Input to ANN	4	RSSI 1, RSSI 2, RSSI 3, and RSSI 4	Obtained from BAN1, BAN2, BAN3, and BAN4
Hidden layers	2	---------	Transfer function: Tan-Sigmoid
Output of ANN	2	x- and y- locations	Transfer function: Linear
Neurons in hidden layers	(5-5), (10-10), (15-15) and (20-20)	---------	Trial and error
Learning rate (LR)	0.82	Obtained from loop	Range: 0.01 to 1
Epoch	1000	---------	---------
Target error (goal)	0.01		---------
Total collected RSSI samples	15,000	3,750 from each anchor node	---------
Error evaluation	Three	MAE, MSE, and RMSE	---------
Data sets	Three	Training, testing, and validation	• 2,626 samples (training) • 562 samples (testing) • 562 samples (validation)

7. Results and Discussion

7.1. ANN performance

The 3,750 RSSI samples collected by MAN are used in three phases: training, testing, and validating the performance of ANN and determining the 2D location of the targeted child in the adopted environment. These samples are divided into 70% for training the ANN, which is 2,626. At the same time, 15% of the samples are used for each testing and validation, which are 562 samples for both. Also, the MSE of different topologies of BP-ANN that are 5-5, 10-10, 15-15, and 20-20 neurons in the hidden layers have been investigated at each phase to evaluate BP-ANN's performance. The 20-20 ANN topology has better MSE than other topologies. Hence, the results of evaluation methods like correlation coefficient, histogram error, Cumulative Distribution Function (CDF), and Probability Density Function (PDF) for this topology will be discussed in all phases.

The MSE of the BP-ANN's activation function during the training phase was investigated when 1,000 iterations were used. The MSE was 7.411m for the 5-5 neurons after 891 iterations, 5.548m after 995 iterations for the 10-10 neurons, and 4.361m after 940 iterations for the 15-15 neurons. Finally, 3.032m for the 20-20 neurons has the best performance, can achieve less MSE after 941 iterations, and reaches the best MSE after 200 iterations, as shown in Fig. 7.

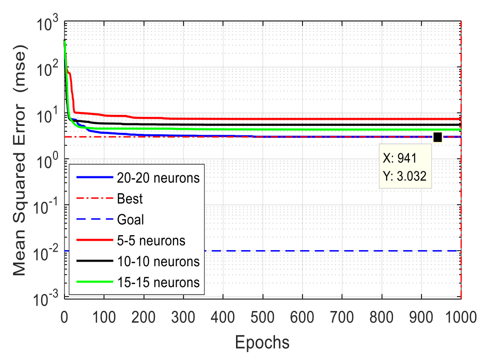
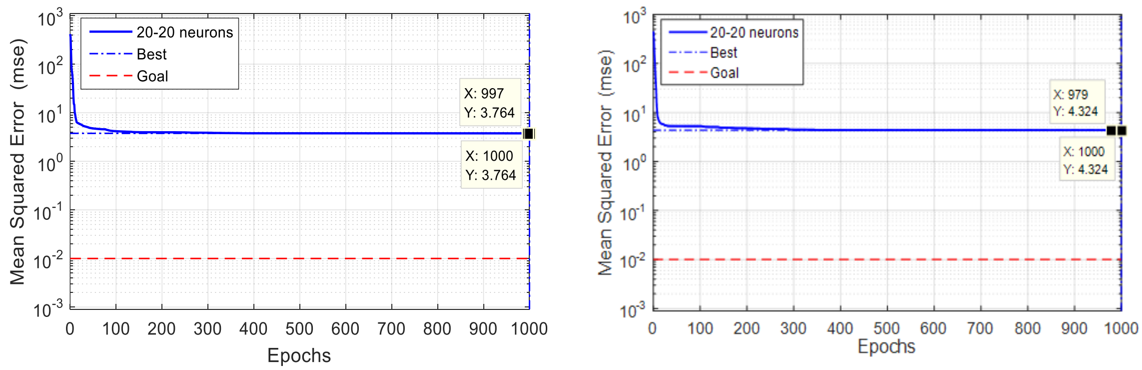


Fig. 7. The MSE at all hidden layers

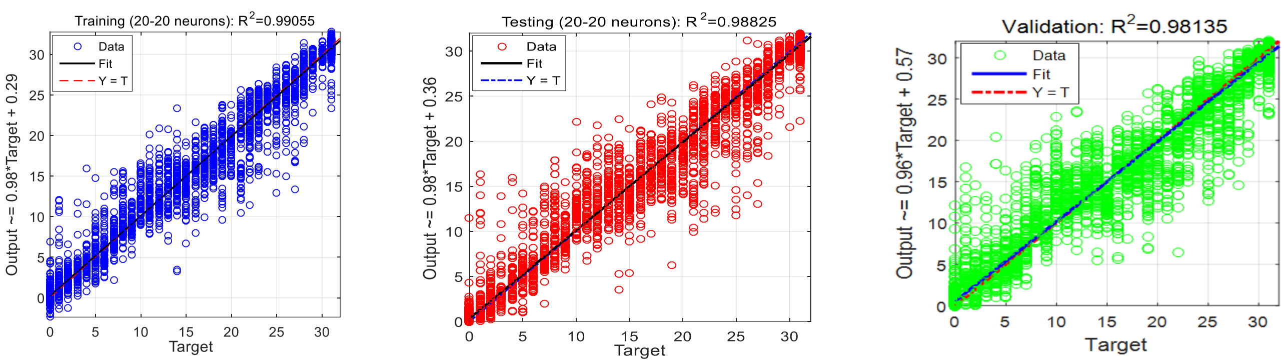
As a result, only the 20-20 neurons were tested and validated using the MSE for ANN performance testing and validation. After 997 iterations, the MSE reached a testing value of 3.764 m. In addition, Fig. 8 illustrates that after 200 rounds, the optimum value was attained 8a. Fig. 8b shows that the validation phase's MSE was 4.324m, attained after 979 iterations. Results indicate that the MSE achieved at testing and validation ANN performance for 20-20 neurons is not as effective as the MSE achieved at training ANN performance after 1,000 iterations.

It is also possible to assess ANNs' performance by comparing the correlation coefficients between measured locations of the targeted child and predicted locations by ANN at various topologies. 20-20 topologies have the best correlation coefficient among different topologies, with reduced training testing and validation errors. According to Fig. 9, the training, testing, and validation ANNs at 20-20 neurons have correlation coefficients of 0.99055, 0.98850, and 0.98130, respectively. As a result, the correlation coefficient in the testing and validation phases is not as high as in the training phase. These results indicated that the proposed ANN topology effectively achieves high localization accuracy and decreases errors in localization between measured and predicted locations.



(a) (b)

Fig. 8. The MSE of ANN performance of 202-20 neurons for (a) testing and (b) validation

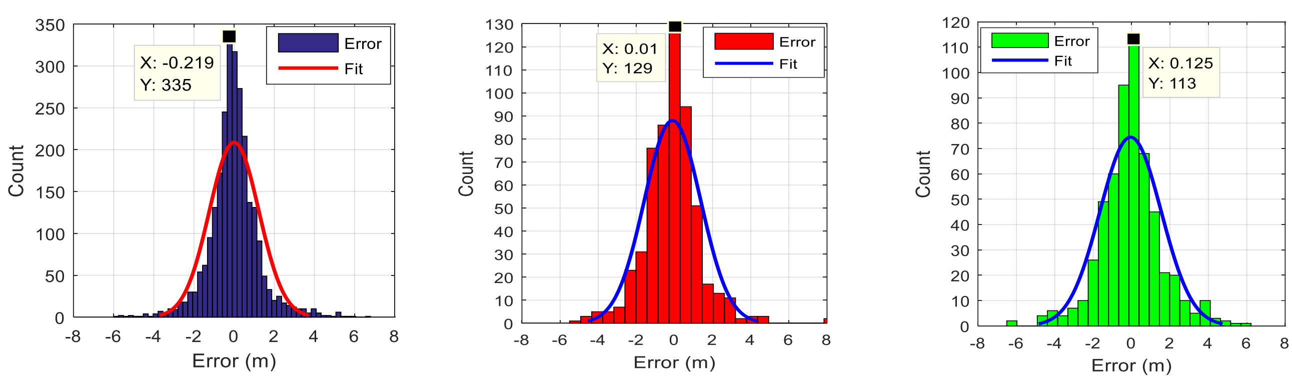


(a) (b) (c)

Fig. 9. The correlation coefficient of the ANN for 20-20 neurons (a) training, (b) testing, and (c) validation

7.2. Error estimation

Fig. 10 shows the histogram error for evaluating ANN training, testing, and validation. Most RSSI sample values for 20-20 neurons fall within -8 to 8. There are 335 samples at a minimum error of 0.219m for training, 129 samples at a minimum error of 0.01, and 113 samples for validation at a minimum error of 0.125m. Consequently, a histogram plot shows that the 20-20 ANN topology reduces training errors more than testing and validation errors.



(a) (b) (c)

Fig. 10. The histogram of error of the ANN for 20-20 neurons (a) training, (b) testing, and (c) validation

CDF can also be used to check the ANN's performance, as seen in Fig. 11. When CDF reaches 90% at 20-20 neurons, the CDF plot shows that training, testing, and validation errors are less than 1.9583m and less than 2.3139m. In contrast, when comparing the training and testing ANNs with their validation, the training ANN will come out on top since it has the lowest localization error when CDF exceeds 90%.

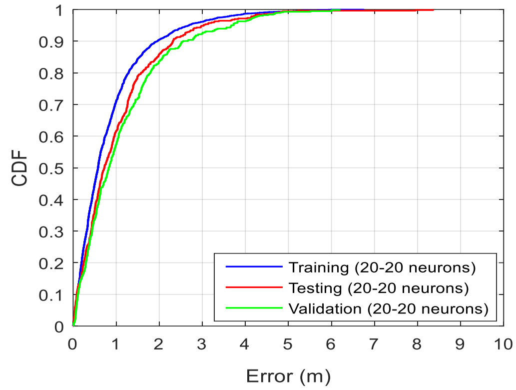


Fig. 11. The CDF of the error for training ANN for 20-20 neurons

PDF is a practical assessment method that can evaluate ANN performance. As a result, the three phases of the PDF curve are used to estimate the localization error. Hence. Fig. 12 demonstrates that the PDF is distributed at training error between (-2 and 2), the testing error between (-3 and 3), and the validation error extending between -3 and 3 based on the PDF curve. Additionally, training testing and validation errors converge to 0 when the PDF is 50%, 36%, and 33%, respectively.

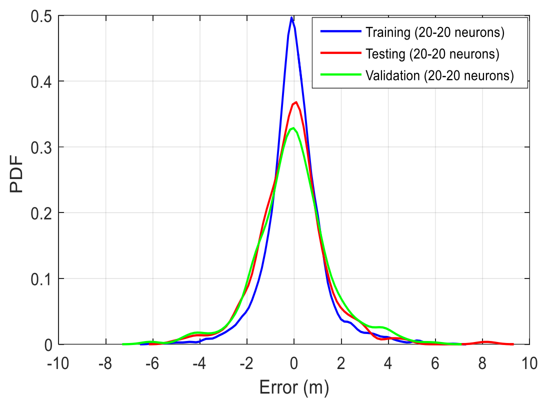


Fig. 12. PDF of the error of the training ANN for 20-20 neurons

A 3D representation of the correlation between the ANN errors as z-axis and X and Y coordination in the real environment at 20-20 neurons is provided in Fig. 13. Training, testing, and validation errors peak at 6.5m, 8.4m, and 6m, respectively. It also illustrates that the smooth progression from black to yellow indicates a gradient error; the black represents a minimal error, whereas the yellow indicates a maximum error.

MAE, MSE, and RMSE at the training, testing, and validation of ANN for 20-20 neurons have been calculated and listed in Table 2. Validation performance has the maximum MAE, MSE, and RMSE, whereas training performance has the minimum MAE, MSE, and RMSE. As a result, the validation error is less than all the training and testing.

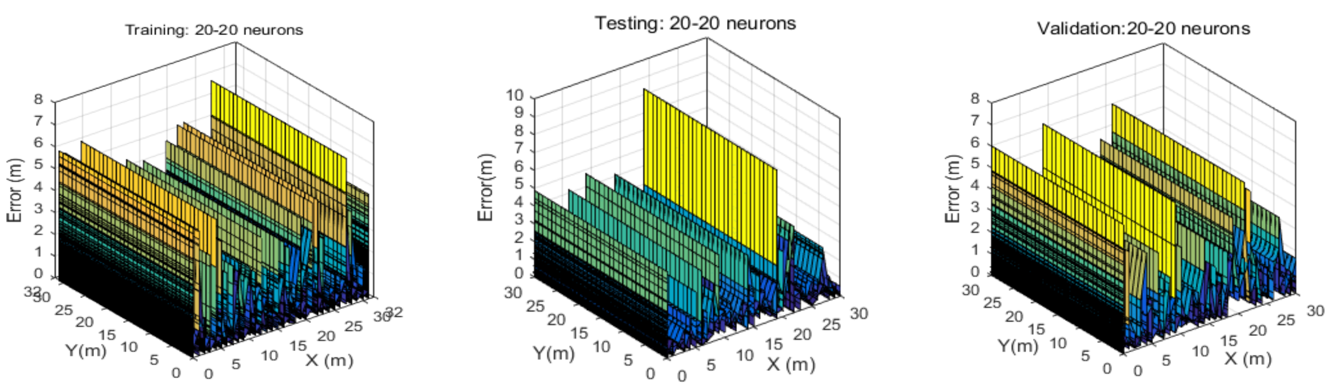


Fig. 13. The error of x-and y-locations for training ANN for 20-20 neurons

Table 2. MAE, MSE, RMSE for 20-20 ANN topology at the three phases

Error (m)	Tri.	Tes.	Val.
MAE	1.0	1.157	1.356
MSE	3.363	4.280	4.940
RMSE	1.833	2.068	2.222

8. Comparison with Previous Works

The localization error of the proposed system by BP-ANN has been compared with the localization error in some of the previous works to prove the authenticity of the proposed system to track children in an indoor environment. In Table 3, the used method and the wireless technique for each work have been introduced. Where RFID, Zigbee, Bluetooth, BLE, WSN, and WiFi are used in the mentioned works. On the other hand, Non-Linear Regression Neural Network (NL-NN), Neural Fuzzy Inference System (ANFIS), Bayesian Graphical Model (BGM), MLE-PSO, Genetic Algorithm (GA), K-Nearest Neighbors (KNN), Feature-Scaling-KNN (FS-KNN), Multilayer Perceptron Neural Networks (MLPNN), Radial Basis Function Neural Networks (RBFNN)), Parametric Loop Division (PLD), Intelligent Water Drops-Continuous Optimization (IWD-CO), CNN-LSTM, Back Propagation Neural Network- Adaptive Genetic Algorithm (BPNN-AGA), ANN, PSO, and PSO-ANN are used to optimize localization error in these works as listed in Table 3. All of these works used either RSSI or CSI to determine the location of MAN in indoor environments. Moreover, Table 3 compares the results obtained from the current research based on BP-ANN with previous works. It can be observed that the localization error of the adopted BP-ANN based on 20-20 topology is less than the localization error in these works, where the errors were 1.0, 1.157, and 1.356 m for training, testing, and validating, respectively.

Table 3. Comparison between the current method and some previous works

Ref	Year	Technique	Method	Localization Error(m)
[40]	2015	WIFI	NL-NN	4.38
[41]	2016	ZigBee	ANFIS	1.4269
[42]	2016	WiFi	PSO-ANN	2.46
[43]	2017	WiFi	position fingerprint algorithm	2.7
[44]	2017	WIFI	BGM	2.9
[45]	2017	WSN	MLE-PSO	4.83
[46]	2018	BLE	GA	2.34
[47]	2018	Bluetooth	PSO-ANN	2.21
[48]	2018	RFID	ANN	1.78
[49]	2018	BLE	KNN	1.8
	2018	WiFi	FS-KNN	1.72
[50]	2019	WSN	MLPNN RBFNN	3.12 3.46
[51]	2019	BLE	Trilateration algorithm nonlinear least squares algorithm	1.149
[52]	2019	ZigBee	PLD	1.91
[53]	2019	WSN	IWDs-CO	1.174
[54]	2019	ZigBee	PSO	3.13
[55]	2020	WiFi	CNN-LSTM	1.0863
[56]	2020	ZigBee	QPSO-GRNN	1. 0143
[57]	2021	BLE	KNN	1.46
[58]	2021	WiFi	BPNN-AGA	4
[59]	2021	WiFi	GA	1.92
[60]	2021	BLE	fusion algorithm	1.76
[61]	2022	BLE	ANN	5.1
This work	2022	ZigBee	BP-ANN	1.00 (training) 1.157 (testing) 1.356 (validation)

9. Conclusion

In this study, a backpropagation artificial neural network and ZigBee wireless sensor network-based indoor tracking system were suggested to find the child in indoor surroundings. Several topologies were examined to find the optimum ANN topology that provides the least amount of tracking or localization error. Four ZigBee XBee S2 anchor nodes were distributed to broadcast RSSIs, where the RSSIs were collected by the mobile node carried by the child. The experiments were conducted on the ground floor of the EETC, which has a maximum available area in the EETC. The collected RSSI samples were used to train, test, and validate the performance of the ANN. Two hidden layers are used with a different number of neurons in the hidden layer, which are 5-5, 10-10, 15-15, and 20-20, to find the MSE, MAE, and RMSE. The conclusions can be drawn as follows.

- The proposed 20-20 ANN topology achieves less MSE than other topologies,
- The error in the training phase of ANN was minimal compared to the testing and validation phases, and
- Increasing the number of neurons in hidden layers increases the localization accuracy of the child.
- In future work, an optimization algorithm can be combined with ANN to achieve higher localization accuracy and less localization error. In addition, the CNN can be adopted instead of ANN to improve the localization accuracy further.

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