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An Innovative Approach to Improve Point Location Detection System with ANFIS using RSSI Signals and Fingerprinting Method

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Abstract: Localization systems have an important place in many areas. GPS (Global Positioning Systems) using data from satellites gives successful results in localization systems. However, localization systems such as GPS, which can be quite successful outdoors, do not achieve the same success indoors because the satellite viewing angle cannot be maintained continuously or due to low reception quality. In this respect, there is a need for localization systems that can provide the most precise localization with the least cost in the interior. This study aims to improve fingerprint-based localization systems, which is a localization method based on Received Signal Strength Indicator (RSSI) data using ANFIS. The proposed system has been shown to give more successful results than the methods frequently used in the literature.

RSSI Sinyalleri ve Fingerprinting Yöntemi Kullanılarak Noktasal Konum Algılama Sisteminin ANFIS ile İyileştirilmesine Yönelik Yenilikçi Bir Yaklaşım

Anahtar Kelimeler
İç Mekân Konumlandırma,
ANFIS,
Parmakizi

Öz: Konumlandırma sistemleri birçok alanda önemli bir yere sahiptir. Uydulardan gelen verileri kullanan GPS (Global Positioning Systems) yerelleştirme sistemlerinde başarılı sonuçlar vermektedir. Ancak GPS gibi dış mekânlarda oldukça başarılı olabilen konumlandırma sistemleri, uydu görüş açısının sürekli korunamaması veya sinyal alım kalitesinin düşük olması nedeniyle iç mekânlarda aynı başarıyı gösterememektedir. Bu bakımdan iç mekânda en az maliyetle en hassas konumlandırmayı sağlayabilecek konumlandırma sistemlerine ihtiyaç duyulmaktadır. Bu çalışma, Alınan Sinyal Gücü Göstergesi (RSSI) verilerine dayalı bir konumlandırma yöntemi olan parmak izi tabanlı yerelleştirme sistemlerini ANFIS kullanarak geliştirmeyi amaçlamaktadır. Önerilen sistemin literatürde sıklıkla kullanılan yöntemlere göre daha başarılı sonuçlar verdiği gösterilmiştir.

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1. Introduction

Recently, intelligent systems, representing a prominent facet of Information Systems, consist of electronic circuits enabling intercommunication among themselves and other user-oriented systems via various protocols. These systems are proficient in recognizing and aiding users through straightforward commands [1]. Furthermore, systems capable of pinpointing location data and offering decision support based on this data are regarded as integral components of intelligent systems [2], [3]. This functionality has given rise to applications commonly known as Location-Based Services (LBS) [4]. LBS encompasses a collection of IT services that connect the location of an entity with contextually relevant information in the vicinity of that entity [5].

Global positioning system (GPS) is one of the main positioning technologies. GPS is a satellite network that regularly sends coded information, measuring the distance between satellites and objects, making it possible to determine their precise location (with margin of error) on earth in real time. However, due to the significant loss in receiving satellite signals inside buildings, it is difficult to obtain reasonable positioning result when GPS is used indoors. Although GPS enables high accuracy location determination outdoors, it cannot provide the same success when direct line of sight (LOS) cannot be achieved with satellites. In this respect, the need for indoor positioning has become an increasing research focus.

Indoor positioning is an increasingly important technology because of the innovations and advanced features provided by the software and hardware systems of recent years and the context awareness is provided for applications that will work by sensing the location information of indoor environments. In addition, the rapid increase of mobile device users and associated information technologies in recent years also makes indoor positioning important [6]. However, current positioning systems cannot fully meet industrial requirements regarding safety, accuracy, functionality and usability [7].

As shown in Figure 1, the operation of an indoor positioning system consists of several steps. First, tags or mobile devices transmit the signals to sensors or receiving nodes, then data collected at sensors or receiving nodes is transmitted to a central data station, which calculates the locations of devices or tags using geolocation methods and algorithms, and finally the calculated location (x, y) along with its coordinates on a map in the user interface [8].

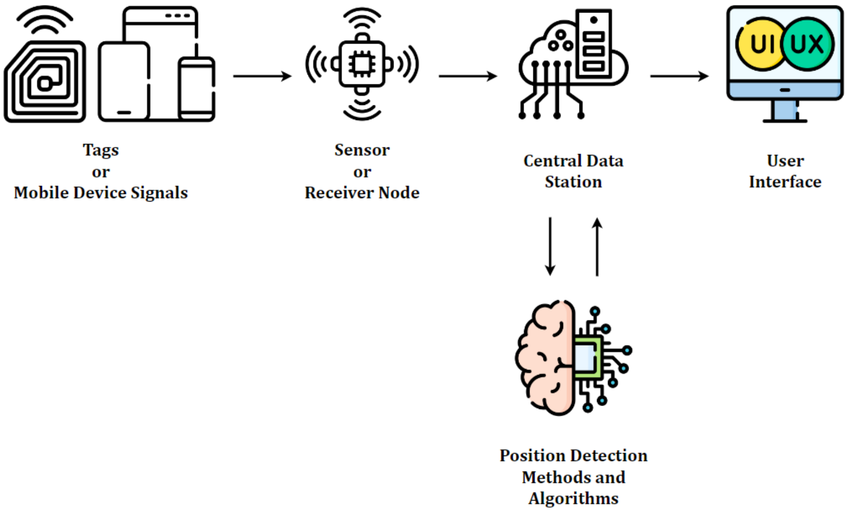

Figure 1. Indoor localization steps

In the field of indoor positioning, many different technologies such as Bluetooth, WiFi, RFID, Ultra-Wideband, Ultrasound and ZigBee, which are among the wireless communication technologies, are used and many different studies have been carried out in the field of indoor positioning with using these technologies in recent years [9], [10], [11].

In addition to the development of various technologies for indoor positioning, various methods have been extensively researched in the last two decades and a series of approaches have been developed [12]. Received Signal Strength Indicator (RSSI) determines the location according to the signal level reaching the receiver [13], Fingerprinting determines the location with the previously collected signal information [14], Angle of Arrival (AoA) determines the position by using the angle of arrival of the signals reaching the receiver [15], Time of Arrival (ToA) determines location using the signal propagation time [16], Time Difference of Arrival (TDoA) determines the location by using the difference between the arrival time of the emitted signals [17] and Triangulation uses the radial distance of the signal received from three different reference points [18] to determine the position.

When the literature is reviewed, it is seen that a great effort has been made to provide reliable and precise indoor positioning and a lot of research has been done.

Malavalli et al. [19] developed a Wi-Fi based indoor positioning system using RSSI information with fingerprint method and machine learning. The system estimates with the Bayesian model and tests are carried out in two different environments. In the first test, f-score of the machine learning model was 0.893 in a corridor with 14 reference points and in the second test, f-score of the machine learning model was 0.994 in a 6-room house. Mascharka et al. [20] aimed to find the best algorithm for indoor positioning by testing machine learning algorithms with data from embedded sensors. They tested the data set consisting of 3110 data obtained from the real environment with 20 machine learning algorithms and found that the K * algorithm gave the best result with average error margin of 0.76 m. Salamah et al. [21] aimed to reduce computation time and increase performance of Wi-Fi based indoor location systems using machine learning approach in their study. They tested the performance of the system they proposed with k-Nearest Neighbor, Decision Tree, Random Forest and Support Vector Machine algorithms. The computation of the system reduced by 70% with Random Forest and 33% with k-Nearest Neighbor. Hsieh et al. [22] used Bluetooth technology and Android-based smart device in their machine learning approach system. They aimed to achieve a more successful result in indoor positioning by applying Kalman Filter algorithm to the RSSI information of the signals from the Bluetooth transmitters. They tested the system they developed with k-Nearest Neighbor, Support Vector Machines and Random Forest algorithms, and the model trained with k-Nearest Neighbor algorithm gave the most successful result. AlHajri et al. [23] developed a system based on two-step machine learning model to achieve higher accuracy position detection for indoor positioning. In the first step, the k-Nearest Neighbor algorithm was used to recognize the environment type, and in the second stage, the most appropriate combination of radio frequency properties was determined according to the defined environment type. In the study, real data obtained from the measured signals were used and the accuracy rate in position detection increased between 50% and 70%. Teran et al. [24] developed an indoor positioning system in which WiFi and Bluetooth technologies are used jointly within the framework of IoT. With the machine learning approach in the system, the location is determined by using the signal / noise ratio, RSSI information and fingerprint method. 4 Bluetooth transmitters and 5 WiFi access points were used in the system, and the accuracy rate in location detection increased by 75% with the k-Nearest Neighbor algorithm.

This study aims to develop an indoor positioning system that can learn the environmental situation from limited training data and provide accuracy close to existing indoor positioning systems, with less cost and shorter training time, using a machine learning approach and the Internet of Things. A model was developed using ANFIS algorithm with RSSI information of the signals received from Bluetooth transmitters in the simulation environment. The following parts of the study are presented as follows: Section 2 consists of the methodology used in the developed closed environment positioning system. Section 3 consists of developed models' results obtained. In Chapter 4, the study was concluded by discussing the results.

2. Material and Method

2.1. Fingerprinting

The fingerprinting method serves as a technique for ascertaining the location of an object or an individual by utilizing pre-acquired signal data. As shown in Figure 2, this method comprises two essential phases: the offline phase, which involves training, and the online phase, responsible for testing and location detection.

During the offline phase, signals from transmitters are gathered, and their Received Signal Strength Indicator (RSSI) information is recorded in vectors [25]. Each RSSI vector corresponds to a known location and is stored in a database for future reference during the online phase [18].

During the online phase, the individual or item of interest sends their RSSI data to a server. The server utilizes a positioning algorithm to gauge the location of the target by comparing the RSSI vector of the target with vectors stored in the database, using particular similarity metrics. Following this, the database provides the position that displays the greatest correlation with the vector transmitted by the server [18].

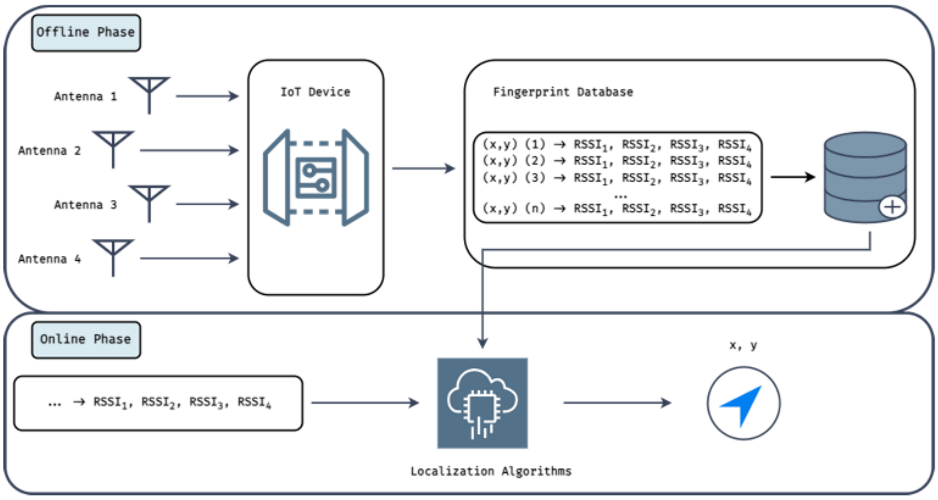

Figure 2. Fingerprinting method

2.2. Bluetooth

Bluetooth is a technology developed for wireless and short range transmission of voice and data between different fixed or mobile devices based on the IEEE 802.11.5 standard. Known as the newest version of Bluetooth technology, Bluetooth Low Energy (BLE) is a very suitable technology for indoor location determination, with a 24 Mbps data rate and 70-100 meters coverage area with higher energy efficiency compared to previous versions. In addition, diversity, low cost and energy efficiency are the advantages of BLE technology. The infrastructure of BLE technology generally consists of 1 type of device; BLE Beacon. The task of the beacons is to announce their presence periodically. BLE Beacons periodically emit a signal that all BLE supporting devices can receive. The content of this signal includes identification information (ID) and RSSI information.

2.3. ANFIS

The Adaptive Network-Based Fuzzy Inference System (ANFIS) represents a class of artificial neural network systems founded on the principles of the Takagi-Sugeno fuzzy inference system. It was initially conceived by Jang in the early 1990s and gained recognition for its efficacy in modeling nonlinear functions and forecasting chaotic time series [26], [27].

The ANFIS network structure is characterized by the assembly of nodes, with each node assigned a specific function, and these nodes are distributed across various layers [28]. ANFIS methodology operates as a hybrid system that integrates fuzzy logic and artificial neural networks [29].

Within ANFIS, the framework encompasses If-Then rules and input-output information pairs inherent to the fuzzy inference system. Nevertheless, training and system control leverages learning algorithms associated with artificial neural networks [26], [30]. If x and y are input and z are taken as output, the basic rule structure of ANFIS is written as follows:

$$\textbf{If} \quad x \in A_i \; and \; y \in B_i \;\; \textbf{Then} \;\; z_i = p_i x + q_i y + r_i$$

In this context, A_i and B_i serve as labels for the sets that partition the x and y variable space into fuzzy subspaces. Meanwhile, p_i, q_i and r_i represent the design parameters that are established through the training process. The variable z_i denotes the output value of a specific rule, and it is contingent on the input variables. Consequently, for any given input pair of x and y, the resultant output value is computed as the weighted average of z_i, which represents the output values generated by all the rules [31]. Based on the first order fuzzy Takagi-Sugeno model, ANFIS model is created based on the following two rules. In these rules p_i, q_i and r_i are equation constants for each rule [32].

$$\textbf{If}\; x = A_1 \; and \; y = B_1 \; \textbf{Then} \; f_1 = (p_1 x + q_1 y + r_1)$$
$$\textbf{If}\; x = A_2 \; and \; y = B_2 \; \textbf{Then} \; f_2 = (p_2 x + q_2 y + r_2)$$

ANFIS architecture created using the above rules is shown in Figure 3 and consists of 5 layers. In the first layer, fuzzyfing layer, fuzzification occurs, where membership functions are applied to the input data. This step transforms the crisp input values into fuzzy values. The second layer, implication layer, is responsible for generating rules based on the principles of fuzzy logic inference. These rules dictate how the input variables relate to the output. In the third layer, normalization layer, a normalization process involving weighted averaging is applied to each node that originates from the rule layer. This step helps balance and normalize the information. The fourth layer, defuzzyfing layer, serves to convert the fuzzy results obtained from the previous layers into numerical values. This is a crucial step in making the results suitable for further processing. In the fifth and final layer, combining layer, the output values from all nodes are combined or added together, resulting in a single output value for the ANFIS system. This aggregated value represents the system's output based on the input data and the fuzzy logic rules.

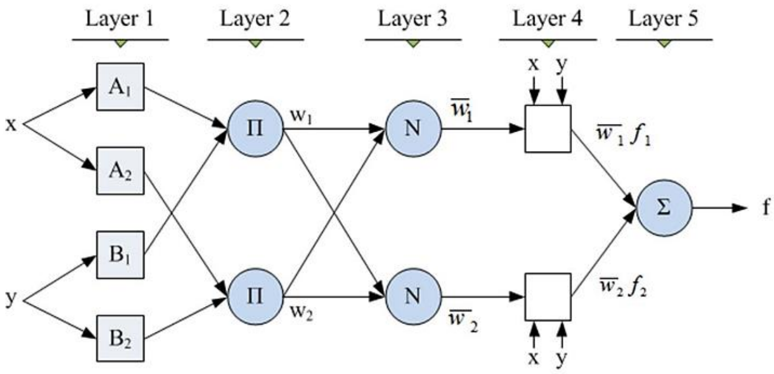

Figure 3. Adaptive network-based fuzzy inference system

2.4. Proposed Methodology

In this study, it is aimed to make a more successful positioning by using machine learning for a system that makes indoor positioning based on the RSSI information received from Bluetooth transmitters by fingerprint method. The model developed in this study consists of three parts. The first part is the preparation of the data set with the RSSI information of the Bluetooth transmitters using Fingerprint method, the second part is the development of machine learning models using ANFIS models and the third part is testing of the developed models and measuring their success. Proposed method is shown in Figure 4.

With the Fingerprint method, RSSI values from each transmitter (five transmitters) were recorded at (x-coordinate, y-coordinate) points of RSSI information received from Bluetooth transmitters in the study area. The fingerprinting method was chosen because it is a reliable method for indoor environments [33], does not require any license fee to read wireless signals traveling in the air, can be easily adjusted according to the desired situation, and can be used with a combination of other wireless technologies. The second part of the system aims to design an indoor positioning system using the ANFIS approach. The reasons for choosing the ANFIS method can be summarized as follows: It exhibits rapid convergence during the training phase, demonstrates a strong resistance to uncertainty, effectively extracts numerical models from numerical data, and allows for effortless expansion of the knowledge base through the incorporation of new rules.

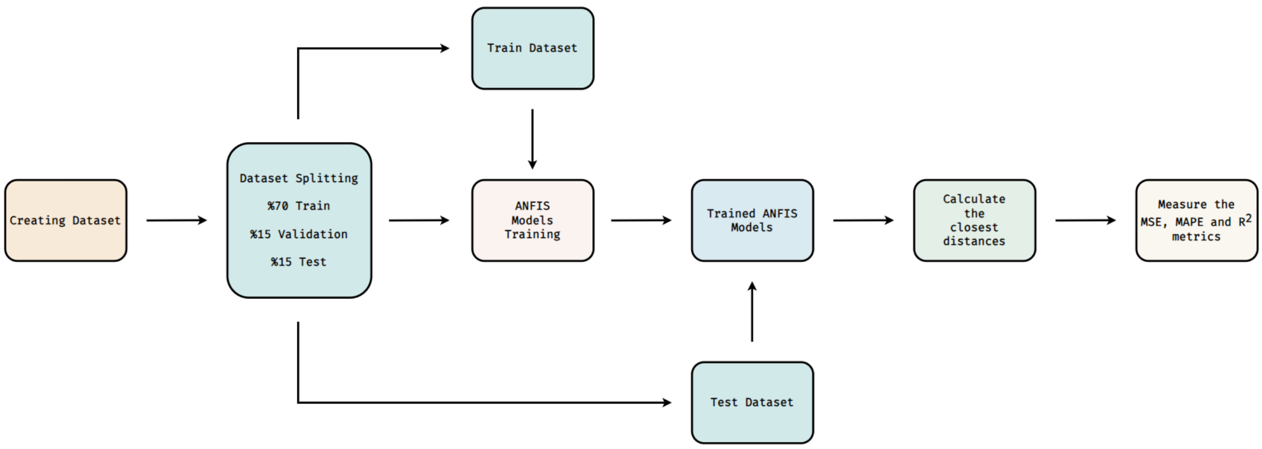

Figure 4. Proposed method

As shown in Figure 5, data was generated in the simulation environment with the "NAVINDOOR" [34] application to build and test the ANFIS model. Black lines represent the simulated existing walls. Red dots mark the locations where measurements were taken in (x, y) coordinates. The placement of beacons (RSSI data signal emitters) at five different points is shown. By taking measurements on constantly changing routes, the distribution of the data set within the data set is diversified. Thus, it is predicted that the model to be developed will behave sensitively according to these changes. RSSI values of five beacons were generated from approximately 1050 locations and stored in the dataset. Table 1 shows sample RSSI values at some locations.

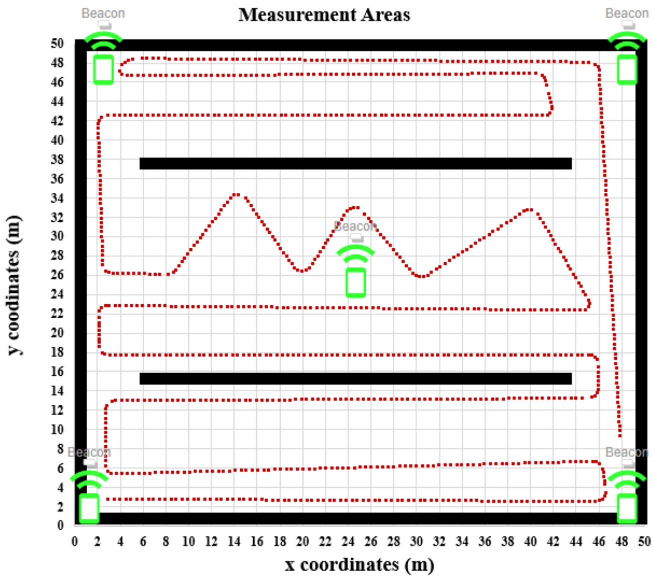

Figure 5. Divided working area

Table 1. An example of RSSI (dBm) data series taken from transmitters at the working area

Area (x coor., y coor.)	Beacon1	Beacon2	Beacon3	Beacon4	Beacon5
(9,2)	-73.3	-66.2	-64.8	-65.3	-68.5
(20,2)	-69.1	-68.5	-64.5	-65.2	-68.7
(39,2)	-66.7	-73.6	-65.5	-64.7	-67.5
(41,6)	-66.6	-73.0	-65.7	-64.9	-67.5
(23,6)	-68.1	-67.3	-65.5	-66.1	-68.8
(22,6)	-68.8	-68.0	-65.4	-65.4	-68.8

2.4.1. Development of the ANFIS Models

In this proposed work, an approach using the ANFIS model is tested by presenting not only RSSI values but also x and y coordinates values from which these values are obtained as input data Figure 3. Assume that at any time t, the receiver node at any (x, y) location receives RSSI values of the signals detected by the receiver node. At instant t at this point;

$$(x_1, y_1)t_1 \;=\; [\mathrm{RSSI1}_{t1}\ \mathrm{RSSI2}_{t1}\ \mathrm{RSSI3}_{t1} \ldots\ \mathrm{RSSI5}_{t1}]$$

signals will be collected. The coordinates (x_1, y_1) serve as factors influencing the distance to the signal sources generating these signals in relation to both the x and y coordinates. As Equation 1 indicates, the RSSI value is directly linked to the distance, and any alterations in the (x, y) coordinate values, either horizontally or vertically, will result in variations in the signal values.

$$d = d_0 \times 10^{(\frac{P_0 - P_d}{10n})} \Leftrightarrow P(d) = P_0 \; - 10n\, log_{10}(\frac{d}{d_0}) \tag{1}$$

With this assumption, the coordinate values of the (x, y) point have an effect on the system as individual input parameters. An ANFIS model that predicts the node value (x_1, y_1) according to the RSSI signal values cannot simultaneously use the x or y coordinate values at this point as both input and output to the system. The solution is pursued by adopting an approach that involves creating two distinct models from the same dataset. A system is then developed to identify the node point, which is essentially the same but is generated differently based on the outputs of these two models. The effectiveness of ANFIS is evaluated within this framework.

In Table 2, two different models, named ANFIS Model 1 and ANFIS Model 2, were created using the same training data sets, the same parametric values and different input and output parameters.

Table 2. ANFIS models input-output parameters

Model's Name	Inputs	Outputs
ANFIS Model 1	x coordinate, RSSI1, RSSI2, RSSI3, RSSI4, RSSI5	y coordinate
ANFIS Model 2	y coordinate, RSSI1, RSSI2, RSSI3, RSSI4, RSSI5	x coordinate

A point in 2D space is composed of two different components, x and y, and the combination of these two values represents the position information. RSSI values vary with distance, and all (x, y) points in the area of interest are matched in the fingerprint database and hold point location information according to their RSSI values. Here, the main determinants of the object's distance to be located to the beacons (hence the measured RSSI value) are the individual x and y points and must be provided as input data to the system for training the models. This assumption clearly explains the reason for using two different models. The general operation of the system will be discussed through the steps of the setup and the architecture summarized in Figure 6.

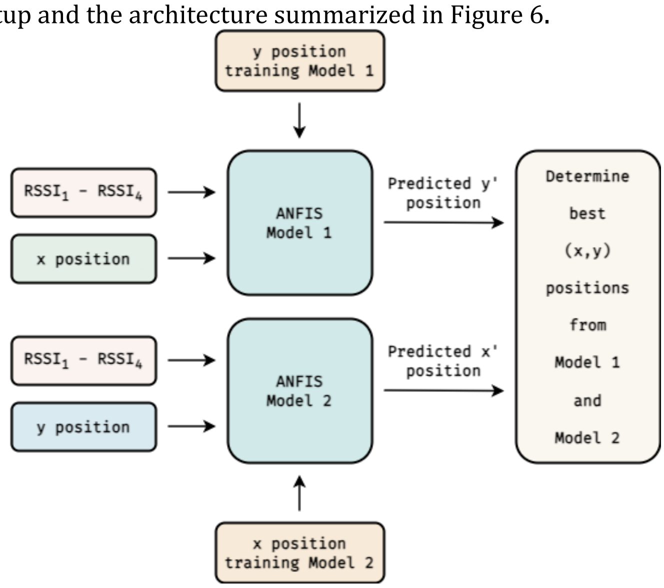

Figure 6. Schematic overview of the system

3. Results

3.1. Training and testing of the ANFIS_1

ANFIS_1 model is defined as the model in which the x value is presented as input with RSSI values (x_1, RSSI1, ... RSSI5) and the possible y'_1 values will be calculated with reference to the y coordinate value. The input parameters of the model and the output parameters produced by the model are shown below.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} [RSS1 \; ... \; RSS5] \rightarrow ANFIS\_1 = \begin{bmatrix} y'_1 \\ y'_2 \\ y'_3 \end{bmatrix}$$

ANFIS models were trained using the data measured on the routes shown in Figure 7 and summarized in Table 1 (Training Dataset). However, the success of the trained model was demonstrated with test data generated on 3 different route scenarios in Figure 7. In these figures, the blue dots constitute the sample route scenario where RSSI values are detected. According to the x values of these points, the accuracy of the y' values generated by ANFIS_1 according to the y reference values were checked. Three test data sets at different points, which were not used in the training of the system, were generated by the data generation program. The results of these sets were evaluated in the trained ANFIS models, and the performance was confirmed.

To ensure that the ANFIS model accurately reflects the pattern structure of the dataset it's trained on, it is essential to determine the parameters and membership functions to reflect the effects on the model. For five inputs is shown in Table 2, the combinations of the membership functions used extensively in the literature were tested and determined to produce the best model for the five inputs [35]. For each input {'pimf' 'gauss2mf' 'gauss2mf' 'gauss2mf' 'gauss2mf' 'gauss2mf' 'gauss2mf'} membership functions were determined as a result of the experiments and used in training the models. During this phase, statistical metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-Squared (R2) [36], were employed to evaluate the results generated by the ANFIS models trained using various combinations of membership functions.

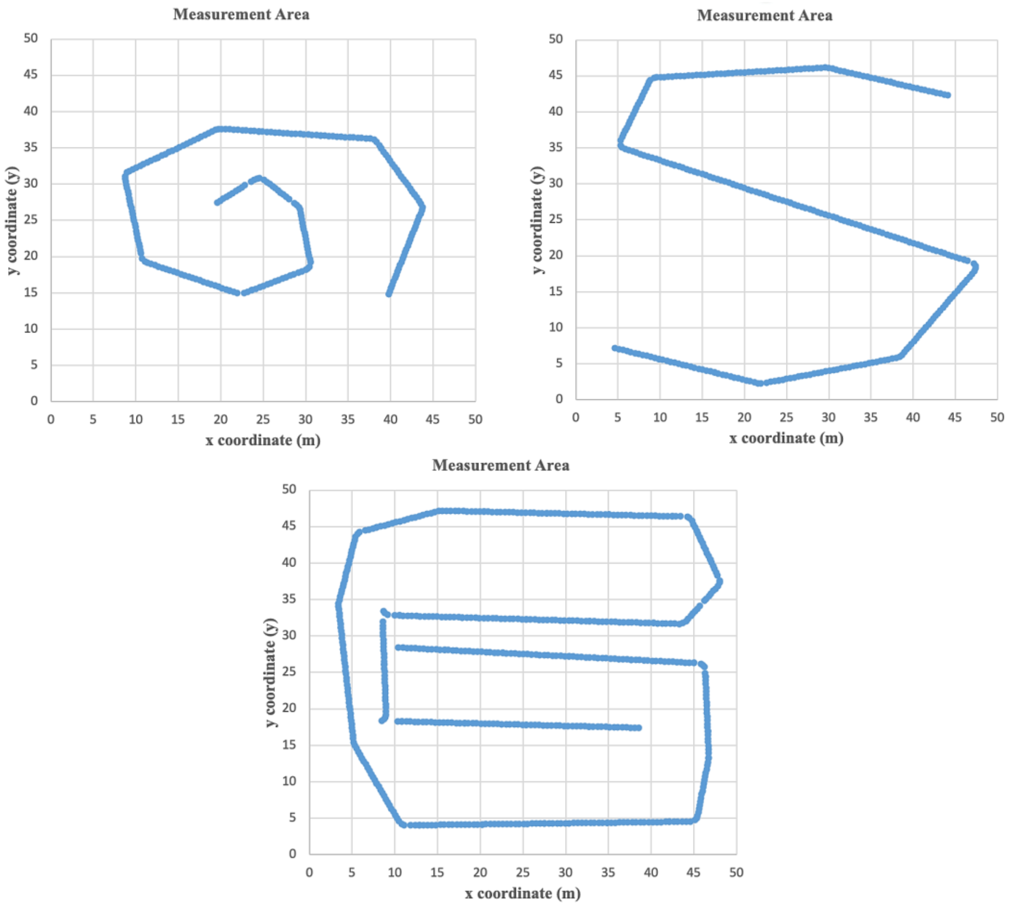

Figure 7. Test dataset 1, 2 and 3

To train and evaluate ANFIS models correctly, the data set is divided into three basic parts. These three parts are training data (80%), validation data (10%) and test data (10%). The training data is used for optimization of weight and parameter settings. The validation data is used to monitor the model's performance during training and to detect overfitting problems. Test data is used to evaluate how the model performs in the real world. These three separate datasets allow an ANFIS model to be trained and evaluated reliably and effectively. While these results obtained using the Datasets are subjected to analysis using statistical metrics, and the primary factor for determining the most effective ANFIS models is the outcomes on the Test Dataset, primarily relying on the R-Squared (R^2) value.

The values of all data sets used in ANFIS_1 model training are shown in Table 3. In addition, the statistical values produced according to the results of the test data sets created to test the success of ANFIS_1 model are presented in Table 3.

Table 3. Result values of ANFIS_1 model

Metrics	Dataset	Training	Validation	Test	Test 1	Test 2	Test 3
R^2	0.9879	0.9925	0.9711	0.9675	0.9567	0.7977	0.9294
RMSE	1.6760	1.3196	2.6074	2.7111	3.4095	3.7682	3.6791
MAPE	0.0941	0.0712	0.1452	0.2262	0.2651	0.1207	0.1395
MAE	1.1758	0.9773	1.8359	2.1015	2.3453	2.6171	2.2164

The variation of the actual locations (x, y) of the Test Datasets produced by the trained ANFIS_1 model and the (x, y') locations produced by ANFIS_1 model is shown in Figure 8.

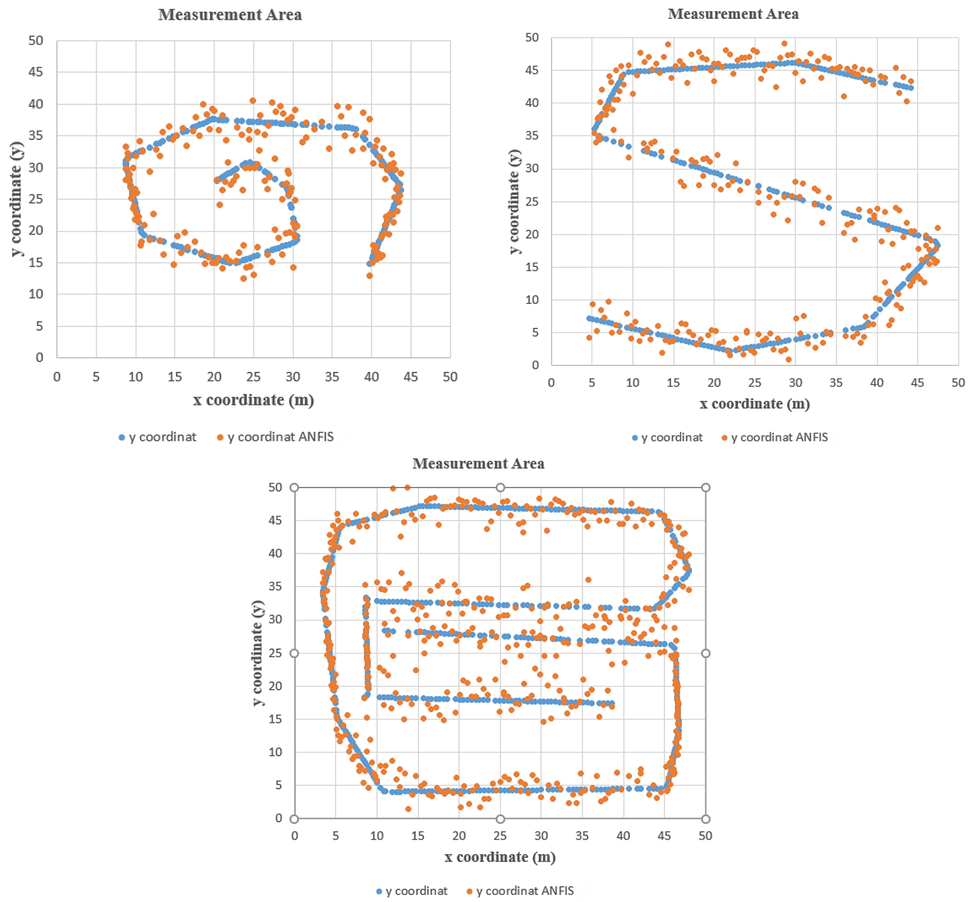

Figure 8. ANFIS_1 test dataset 1, 2 and 3 results

The error plots between the actual y coordinate values and the y' coordinate value generated by the ANFIS_1 model with x coordinate and RSSI values are shown in Figure 9 in descending order.

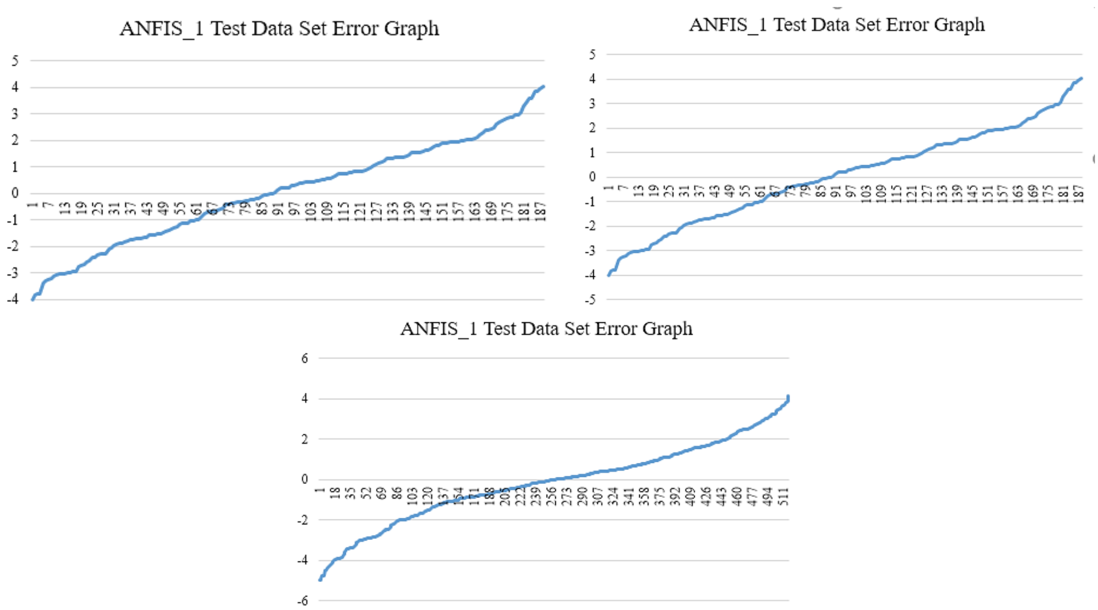

Figure 9. ANFIS_1 test dataset error graph

3.2. Training and testing of the ANFIS_2

In the same way as the ANFIS_1 model, ANFIS_2 model is defined as the model in which the coordinate data y is presented as input with RSSI values (y_1, RSS1...RSS5), and the possible x'_1 values will be calculated with reference to the x coordinate value. The following figure shows the input parameters of the model and the output parameters produced by the model.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} [RSS1 \ldots . RSS5] \rightarrow ANFIS\_2 = \begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \end{bmatrix}$$

The values of all data sets used in ANFIS_2 model training are shown in Table 4. In addition, the statistical values produced according to the results of the test data sets created to test the success of the ANFIS_2 model are presented in Table 4.

Table 4. Result values of ANFIS_2 model

Metrics	Dataset	Training	Validation	Test	Test 1	Test 2	Test 3
R^2	0.9811	0.9912	0.9486	0.9398	0.9627	0.7772	0.9585
RMSE	1.9673	1.3277	3.4314	3.5784	2.5537	5.7589	3.0462
MAPE	0.1194	0.0677	0.4049	0.2474	0.5883	0.2287	0.2224
MAE	1.2825	1.0052	2.3818	2.3990	1.8217	3.3821	1.9636

The variation of the actual locations (x, y) of the Test Datasets generated by the trained ANFIS_2 model and the (x, y') locations generated by ANFIS_2 model is shown in Figure 10.

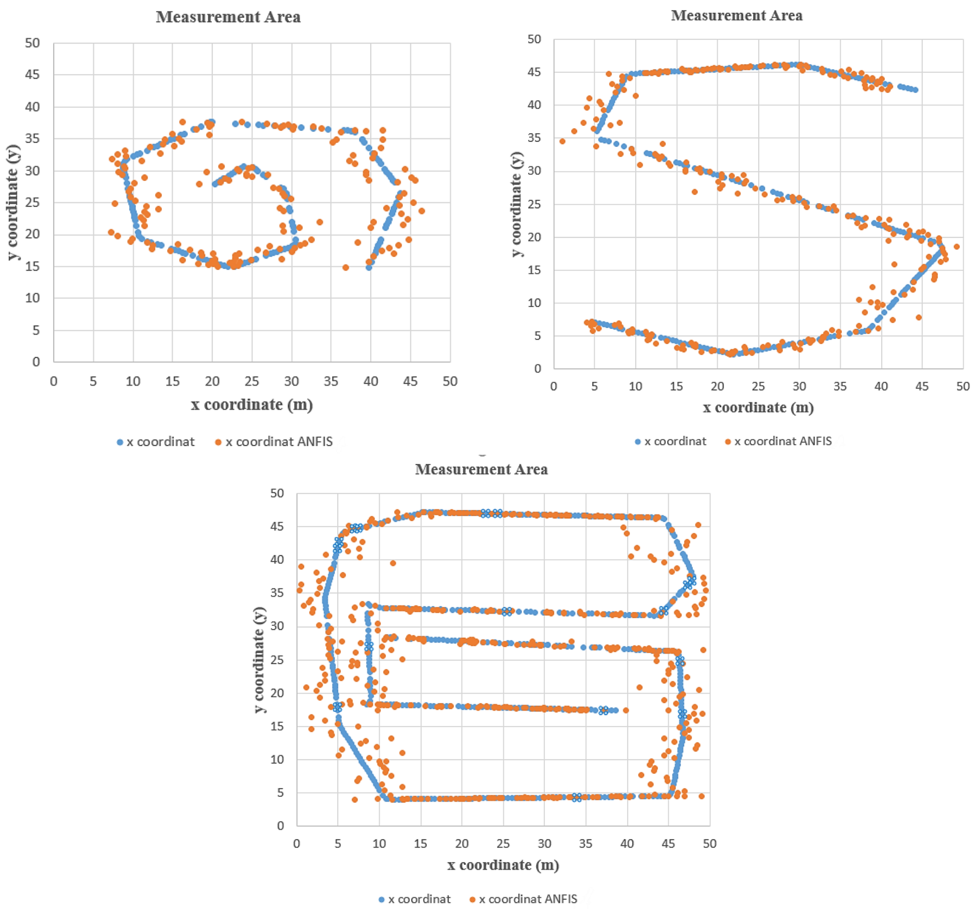

Figure 10. ANFIS_2 test dataset 1, 2 and 3 results

The error plots between the actual y coordinate values and the y' coordinate value generated by the ANFIS_2 model with x coordinate and RSSI values are shown in Figure 11 in descending order.

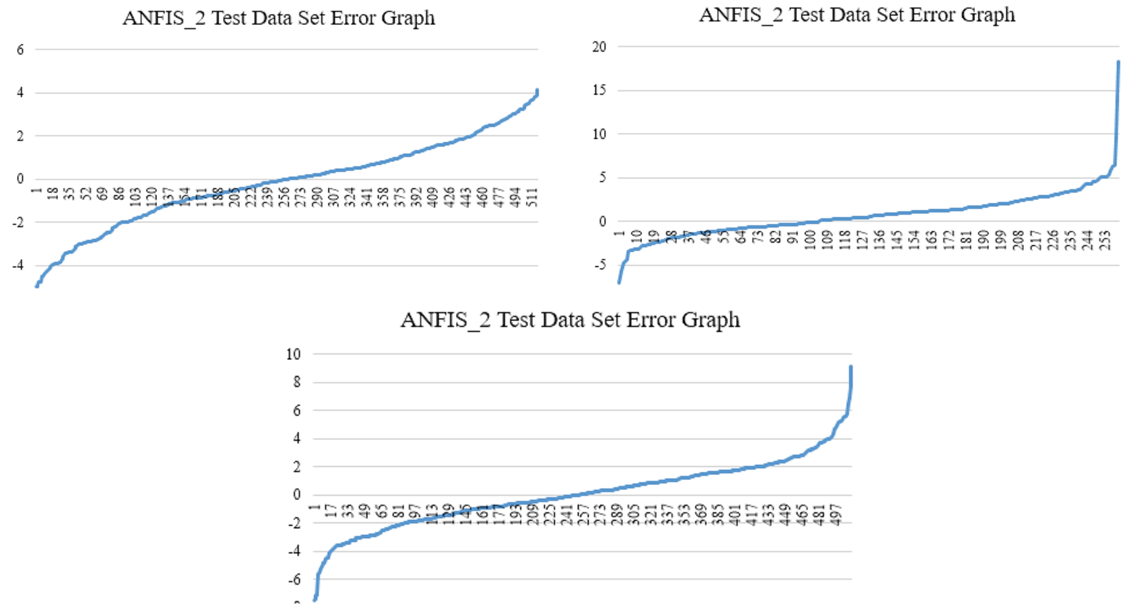

Figure 11. ANFIS_2 test dataset error graph

3.3. Position detection model

ANFIS_1 and ANFIS_2 are developed with the logic that x and y coordinates are separate inputs and outputs. The object at any (x, y) point detects the values between RSSI1-RSSI5, and the main idea of this study is to find the unknown x,y values from these data with minimum deviation. The flow of the computational steps of the proposed new model is shown step by step in Table 5. In summary, the dataset used to train the ANFIS model is acquired through a hardware setup in the workspace and stored in a database table. This dataset is then partitioned into training, testing, and validation subsets. Following the allocation of values to these subsets, the models are trained using the training data. The post-training ANFIS models consist of two separate models, both employing the same dataset and parameters but different inputs. The first model is designed to generate y'-coordinate information as output for each x-coordinate data, using the RSSI information from the training dataset and the corresponding x-coordinate information as input. The second model is configured to take the nine RSSIs from the training dataset and the associated y-coordinate data as input, producing x'-coordinate information as output for each y-coordinate data. The goal is to find a point that corresponds to the [(x, y')] matrix produced by the first model and the [(x', y)] matrices produced by the second model, aiming to locate the same point.

Table 5. Proposed System Process Steps

Proposed System
• ANFIS_1 Input → [x , RSSI1-5], Output → [y]
• ANFIS_2 Input → [y , RSSI1-5], Output → [x]
• The environment (represented by "T") where position sensing is to be performed is divided into grids with x and y coordinates at 0.5-meter intervals. x → [0.5, 1, 1.5, 2, … 50] y → [0.5, 1, 1.5, 2, … 50]
• The sample object to be located (represented by "O") is at an unknown point (x, y) in the environment T.
• The RSSI=[RSSI1, RSSI2, RSSI3, RSSI4, RSSI5] values received by O at this point are read.
• ANFIS_1 Model: Calculates [y'] values for each x grid value within the [RSSI] vector and the [x] vector. ○ [x] ANFIS_1 [RSSI] → generates the vector [y'].
• ANFIS_2 Model: Calculates [x'] values for each y grid value within the [RSSI] vector and the [y] vector. ○ [y] ANFIS_1 [RSSI] → generates the vector [x'].
• Two different possible location maps are created, represented by ([x, y']) and ([x', y]) matrices, trained with different input and output parameters. Here, the study is finalized by searching for the points where the [RSSI] vectors form a similar pattern in both matrices and determining the point that is closest to each other as the location point of O.

3.4. Testing the system developed for positioning

The test of the success of the proposed system can be examined by following the steps summarized in Table 5 on a sample point taken from the Test Datasets. The model is tested by selecting the measurement data of any point produced in "Test Dataset 1", shown in Table 6.

Table 6. Proposed System Process Steps

x	y	RSSI Values				
42	17	-65.8	70.3	-67.7	-65.7	-69.1

As shown in Figure 12, RSSI values and x were presented to the model one by one by increasing x by 0.5 m intervals, and y' values were calculated. With the same approach, as shown in Figure 12, RSSI values and y were incremented by 0.5 m intervals and presented to the model one by one, and x' values were calculated. When the representative positioning graphs of all values produced by the ANFIS models are examined, it is seen that some values are out of interest or even unacceptable values. As shown in Figure 13, when the outputs produced by the two ANFIS models are combined in a graph, it is easily understood that the unknown (x, y) position values of the searched object are actually the same point calculated separately by both models.

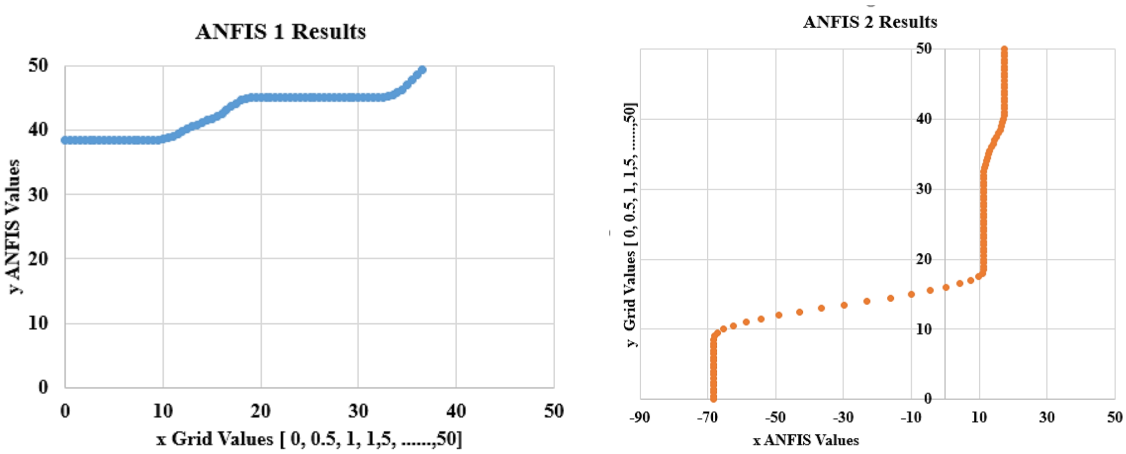

Figure 12. ANFIS_1 and ANFIS_2 model results

As shown in Figure 13, the desired set of location values consists of coordinate values where the results generated by ANFIS_1 (blue circles) and ANFIS_2 (orange circles) intersect or are in close proximity. To pinpoint the precise point, the distances between the points produced by the two models are computed, and only points that are within a specific tolerance are further examined, while those outside this tolerance are excluded from the analysis. In this process, the emphasis is placed on the Region of Interest (ROI) area, where the points calculated differently by the two models are in close proximity to each other.

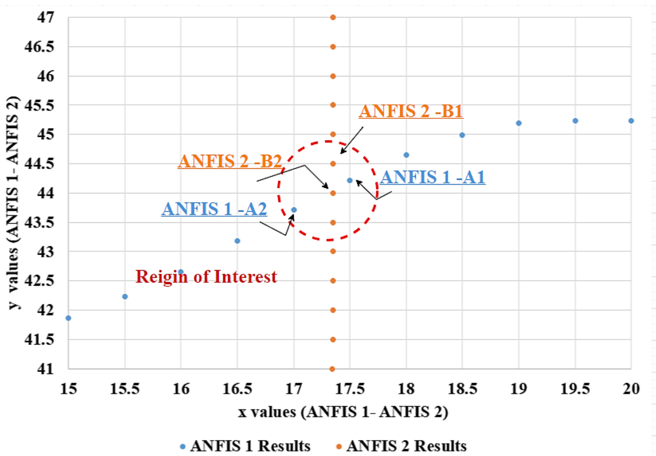

Figure 13. ANFIS models results (together)

The distances of the points (x, y') and (x', y) are calculated by the equation given below, similar to the Euclidean formula.

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (2)$$

As shown in Figure 12, close points are identified as ROIs, and examinations are continued on the calculated values. As can be understood, the number of points, initially 50x50, is reduced to 4 points in this example.

As shown in Figure 12, A1 and A2 correspond to points generated by ANFIS_1, while B1 and B2 represent points generated by ANFIS_2. It is assumed that the point pairs in groups A and B actually correspond to the same location, as intended during model creation. Consequently, we aim to identify which pairs represent the same points by assessing the proximity between A1 and B1 or A2 and B2. If we reduce the tolerance value applied for the test to 4 points, the number of points in various scenarios may increase. Hence, the same relationship, as described earlier, should be extended to include these points. Table 7 provides a summary of this process. The primary goal of this procedure is to determine the desired location information, which is calculated by Model 1 and Model 2 using different parameters but represents the coordinates of the same point within the measurement area. The proximity of the points plays a crucial role, effectively employing a small clustering method.

Table 7. Algorithm of Choosing the Best Point

Choosing Best Point
• Calculate distances between points calculated by ANFIS_1 and ANFIS_2 models (pairs A and B)
○ A1→ (x_{A1} , y_{A1}) A2→ (x_{A2} , y_{A2})
○ B1→ (x_{B1} , y_{B1}) B2→ (x_{B2} , y_{B2})
○ A1→ B1 and A2→ B2
• Identify the smallest distance between these pairs of points
○ Distance between A1 and B1 → d1
○ Distance between A2 and B2 → d2
• Combine coordinates in short-distance pairs
○ If d1 < d2, the searched position = (x_{A1} , y_{B1})
○ If d2 < d1, the searched position = (x_{A2} , y_{B2})

Table 8 shows the implementation of the algorithm summarized in Table 7 on the sample test data.

Table 8. Developed Model Point Calculation Values

<table>
<tr><th colspan="4">Model Point Calculation Values</th></tr>
<tr><td rowspan="5">Coordinates of Reducing Points</td><td></td><td>y coor.</td><td>x coor.</td></tr>
<tr><td>A1</td><td>17.5</td><td>42.81</td></tr>
<tr><td>A2</td><td>17</td><td>43.71</td></tr>
<tr><td>B1</td><td>17.31</td><td>43</td></tr>
<tr><td>B2</td><td>17.34</td><td>44.5</td></tr>
<tr><td rowspan="2">Distances Between Points</td><td colspan="2">A1 → B1</td><td>A1 → B2</td></tr>
<tr><td colspan="2">0.34</td><td>0.86</td></tr>
<tr><td rowspan="2">Sought Point</td><td colspan="2">x coor.</td><td>y coor.</td></tr>
<tr><td colspan="2">42.81</td><td>17.31</td></tr>
<tr><td rowspan="2">Test Point</td><td colspan="2">x coor.</td><td>y coor.</td></tr>
<tr><td colspan="2">42</td><td>17</td></tr>
</table>

To examine the results of the model's success, the data calculating the distances (errors) between the point values produced by the model for 2 different points selected from each test set are listed in Table 9.

Table 9. Outputs of Test Data

	Item No	x Coordinate Test	y Coordinate Test	x Coordinate ANFIS Model	y Coordinate ANFIS Model
Test 1	1	27	29	27.74	26.94
Test 2	2	34	24	33.45	25.13
Test 3	3	4	20	3.3422	19.45
Test 1	4	30	21	31.03	21.73
Test 2	5	31	4	31.65	4.873
Test 3	6	14	18	13.237	16.93

A visual comparison of the test data generated by the ANFIS system, which has never been presented to this system before, is shown in Figure 14.

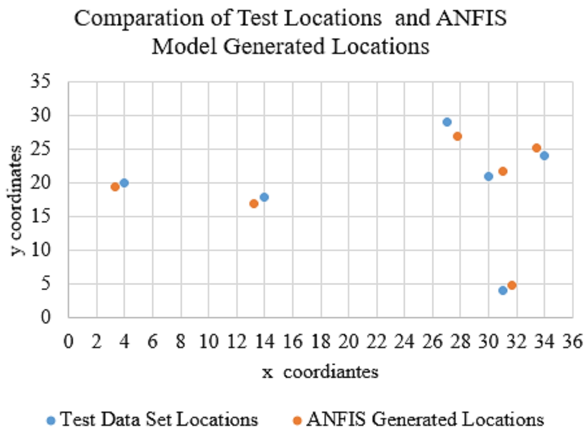

Figure 14. Visual comparison of test data and ANFIS data

4. Discussion and Conclusion

The importance of indoor positioning technologies and methods is constantly increasing due to the high number of applications developed on the concept and its wide range of applications. Moreover, the increasing prevalence of the Internet of Things (IoT) serves as another factor that elevates the significance of indoor positioning. In this context, achieving the most precise and consistent indoor positioning is a pivotal stride toward establishing an efficient indoor positioning system. Extensive research has been conducted at both academic and industry levels to attain this objective. Differing from its counterparts in the existing literature, this study endeavors to design an indoor positioning system utilizing the ANFIS model, aiming to enhance its performance. While "RSSI-based technologies offer advantages such as simplicity of use, easy installation, no requirement for specialized equipment, cost-effectiveness, high energy efficiency, and seamless integration into numerous ecosystems, the "Fingerprint" method presents advantages in terms of being cost-free, flexible, and compatible with a wide range of devices and environments. An enhanced model is introduced, rooted in the ANFIS theory, which is one of the machine learning methodologies.

To determine the unknown locations of the objects in the ROI area, RSSI values and possible location (x, y) values are presented to the system separately for ANFIS training. With two different ANFIS models, the location information was generated by determining the closest ones to the solution from the x' and y' location information produced by these inputs.

The dataset shown in Figure 5 was created not by measuring the entire indoor environment where the measurements were made very precisely but by measuring more superficial and intermittent measurements. The aim here is to demonstrate the success of the proposed model in such an environment by using a dataset that does not represent the environment very well. As shown in Table 7 and Figure 14, the model produced good performance despite this disadvantage of the data set. With this study, a different approach has been used that will shed light on similar studies in the literature, and an acceptable improvement has been achieved.

The results obtained in this study also provide information about the design and installation of the system in an indoor environment. To achieve a satisfactory success rate, parameters such as the number and placement of access points in the system, the number of data, and the data collection method should be well determined. In future studies, the system's success can be increased by determining these parameters more optimally. A machine learning approach can be used for better placement of access points and a better balance between cost and accuracy. Considering the importance of correctly training machine learning models for the system's success, the system can be trained with more training data.

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