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Adaptive neuro-fuzzy Inference System(ANFIS) localization model for enhanced position estimation in Wireless Sensor Networks

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Abstract
Accurate localization plays a key role in the performance of Wireless Sensor Networks (WSNs), especially when deployed in anisotropic environments where irregular signal propagation leads to large positioning errors. In this study, an Adaptive Neuro-Fuzzy Inference System (ANFIS) based localization model is developed using Received Signal Strength Indicator (RSSI) values as input and estimated node distances as output. The proposed system integrates the learning ability of neural networks with the linguistic reasoning of fuzzy logic and is implemented using a Sugeno-type fuzzy inference structure. The model is trained using 100 RSSI samples, and performance is evaluated using Root Mean Square Error (RMSE) and Relative Localization Error (RLE). Simulation results demonstrate that the proposed ANFIS model significantly improves localization accuracy compared to traditional fuzzy and ANN methods. The RLE results show a decreasing trend as the number of anchor nodes increases, and the bell-shaped membership function delivers the lowest RMSE value among all tested configurations. The findings confirm that the proposed ANFIS-based model provides an effective and scalable solution for accurate localization in anisotropic WSN environments.

Keywords: RMSE, rle, anfis, wireless sensor networks, anisotropic environments

Introduction

Wireless Sensor Networks (WSNs) have emerged as one of the most important technologies in modern communication systems due to their capability to sense, process, and transmit data autonomously. They are widely deployed in critical applications such as environmental monitoring, healthcare systems, smart agriculture, disaster response, industrial automation, and military surveillance [1].

In most of these applications, the physical location of a sensor node plays a vital role, as the sensed data is meaningful only when associated with an accurate geographical reference. As a result, localization has become a fundamental research area within the domain of WSNs. However, achieving accurate localization remains a major challenge, especially in anisotropic environments where environmental conditions and unpredictable signal propagation patterns adversely affect localization performance [2].

Traditional localization approaches, including Received Signal Strength Indicator (RSSI)-based techniques, range-free methods, multilateration, and centroid algorithms, often suffer from significant inaccuracies due to environmental noise, multipath fading, irregular radio propagation, and limited anchor nodes [3]. Range-based methods such as Time of Arrival (ToA) and Time Difference of Arrival (TDoA) offer accuracy but require specialized hardware, leading to increased cost and energy consumption. Therefore, recent research has shifted toward intelligent computational models capable of adapting to real-world uncertainties and noise-driven conditions commonly found in WSN deployments [4].

Artificial intelligence (AI) and soft computing techniques have shown increasing potential in improving localization accuracy. Machine learning models, including neural networks and fuzzy logic systems, have been implemented to analyze nonlinear relationships between RSSI and distance [5]. However, neural networks require large training datasets and lack interpretability, while classical fuzzy logic systems struggle to optimize their rule sets and membership function parameters during real-time learning. To overcome these limitations, hybrid intelligent systems such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have gained attention as they combine the adaptive learning capability of neural networks with the reasoning capability of fuzzy systems.

ANFIS provides a structured framework capable of learning and optimizing fuzzy if–then rules through a training process, enabling it to model highly nonlinear systems accurately. When applied to WSN localization, ANFIS can interpret RSSI variations caused by anisotropic environmental characteristics and produce more accurate distance estimations. Its ability to refine membership functions and rule bases during training improves the performance over classical fuzzy logic and standalone artificial neural networks [6].

Despite several advancements, achieving a balance between accuracy, computational efficiency, and scalability remains a challenge. There is still a need for lightweight and reliable localization models capable of maintaining accuracy across varying noise conditions, limited anchor nodes, and dynamic deployment environments [7]. This research contributes to ongoing efforts by proposing and evaluating an ANFIS-based localization framework designed for anisotropic WSN environments. Using RSSI as the input and applying MATLAB-based simulation, the system is evaluated using standard accuracy metrics such as Root Mean Square Error (RMSE) and Relative Localization Error (RLE). The findings demonstrate that ANFIS has strong potential to deliver improved localization performance and serve as a feasible approach for real-world WSN deployments [8].

Methodlogy

- **Establishment of ANFIS Structure**

The ANFIS system is founded on the integration of information, methods, and approaches derived from many diverse sources. Some fundamental rules for constructing fuzzy set 'IF_THEN' rules with membership functions may be derived from the ANFIS approach.

These algorithms are utilized to produce a predetermined input-output equivalence by combining the methods of least squares estimation and Back Propagation (BP). The membership functions modify this Input_Output Information (IOI). The initialization of FIS with a BP algorithm is performed in ANFIS after collecting IOI. Thus, the FIS and NN are the two complementing techniques employed in ANFIS. The main goal is to integrate a neural network with a fuzzy inference system (FIS) to optimize the learning capacity of the neural network, which is advantageous from the perspective of the FIS. From the perspective of a neural network, this system offers several inherent benefits.

This study examines the logic of language rules and proposes an integration that efficiently simplifies the learning processes in the current FIS. The FIS has three phases: (i) a database with membership functions embedded in the fuzzy rules, (ii) a rule-based structure that chooses the fuzzy rules, and (iii) a reasoning strategy that makes inferences based on the rules and given facts to provide a logical output. This Fuzzy Inference System (FIS) utilizes two systems, Takagi_Sugeno and Mamdani, to process the results. The Takagi_Sugeno approach is a computationally efficient and compact system that allows for the deployment of an adaptive methodology utility to construct fuzzy systems, surpassing the Mamdani method.

Accurate data modeling in the FIS system is achieved by implementing Adaptive Learning Techniques (ALTs) to optimize fuzzy membership functions, known as ANFIS. However, the combined use of FIS and NN results in ANFIS, which outperforms both ANN and FL approaches. The ANFIS system executes a multitude of membership functions and selects a suitable type to guarantee optimal performance. Thus, the minimization of mistakes is achieved during the training and data monitoring procedure.

To simplify the adaptation and learning process, our suggested ANFIS approach is built on a fuzzy Sugeno paradigm. The Takagi_Sugeno is an implementation of the Sugeno fuzzy paradigm, which is a systematic approach for developing fuzzy rules based on an input/output dataset. The ANFIS model takes into account three inputs: RSSI values, distance output, two rules, and the first-order Takagi_Sugeno method. The FIS regulations are presented in the equations below.

Regulation 1: If x = $A_1, y = B_1$ and z = c_1, then $g_1 = m_1 x + n_1 y + p_1 z + r_1$

Regulation 2: If x = $A_2, y = B_2$ and z = c_2, then $g_2 = m_2 x + n_2 y + p_2 z + r_1$

Let x, y, and z denote input vectors, and g signify an output function.

Ai, Bi, and Ci signify the membership functions of the inputs, while p, m, n, and r represent the output variables.

Figure illustrates the architectural framework of ANFIS. This structure consists of five layers that can be achieved through various approaches. The diagram illustrates circular and square nodes, with the circular node denoting a fixed node and the square nodes designated as adaptive nodes. The ANFIS architecture is illustrated in the figure below.

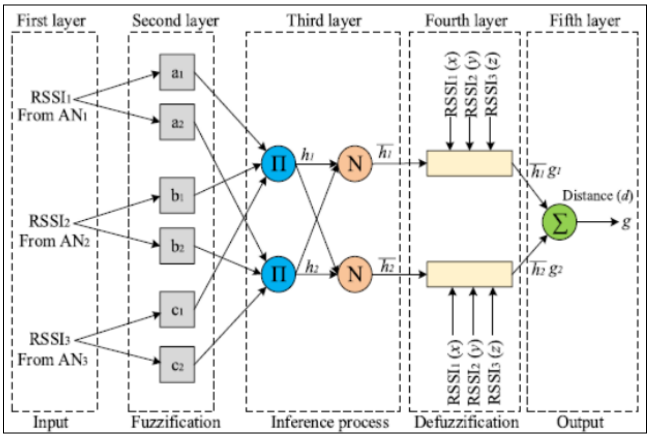

Fig 1: ANFIS framework

- **First Layer (Input)**

The first layer (mfs) is the starting layer with input variables. Within this layer, every individual node is regarded as an adaptive node. The adoption of the generalized bell-shaped membership function (bell mf) is based on the output values of the nodes in this layer, as represented by Equation (3.7). This output contains membership functions that incorporate input values of degrees and also achieve fuzzification in this layer. The curvilinear magnetic field (MF) with a minimum value of 0 and a maximum value of 1, as defined in Equation

$$\mu A_i = {}^{1}/[\,1 + / \,(x - c_{i)/a_i} \,/\, 2b_i] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.1)$$

Here, the variables a_i, b_i, and c_i denote the parameters that might alter the structure of the bell mf equation. The bell-shaped magnet-force fields have the benefit of being uniformly smooth and non-zero at every place.

Consequently, these characteristics are utilized to adjust the input membership degrees. These modifications occur throughout the network's training phase. Alternative forms of multifractal functions (MFs) that may be utilized encompass trapezoidal, triangular, Gaussian, and pi-shaped curves, the difference between two sigmoid functions, two-sided Gaussian curves, and the product of two sigmoid functions.

Within the first layer, the output values ($0_{1,i}$) are represented by Equation (3.8). The RSSI values are obtained from the data inputs associated with AN1, AN2, and AN3 correspondingly.

$$0_{1,i} = \mu A_i \text{ (x)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.2)$$

Secondary Layer

In the second layer, the nodes are depicted as square shapes, and the output is derived by employing t-norm operators on the input signals. In this implementation, the FIS process is conducted, and the output of each node signifies the level at which the rule is applied. Determine the firing level by multiplying the magnetic field strengths (MFS) of all inputs. The output layer (O2; i) can be quantitatively expressed by the subsequent equation

$0_{2,i} = h_i\ \mu A_i$ (x) $\times\ \mu B_i$ (y) $\times\ \mu c_i$ (z) i=1,2,3……………………………(1.3)

- **The Third Layer (Regulations)**

The third layer of ANFIS is denoted by the use of circular forms (N). This layer implements a normalization mechanism in which each node's firing vigor is proportional to the overall firing level determined by the ith rule.
Accordingly, the normalized firing level may be represented by Equation.

$$o_{3,i} = h_t = h_i\ (h_1/h_2) \text{ i= 1,2,3} \quad \ldots\ldots\ldots\ldots (1.4)$$

- **Fourth Layer (Out mfs)**

The fourth layer consists of nodes represented by square shapes, at which the output of rule Inference is received as input. This layer establishes an adaptive connection between the firing values of normalization, which is the output of a third layer. And the resultant function (g) correspondingly. This stratum does a defuzzification procedure as described in Equation (3.11).

$$0_{4.1} = h_l g_i = h_l(m_i x + n_i y + p_i z + r_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.5)$$

Let h_l signify a third layer output, while m_i, n_i, p_i, and r_i are outcomes parameters.

- **Output Fifth Layer**

Symbolised by a single circle and designated as P, this layer is the last layer of the ANFIS. The output signal is obtained by summing the input signals from the preceding fourth layer, as shown below. All inputs at each layer are accumulated and then the fuzzy outcomes are transformed into a precise numerical value.

$$0_{s,i} = \sum h_i\ g_i = \sum_i h_i\ g_i\ /\ \sum_i h_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.6)$$

Based on the ANFIS technique (dANFIS), the fifth layer produces the estimated final distance as its final output. Hence, the Mean Absolute Error (MAE) may be calculated using the Analysis of Nonlinearity (ANFIS) as provided in Equation (3.13).

$$\text{MAE} = (\tfrac{1}{k}) \sum_{i=1}^{k} /\ d_{actual} - d_{ANFIS} \quad \ldots\ldots\ldots\ldots\ldots (1.7)$$

Let k be the known and verified number of sample distances based on ANFIS.

Results

A MATLAB implementation of the suggested ANFIS based localization technique. The training process utilizes a total of 100 samples. The model is trained using RSSI values as input and the known locations as the output.
An autonomous node permitted to traverse a predetermined route. The signal propagation route loss model is defined as follows. Equation

$$p_r = p_t + \text{c} - 10\ \eta lg\ (\tfrac{d}{d_0}) + x_\sigma \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.8)$$

Where, In this context, P_t represents the transmitted power (dBm), c is a unitless constant that is influenced by the environment, d_0 is the reference distance, η and is the route loss coefficient. The path loss coefficient x_σ is a Gaussian variable that takes into account fading effects.

Table 1: Calculation of parameter values for simulation

Simulation parameters	Values
p_t	-1dBm
d_0	0.1m
C	-20dB
η	2
N	100
N	50
$\sum$	4.5 dB

Comparative analysis of the proposed ANFIS model with FUZZY and ANN models using Relative Localization Error (%) and Root Mean Square Error (RMSE). Utilizing Equation (3.15), the Relative Localization Error (%) of the suggested model is computed.

The Relative Localization Error (%) = $\frac{1}{(N} \sum_{i=1}^{N} RLE_i)\ \times 100$ is calculated as (3.15) times the difference between the real and tested distances, where k is the number of samples. The root mean square errors (RMSEs) of the proposed localization are computed as follows Linear equation

$$\text{RMSE} = \sqrt{\tfrac{1}{N} \sum_{i=1}^{n} (d_{actual} - d)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.9)$$

Table 2: RLE performance estimation of the ANFIS model

Number of anchor nodes	RLE-%		
	FUZZY	ANN	ANFIS
2	21	18	14
3	15	12	9
4	14	10	6
5	11	8	4
6	7	7	3

Figure 3 displays the RLE performance of the ANFIS model. The proportion of RLE decreased as the number of anchor nodes increased. ANFIS has the lowest Reduced Linear Error (RLE) in comparison to other approaches.

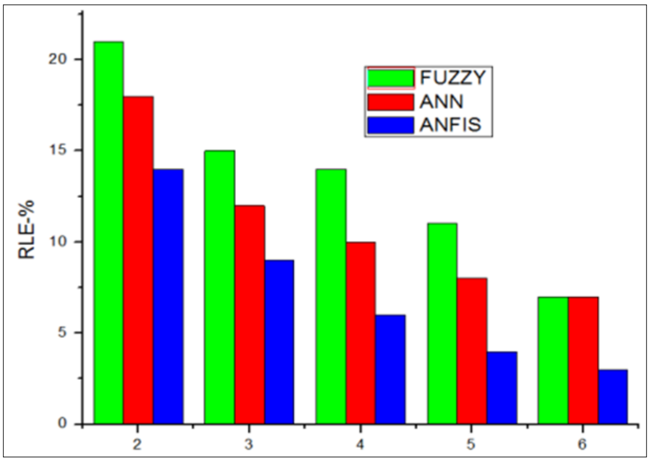

Fig 3: RLE performance of the suggested ANFIS model

Table 3 presents the RMSE performance assessment of the ANFIS model for different membership functions. Various membership functions were trained and evaluated for the proposed model, including the Gaussian curve (gauss), two-sided Gaussian curve (gauss2), a difference of two sigmoids (design), a product of two sigmoids (psig), triangular (tri), trapezoidal (trap), pi-shaped curve (pi), and bell-shaped (bell) functions. The computational model was executed for 1,000 epochs. Among all the membership functions, the bell-shaped mass function yields superior results.

Table 3: RMSE assessment of the ANFIS model

mf type	RMSE		
	Three mfs	Five mfs	Seven mfs
Tri	3.77	2.26	1.30
Trap	4.07	2.62	2.64
Gbell	3.4	1.58	0.05
Gauss	3.68	1.74	0.52
gauss2	3.51	1.50	1.25
Pi	3.76	2.36	2.50
Dsig	3.66	2.39	1.01
Psig	3.54	2.06	1.01

Conclusion

The proposed ANFIS-based localization model successfully enhances positioning accuracy in anisotropic wireless sensor environments, demonstrating clear improvement over traditional fuzzy and neural-network-based localization techniques. The results confirm that increasing anchor nodes reduces localization error, indicating that the model performs efficiently even under irregular signal propagation conditions. Membership function analysis further showed that the bell-shaped function achieved the lowest RMSE values, making it the most suitable configuration for the tested dataset. Overall, the evaluation confirms that ANFIS is a reliable and adaptable approach for WSN localization, offering improved precision without increasing computational cost significantly. Future work may include validating the model on real-time hardware deployments and integrating hybrid optimization to further enhance convergence and robustness.

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