Efficient Artificial Intelligent-based Localization Algorithm for Wireless Sensor Networks

M. Abdelhadi, M. Anan, and M. Ayyash

***Abstract*—Recent advancement in wireless communications and electronics has enabled the development of Wireless Sensor Networks (WSN). WSNs are being deployed in a variety of location-aware applications, where the measurement of data is meaningless without accurate location. Many localization algorithms have been proposed in order to increase the accuracy and minimize the cost requirements. Artificial intelligence techniques such as fuzzy logic and neural networks can be utilized as effective methods to satisfy these requirements. In this paper, we present two efficient artificial intelligence-based localization algorithms for WSNs. In the first algorithm, we implement a Sugeno-type fuzzy system with a collaborative communication feedback to achieve an accurate and cost effective two-dimensional (2D) localization system. In the second algorithm, the idea of the 2D localization using neural network is extended to achieve a three-dimensional (3D) localization with simplicity, location accuracy, and low cost. The proposed approach is able to localize mobile nodes with unpredictable movement patterns. The simulation results depict the performance and the effectiveness of each approach.**

***Index Terms*— Wireless sensor network, Fuzzy logic, Neural networks, Localization, Location accuracy, Mobility.**

I. INTRODUCTION

RECENT advances in radio communication and Micro-Electro-Mechanical Systems (MEMS) have enabled the proliferation of Wireless Sensor Networks (WSNs). WSNs are complex wireless networks of wireless nodes equipped with a variety of sensors including infrared, ultrasonic, pressure, cameras, sonar, radar, and orientation to support different types of sensing functionalities. Sensor nodes are fitted with at least one microcontroller, which provides the processing capability. They are also equipped with RF transceiver with usually an omnidirectional antenna to allow the communication with each other or a central unit. As for the power source, sensor nodes usually rely on small batteries with a limited lifetime and sometimes rely on solar cells. These tiny sensor nodes, which consist of sensing, data processing, and communicating components, influence the idea of sensor networks based on collaborative effort of a large number of nodes. WSNs have broad applications in scientific data gathering, performing search and rescue operations, real-time information processing for disaster response, surveillance, security, and military applications [1].

One of the fundamental challenges and active research areas in wireless sensor networks is node localization. Node localization refers to determining the physical location of each node in the network. Most WSN applications need to have location information of the sensor nodes in order to make the measured data significant. Node localization is required to report the origin of events, assist group querying of sensors, routing and to answer questions about the network coverage [2]. Also, location information is used in many location-aware applications such as navigation, tracking, searching, and rescue operations [3]. One way to localize sensor nodes is by using Global Positioning System (GPS) on each node. Unfortunately, many prerequisites have to be met for proper GPS function. The GPS antenna must have an unobstructed line-of-sight to the sky, making it difficult for use indoors or in urban canyons. Also, the power consumption of such devices greatly shortens the lifetime of the sensor nodes. Moreover, in a network with large number of nodes, using GPS significantly increases the production cost of each node. For these reasons, an alternate solution of GPS is required, and it should be cost efficient, rapidly deployable and can operate in diverse environments.

Many localization algorithms have been proposed to overcome GPS problems and to provide efficient localization. Localization algorithms for WSNs can be classified into two main categories: the range-based approaches and the range-free approaches [4]. Range-based localization algorithms require precise internode measurements like distance or angle. Such measurements require extra hardware implementation and therefore become costly. Furthermore, the power consumption in these localization algorithms is high, and influences the lifetime of sensor nodes. On the other hand, the neighbor distance/angle information is assumed to be unavailable for node localization in range-free algorithms. Hence, such algorithms usually rely on the information of proximity of the reference nodes to estimate the location. Although range-based localization algorithms provide more accuracy, range-free localization algorithms are simpler, faster and more economical. However, the appropriate localization technique heavily depends on WSN intended application.

In this paper, we propose two efficient localization algorithms for WSN using artificial intelligence techniques: Fuzzy Logic [5] and Neural Networks [6]. The proposed approaches address some of the major problems in node localization such as cost, accuracy, 2D/3D case, and mobility. They primarily aim to localize all sensors in a network given a minimum static set of well-known location reference nodes.

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II. Related Work

A. Node Localization using Fuzzy Logic

The ability of fuzzy logic to describe the expertise in more intuitive, human-like manner and to works well with optimization, adaptive, and non-linear techniques have enabled the propagation of a lot of fuzzy-based applications, including WSNs applications. Fuzzy logic can be used without additional hardware implementation to perform fast reasoning, and data processing. In [7], the authors propose a range-free localization algorithm that uses the broadcasted anchor node position $(\mathrm{X_i}, \mathrm{Y_i})$ by anchor beacons. In their algorithm, each sensor node computes its position as a centroid of the positions of all connected anchor nodes to itself by:

$$(\mathrm{X_{est}}, \mathrm{Y_{est}}) = \left(\frac{\sum_{i=1}^{n} \mathrm{X_i}}{\mathrm{N}}, \frac{\sum_{i=1}^{n} \mathrm{Y_i}}{\mathrm{N}}\right) \quad (1)$$

where $(\mathrm{X_{est}}, \mathrm{Y_{est}})$ represents the estimated position of the sensor node and is the number of the connected anchor nodes to the sensor node. The scheme is simple and economic. However, it shows large localization errors. An improved version of [7] was proposed by the authors of [10]. In their approach, the location of a sensor node is calculated by using edge weights of anchor nodes, which is connected to that sensor node. Therefore, each sensor node computes its position by:

$$(\mathrm{X_{est}}, \mathrm{Y_{est}}) = \left(\frac{\sum_{i=1}^{n} \mathrm{X_i} \times \mathrm{w_i}}{\sum_{i=1}^{n} \mathrm{w_i}}, \frac{\sum_{i=1}^{n} \mathrm{Y_i} \times \mathrm{w_i}}{\sum_{i=1}^{n} \mathrm{w_i}}\right) \quad (2)$$

where $\mathrm{w_i}$ is the edge weight of i^{th} anchor node connected to the sensor node. The performance of this approach highly depends on the design of the edge weights and the number of anchor nodes involved in the localization process. In [19], the authors propose a combined Mamdani-Sugeno fuzzy approach that relies on the weighted average formula used by [10], in order to estimate the position of a sensor node. The approach shows good results. However, it deploys many anchor nodes comparing to the number of the sensor nodes, which is not cost efficient and is hard to be deployed in large areas. Another similar approach is proposed by [8]. The approach uses the weighted average formula used by [10, 19], to calculate the estimated position of a sensor node. However, it uses a lower number of anchor nodes than [19]. Also, it is used for indoor tracking and sensor nodes need to be deployed somewhere near the middle of the testing environment in order to get accurate results.

B. Node Localization using Neural Networks

Successful training can result in artificial neural networks that perform tasks such as predicting an output value, classifying an object, approximating a function, recognizing a pattern in multifactorial data, and completing a known pattern. Hence, neural networks can be used for any complex application including the localization of WSNs. Although neural networks are not commonly used in localization, there is some work in that area. In this section, we summarize some of the related work to three-dimensional (3D) localization and localization using neural networks.

In [11], the authors propose a 3D-Weighted Centroid Localization algorithm (3D-WCL). The algorithm restricts the number of anchor nodes involved in the localization process by setting the weight to either 0 or 1 to each. The approach reduces the cumulative error caused by the variation in the Received Signal Strength Indicator (RSSI) values. Although this approach achieves better performance than the traditional Monte Carlo Localization (MCL) algorithm [12], it requires a large number of anchor nodes, which is hard to be deployed in reality. The authors of [13] followed a similar approach by using Mamdani and Sugeno fuzzy interface system to determine the weight of each anchor node. The system shows better performance than the simple centroid method. However, large number of anchor nodes must be deployed to achieve good results. In [14], the authors propose a Complexity-reduced 3D trilateration Localization Approach (COLA) based on RSSI values. In this approach, a set of super anchor (SA) nodes are utilized for range estimation. The sensor nodes need to find the reference nodes that lie on the same x-y plane to reduce the 3D localization to 2D. The COLA approach achieves high location accuracy. However, to achieve good results, super anchor nodes need to be distributed uniformly, which is hard to be achieved in reality.

In [15], the authors propose a recursive localization algorithm in 3D wireless sensor networks. The approach requires at least three anchor nodes to locate one sensor node. Also, it implements a recursive method for propagating position information throughout a sensor network given a limited number of reference nodes. The approach shows better performance than APIS [16] and the novel centroid algorithm [17].

In [18], the authors compare the efficiency of using neural networks with Kalman filter in the 2D localization. They also compare the usage of three main types of neural networks (MLP, RBF, and RNN) in localization in terms of accuracy and memory requirements. As a result, they show that neural networks in general provide better accuracy than Kalman filter, where noise parameters are not expected to change. In contracts, Kalman filter is the best option if a flexible and easily modifiable method is required. Also, they show that neural networks perform well only for the area in which they have been trained. If the tracked object passes beyond the boundaries of the area where the neural network has been trained, the neural network will not be able to localize. As for the types of neural networks, they show that MLP neural network provides the best trade-off between accuracy and memory requirements. In this paper, we extend the work presented by [18] to achieve a 3D localization with location accuracy, mobility, and low cost.

III. Proposed Approaches

A. A Fuzzy-based Collaborative Localization Algorithm for Wireless Sensor Networks

Using artificial intelligence in general and fuzzy logic in particular provides fast node localization. Fast node localization is highly important for mission-critical applications, where the delay is not accepted [9]. In this section, we propose a fuzzy-based localization algorithm with a collaborative communication feedback. The proposed algorithm is a range-free algorithm and it relies on RSSI measurements across the wireless channel to determine the distance between the anchor nodes and the sensor nodes. The algorithm implements a Sugeno-type fuzzy interface system to determine the estimated location of each sensor node. The algorithm is centralized in which it requires the presence of a central processing unit to enhance the localization process. In order to improve the accuracy of the localization, we integrate a collaborative communication feedback, which allows sensor nodes to assist anchor nodes in the localization process without extra hardware implementation. The proposed approach is a 2D approach and the wireless network is stationary. Furthermore, in order to increase the accuracy of the estimation, we implement a collaborative communication feedback, which gets the ordinary sensor nodes involved in the localization process along with the anchor nodes. The proposed approach takes the advantage of the accurately located nodes to enhance node localization in cost efficient way.

The proposed approach consists of two main phases: phase I and phase II, where both of them operates in the awake cycle of the sensor node. In this approach we assume that each sensor node is synchronized with at least four anchor nodes. Therefore, it can exchange data with them on the same cycle and is able to listen to location beacons. Location beacons are important to determine the distance to each anchor node. In the communication process of phase I, which is shown in Figure 1, each anchor node frequently transmits beacons to broadcast its position. Sensor nodes periodically listen to these beacons, and once a sensor node receives at least four beacons from four different anchor nodes, it stops listening to more beacons. After that, the sensor node gets the positions of the four anchor nodes from the received beacons and calculates the distance to each anchor node. The distance to each anchor node is calculated by measuring RSSI values of each signal. RSSI is implemented in almost every sensor node and does not require extra hardware implementation. After calculating the distances, each sensor node uses the fuzzy-based system, which is shown in Figure 2, to get its estimated initial position.

The fuzzy-based system has a Sugeno-type FIS, which in turn has one input and one output. The input of the FIS is the calculated distances from the received beacons, and the output is the weight values that interpret the distances. Each weight value that represents certain distance is obtained based on the fuzzy rules that described in Table I. The relationship between the distance and the weight is an inverse relationship. The weight value is important because it determines the effect of each anchor node on the localization of each sensor node. The weight value varies between 0 and 1, and it is controlled by the value of the distance. If the distance to one of the anchor nodes is small, the weight value is high and this indicates that the effect of that anchor node in localization is high. In contracts, if the distance is high, the effect of the anchor node will be small. Therefore, the weight value will be small. The distance is set to have five truth values. A = {*low, slightly low, medium, slightly high, high*}. The membership functions of the distance are shown in Figure 3. Two types of membership functions are used: trapezoidal and symmetric triangles membership functions.

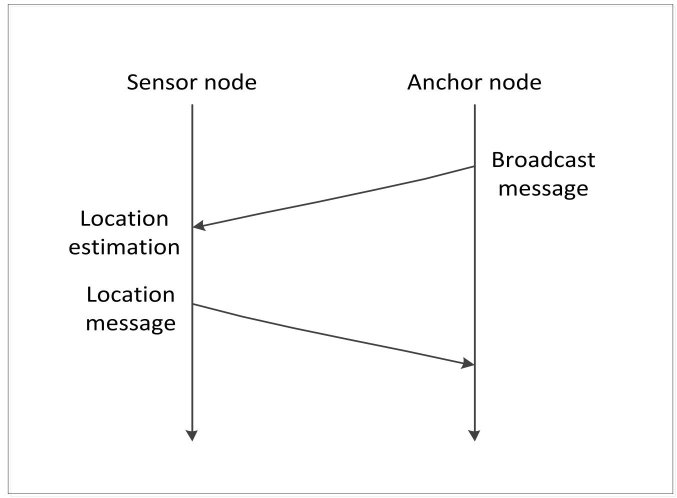

Fig. 1. The communication process of phase I

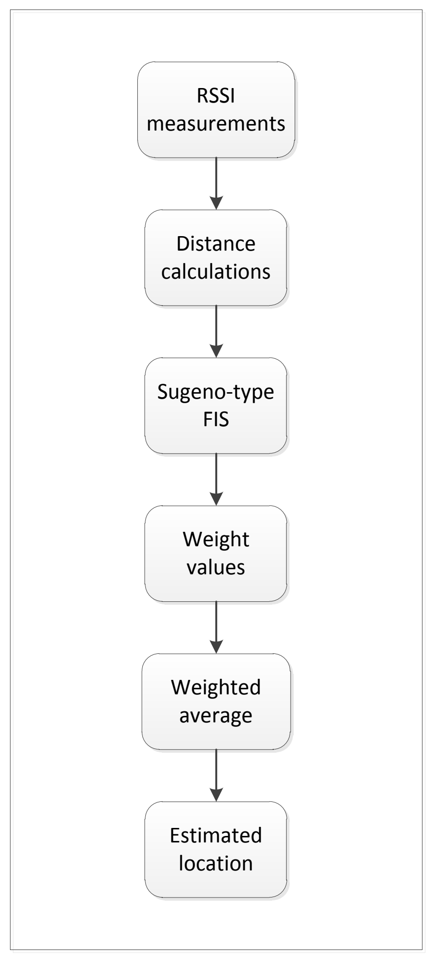

Fig. 2. Fuzzy-based system used by each sensor node

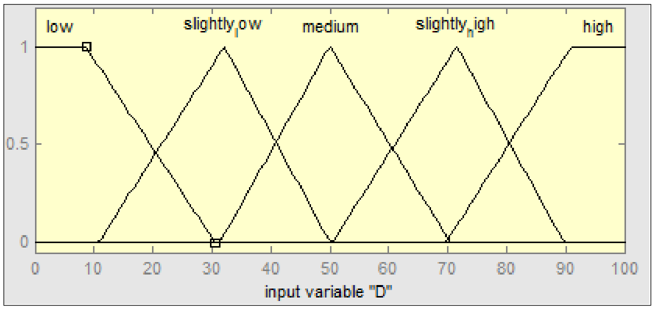

Fig. 3. Distance membership functions

Table I

Fuzzy rules for the proposed approach

Rule	**IF: Distance is**	**THEN: Weight is**
1	Low	High
2	Slightly low	Slightly high
3	Medium	Medium
4	Slightly High	Slightly low
5	High	Low

The relationship between the distance and the weight can be described as follows:
IF D is A, THEN W is $W = f(A)$, where D is the distance, W is the weight, A is a set of distance truth values, and f (A) is a polynomial function in the input of A, which describes the output of the system within the fuzzy region specified in the antecedent of the rule to which it is applied. As a result, the output weight value W has five truth values: W = {*low, slightly low, medium, slightly high, high*}, where each one has the following fuzzy region: W(0)= *low*= [0 0.3], W(1) =*slightly low*= [0.1 0.5], W(2) = *medium* = [0.3 0.7], W(3) = *slightly high*= [0.5 0.9], W(4)= *high*= [0.7 1]. The output weight values from the FIS and the positions of the anchor nodes are then used as input arguments in the weighted average formula to calculate the estimated position (X_{est}, Y_{est}) of a sensor node as follows:

$$X_{est} = \frac{\sum_{i=1}^{n}(X_i \times w_i)}{\sum_{i=1}^{n} w_i} \quad (3)$$

$$Y_{est} = \frac{\sum_{i=1}^{n}(Y_i \times w_i)}{\sum_{i=1}^{n} w_i} \quad (4)$$

where X_i and Y_i are the x-y coordinates of the i^{th}anchor node, and w_i is the weight value of the i^{th}anchor node. As a result, each sensor node will have its initial estimated position at the end of phase I.

Weighted average is an important concept in descriptive statistics and mathematics. If all quantities are weighted equally or contribute equally, while calculating the average, it is equal to the arithmetic mean. Weighted average accuracy is highly dependent on two factors: 1) the accuracy of weight values and 2) the number of anchor nodes. As for the first factor, the weight values are calculated from the Sugeno-type FIS, which provides an adaptive interpretation of distance values in a way to get the most representative weight value for each one. Hence, the main advantage of using Fuzzy logic in this approach is get accurate weight values. On the other hand, the second factor depends on the number of anchor nodes, which can be increased in order to achieve higher accuracy. However, this leads to higher production cost and a difficulty in deployment, especially in urban areas. In order to solve this issue, we integrate a communication feedback to apparently increase the number of anchor nodes. The communication feedback is part of phase II.

In phase II, each sensor node sends a location message to one of the anchor nodes that elected to be the master of the network or the cluster. The location message includes the estimated position from phase I. The master node processes and correlates each location and based on the degree of the accuracy, it classifies the nodes into two groups: precisely located (PL) nodes and not-precisely located (NPL) nodes. Here, we assume that the node is precisely located if its localization error is less than 5%, and not precisely located, if its localization error is greater than or equal to 5%. The classification process is important since PL nodes will be used as location references along with the anchor nodes.

After classifying each node, the master node sends an order message to each PL node, which informs it to broadcast its position (see Figure 4). After broadcasting position information by each PL node, each NPL node uses the positions of the PL nodes to recalculate its position again. Each NPL node measures the RSSI value from each broadcasted message, and accordingly calculates the distance to each PL node. As in phase I, each NPL uses the Sugeno-type FIS in Figure 2, to obtain new weight values. By adding the new weight values to the weighted average formula, each node recalculates a new position. The process in phase I will be repeated considering each PL node as an anchor node. Therefore, the number of anchor nodes apparently increases without any physical deployment of new anchor nodes. Consequently, each sensor node will have more localization references, and that increases the accuracy of the weighted average formula and therefore increases the accuracy of the localization. Finally, each NPL node sends back its new estimated location to the master node in a location message.

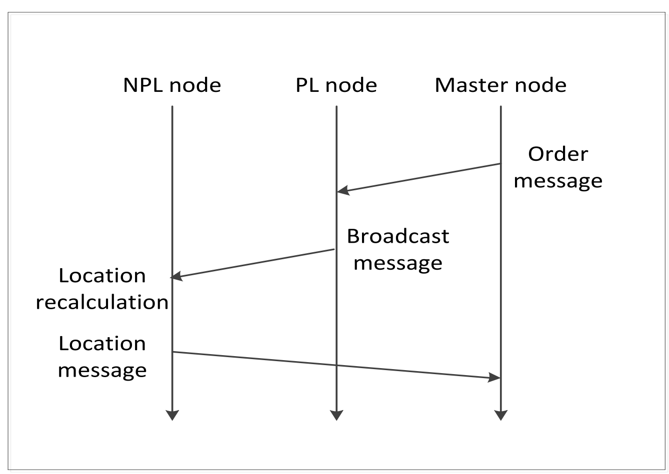

Fig. 4. Communication process in phase II

B. *A Three-Dimensional Localization Algorithm for Wireless Sensor Networks Using Artificial Neural Networks*

Many localization algorithms for WSN have been proposed in the literature. However, localization in three-dimensional (3D) space has not been studied sufficiently. Also, artificial neural networks are not commonly used in localization. In this section, we present a 3D localization algorithm for wireless sensor networks using artificial neural networks. In the proposed approach, the idea of 2D localization using neural network is extended to achieve 3D localization with low cost, location accuracy, and mobility. The first proposed approach relies on fuzzy logic to provide cost efficient way to localize sensor nodes. However, it is designed for 2D localization, and sensor nodes assumed to be stationary. Furthermore, the approach requires the presence of a central unit, which increases the communication overheads and memory requirements. Here, we present a different approach for node localization using artificial neural networks. Although, both approaches are range-free and they depend on the presence of anchor nodes as well as RSSI measurements, they use different artificial intelligence techniques to achieve cost efficient localization. In this approach, the idea of the 2D localization using neural networks is extended to cover the localization in 3D space. The proposed approach is implemented in a distributed way, where each sensor node is able to locate itself without a central unit. Consequently, this reduces the communication traffic and the computing complexity in the network. Furthermore, the proposed approach is capable of localizing mobile nodes that have unpredictable movement patterns.

The proposed approach utilizes three types of sensor nodes: anchor nodes, mobile nodes, and sink nodes. Anchor nodes are used as localization references. Mobile nodes are the nodes that perform the sensing and data gathering operations. Mobile nodes usually have predicted or unpredictable movement patterns, which allow them to move and cover large areas and perform more functionalities. Hence, they are the target of the localization process. In order to save the energy of mobile nodes, sink nodes are utilized to collect the measured positions and the collected data from each mobile node.

In the awake mode, each anchor node transmits beacons to broadcast its position. RSSI-based measurements are used to measure the distance between the anchor nodes and the mobile nodes. When a mobile node receives at least one beacon from four different anchor nodes, it uses RSSI to calculate the distance to each anchor node. After that, the calculated distances are used in the localization process. In this approach we assume that each mobile node is synchronized with at least four anchor nodes, so that it can exchange data with them and listen to the location beacons on the same cycle. This method assists in reducing node localization time and in decreasing power consumption due being awake without reason. The approach is a distributed approach, that is, the localization process is a decentralized, where each mobile node is able to locate itself without the need of a central unit to achieve that, unlike the fuzzy-based approach where the need of a central processing unit is highly important to increase the accuracy of the localization.

In practice, RSSI measurements are highly varied and unstable under the environmental noise and the mobility of sensor nodes. Therefore, localization process of each mobile node is done using a MLP neural network. A major benefit of using a neural network is that prior knowledge of the environment and noise distribution is not required. Also, neural networks generally provide more accuracy than other techniques such as Kalman filter [18]. Furthermore, we chose to use a MLP neural network because it has the best trade-off between accuracy and memory requirements among other types of neural networks.

As shown in Figure 5, the MLP neural network, which is used in this approach, is a three-layer network composed of four nodes in the input layer, ten nodes in the first and the second layers, and three nodes in the output layer. The nodes in the first layer use the hyperbolic tangent sigmoid activation function, the second layer uses a Log sigmoid activation function, and the third layer uses a linear activation function.

The network has four inputs (D_{1-4}), which are the measured distances to each anchor node. Also, it has three outputs (X, Y, and Z) which are the coordinates of the estimated position of the mobile node. The proposed algorithm is designed to locate mobile nodes that have unpredictable movement patterns. To keep track of the movements, each mobile node has to send its updated location to the sink node after each movement. The sink node keeps these locations for other purposes such as studying the behavior of the mobile nodes and providing new training data that could improve the accuracy of node localization.

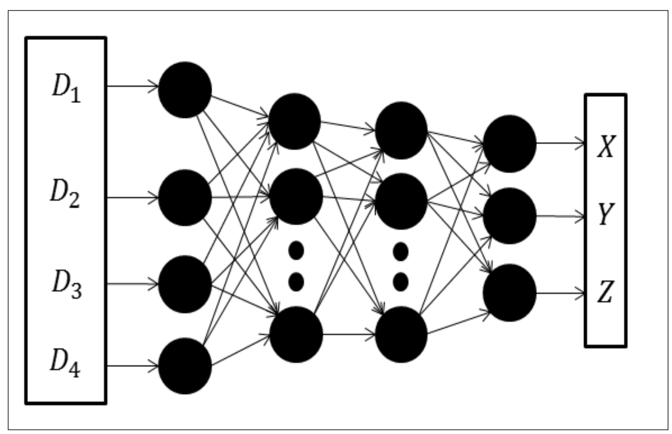

Fig. 5. Neural network structure

IV. Simulation Results and Discussion

A. *A Fuzzy-based Collaborative Localization Algorithm for Wireless Sensor Networks*

The performance of the fuzzy-based algorithm is evaluated using MATLAB. The simulation environment is shown in Figure 6. It consists of: 100m X 100m square area, 4 anchor nodes located at each corner of the squared area and a number of randomly distributed sensor nodes with unknown positions. The transmission range of each anchor node is assumed to be reachable by all sensor nodes. Also, RSSI measurements are assumed to be accurate, therefore the calculated distances are accurate. In the simulation process, we initially evaluate the performance of phase I. Then, we evaluate the performance of the proposed approach which is a combination of phase I and phase II.

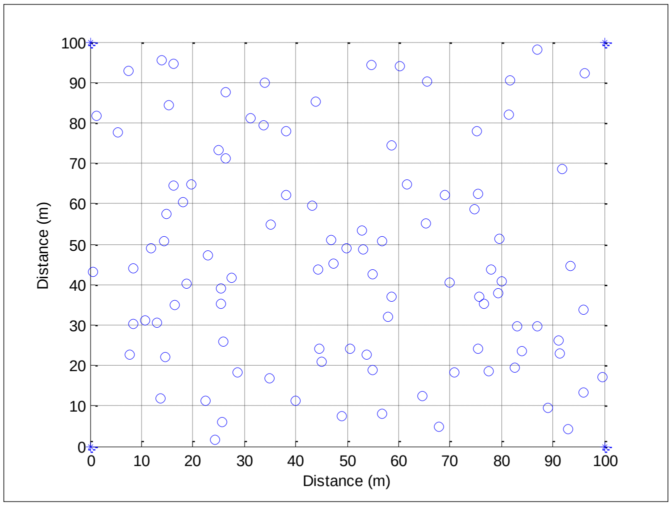

Fig. 6. Simulation environment of the first approach

As shown in Figure 7, the number of precisely located nodes in the proposed approach is higher than the number of the precisely located nodes in phase I. Also, as the total number of nodes increases, the proposed approach shows better localization estimations than phase I. This improvement is due to the adding of the collaborative communication feedback, which considers the effect (weight) of the PL nodes along with the anchor nodes in the weighted average formula. Hence, the proposed approach achieves better accuracy with minimal cost. However, the proposed approach still does not provide high accuracy for all sensor nodes. It provides high accuracy for a good percentage of them, though.

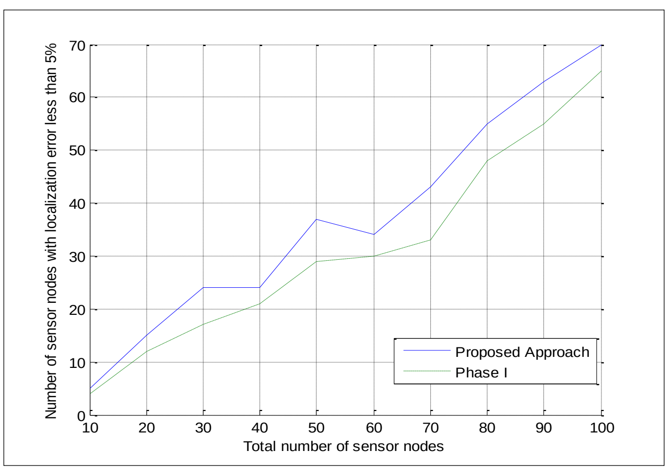

Fig. 7. Phase I vs. the proposed approach

As for the cost, the proposed approach only deploys four anchor nodes to obtain the location of 100 sensor nodes as shown in Figure 8. In [19], the authors use 121 anchor nodes to estimate the location of 60 sensor nodes which is not cost efficient and is hard to be deployed in large areas. In contrast, the proposed approach increases the number of localization references without any extra cost. Furthermore, the proposed approach estimates the location of higher number of sensor nodes than [8], they both use the same number of anchor nodes, though.

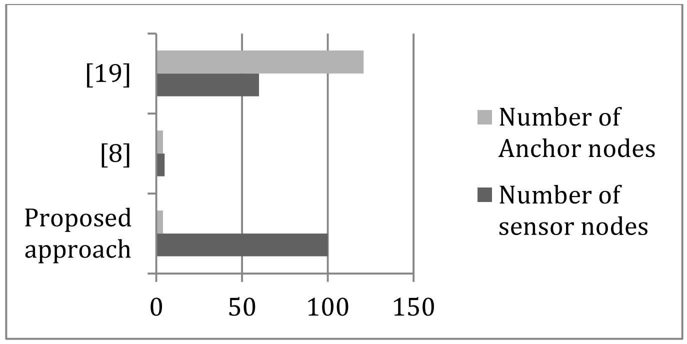

Fig. 8. Comparison between the numbers of nodes used in each approach

B. *A Three-Dimensional Localization Algorithm for Wireless Sensor Networks Using Artificial Neural Networks*

The performance of the second proposed algorithm is evaluated using MATLAB. The simulation environment is shown in Figure 9. It consists of: 100m X 100m X 100m cubic environment, and four anchor nodes. Each anchor node is represented by an asterisk (*). The Anchor nodes are placed at 4 corners of the cubic environment. A 100 mobile nodes are randomly distributed and each one represented by small letter (o). All mobile nodes are in one hop distance from all anchor nodes. The RSSI measurements and the calculated distances are assumed to be noisy. The simulation process consists of two phases: an offline phase and an online phase.

In the offline phase, the proposed neural network is trained. Error back propagation training is performed using the Levenberg-Marquardt algorithm [20]. The objective of the training is to build an accurate model with good estimation capabilities when confronted with noisy input values. The neural network is trained for 441 epochs. The distances from the four anchor nodes are the input values, and the exact locations of the sensor nodes are the target values. After training the network, it is used in the online phase.

In the online phase, 3D localization with different mobility patterns is evaluated based on three scenarios. The average localization error for each mobile node in each scenario is the average distance between the estimated coordinates and the actual coordinates.

$$D_i = \sqrt{(X_{esti}\text{-}X_{0i})^2 + (Y_{esti}\text{-}Y_{0i})^2 + (Z_{esti}\text{-}Z_{0i})^2} \qquad (5)$$

$$L_{ei} = \frac{\sum_s D_i}{S} \qquad (6)$$

Where, L_{ei} is the average localization error of the i^{th}, D_i is the localization error of the i^{th} mobile node, X_{esti}, Y_{esti}, Z_{esti} are the estimated coordinate of the i^{th} mobile node, X_{0i}, Y_{0i}, Z_{0i} are real coordinate of the i^{th} mobile node, and S is the number of movements. To begin with, S is set to be five movements, then the proposed approach is evaluated based on the following scenarios.

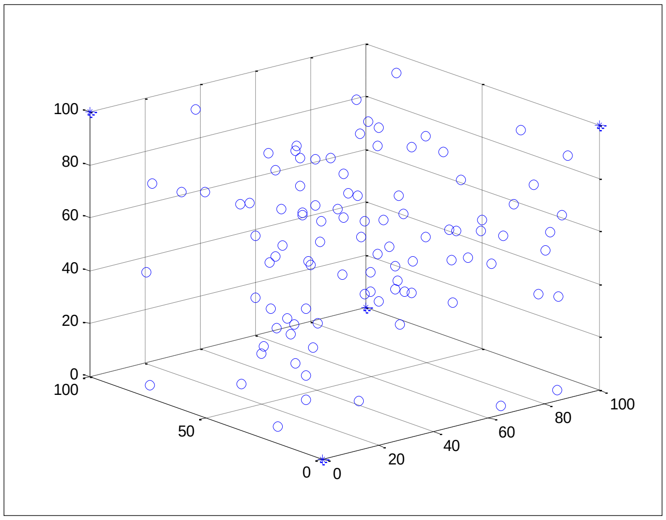

Fig. 9. Simulation environment of the second approach

Scenario I: One-dimensional Movement

Initially, the effect of the one-dimensional movement on the localization is evaluated. The one-dimensional movement represents the movement of earth bound vehicles such as trains and cars. In this scenario, each mobile node performs five random one-dimensional movements along the x-axis with different speeds. Here, the displacement in each movement varies between 0.1- 3.0 m. Figure 10 shows the average localization error in meters for each mobile node after five movements. As shown in the figure, all mobile nodes have an average localization error less than 1 m. The overall average localization error in this scenario is 0.4706 m.

Scenario II: Two-dimensional Movement

In this scenario, 3D localization with two-dimensional random movement is evaluated. A good example of two-dimensional movements is pedestrian mobility or robot movements. As in the first scenario, five random movements are applied with different speeds and again the displacement varies between 0.1-3.0 m. As shown in Figure 11, 95% of the mobile nodes have a localization error of less than 0.8 m. The overall average localization error in this scenario is 0.4855 m.

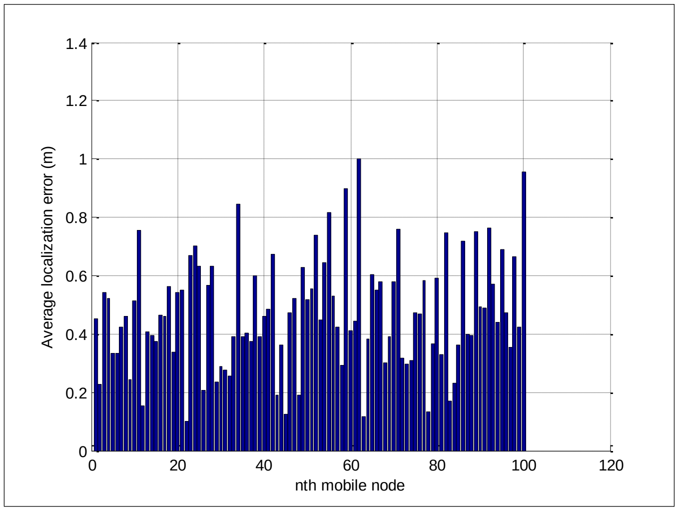

Fig. 10. Localization error in scenario I

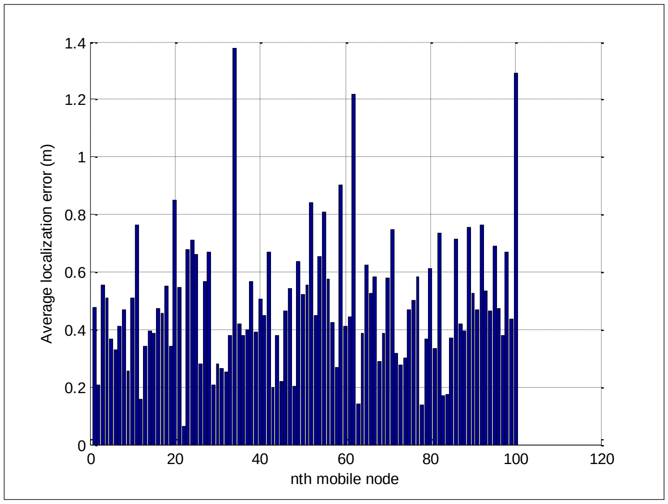

Fig. 11. Localization error in scenario II

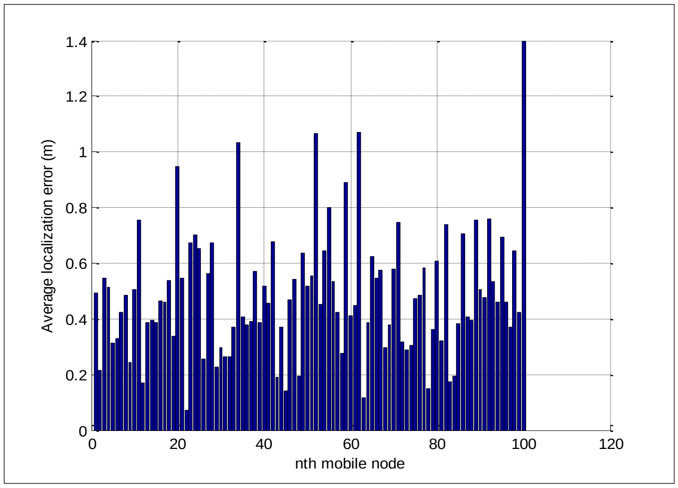

Fig. 12. Localization error in scenario III

Scenario III: Three-dimensional Movement

Finally, each mobile node is set to perform five random 3D movements. This type of movement could represent marine and submarine mobility or aerial mobility. Similar to the previous scenarios, the displacement of each movement varies between 0.1 to 3.0 m. As shown in Figure 12, 94% of the mobile nodes have a localization error less than 0.8 m. The overall average localization error in this scenario is 0.4879 m.

To show the effectiveness of the proposed approach, we compare it with two 3D localization algorithms. The 3D-WCL proposed in [11] and Mamdani/Sugeno FIS proposed in [13]. Table II illustrates a comparison between the three approaches. The performance of the proposed algorithm outperforms the other two approaches. Also, it is important to note that the number of anchor nodes involved in the proposed approach is only four, while the other two approaches require a large number of anchor nodes. Hence, the proposed approach is cost efficient and can be implemented in reality.

Table II

Comparison of different 3D localization algorithms

Localization Algorithm	Average Localization Error (m)
3D-WCL	3.6
Mamdani and Sugeno FIS	3.0
Proposed Algorithm	0.5

As exposed in each scenario, the proposed algorithm achieves high localization accuracy with different types of unpredictable movement patterns. However, what if the number of movements S increased? Figure 13 shows the effect of increasing S on the average localization error. As shown in Figure 13, the average localization error increases as the number of movements S increase, and this indicates that the neural network is not able give accurate results after certain number of movements. For instance, if the number of movements reached 60, the average localization error will reach 12m, which is high. Therefore, the neural network must be trained periodically with a new training data to keep on providing high accuracy.

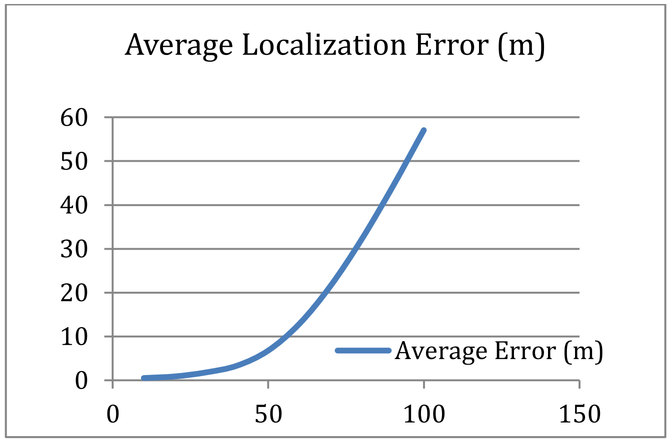

Fig. 13. The effect of increasing S on the average localization error

V. Conclusion

In this paper, we propose two efficient localization algorithms for WSN using two artificial intelligence techniques: Fuzzy logic and neural networks. The first approach uses a Sugeno-type FIS along with a collaborative communication feedback to achieve accuracy with minimal cost. The approach is centralized and is designed for 2D localization. In the second approach, we use a MLP neural network to achieve 3D localization. The approach is distributed and is able to locate mobile node with unpredictable movement patterns.

The proposed approaches have their own merits and drawbacks, making them suitable for unique types of topologies. For instance, the fuzzy-based approach is suitable to stationary WSN, where sensor nodes reside in static positions. Also, it is suitable to the applications that only require 2D localization. Moreover, it is apposite to the applications, where the presence of central processing units is certain. On the other hand, the neural network-based approach is suitable to the applications, where 3D localization is essential. It is also suitable to the distributed type of networks, which include sensor nodes that are independent and have mobility patterns. Although the proposed approaches appear to support different types of applications, they both provide cost efficient node localization. The proposed approaches are summarized in Table III.

In our analysis, we rely on the simulation to determine the degree of efficiency of each proposed approach. However, in simulation-based environments, many assumptions need to be made. Also simulation does not give a realistic performance about some factors such as power budget and noise distribution. In the future, we plan to perform experiments to validate the simulation results. On the other hand, it is obvious that all approaches have their own merits and drawbacks, making them limited for certain types of applications. In the future, we plan to combine several techniques to support broad type of applications with high localization accuracy.

Table III

Summary of the proposed approaches

Algorithm	Type	Processing	2D/3D case	Accuracy	Communication overheads and memory requirements	Deployment cost of anchor nodes	Mobility
Fuzzy-based approach	Range-free	Centralized	2D	Depends on the weighted average	High	Low	Not supported
Neural network-based approach	Range-free	Distributed	3D	Depends on network training	Low	Low	Supported

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