Location Finding in Wireless Sensor Network Based on Soft Computing Methods

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***Abstract*—Sensor Localization is a crucial part of many location-dependent applications that is utilized in wireless sensor networks (WSNs). Several approaches, including range-based and range-free, have been proposed to calculate the position of randomly deployed sensor nodes. With specific hardware, the range-based schemes typically achieve high accuracy based on either node-to-node distances or angles. On the other hand, the range-free mechanisms support less positioning accuracy with less expense. The proposed scheme is based on range-free localization, which utilizes the received signal strength (RSS) from the anchor nodes. In this work, genetic fuzzy and neuro-fuzzy methods are used to become more accurate localization. For more realistic evaluation, the enhanced localization algorithms are examined in different environmental noises.**

Keywords: : Fuzzy logic, Genetic algorithm, Localization, Neuro-fuzzy, Range Free, Sensor Networks, Weighted centriod Localization (WCL).

I. INTRODUCTION

Wireless sensor networks (WSNs) are a framework for the future ubiquitous environment and have many applications for home, environment, health, military, and industry [1]. The inherent characteristics of these sensor networks make a node's location an important part of their state. WSN localization techniques are applied to estimate the locations of each sensor node with initially unknown position in a network using the available priori-knowledge of positions of a few specific sensors in the network and inter-sensor measurements such as distance, time difference of arrival, angle of arrival and connectivity. Sensors with initial known location information are called anchors which can be located using a global positioning system (GPS), or by installing anchors at points with known coordinate, etc. In applications requiring a global positioning system, the anchors will discover the location of the sensor network in the global coordinate system. In applications where a local positioning system suffices (e.g., in smart homes and hospitals where a sensor monitors if the facilities are sufficient), these anchors explain the local coordinate system to which all other sensors are referred [2].

The current approaches for this aim are categorized into two categories: range-based and range free [3]. Range-based approaches assume that sensor nodes are able to measure the distances, or even relative directions of their neighboring nodes, based on Time of Arrival (TOA) [4], Time Difference of Arrival (TDOA) [5], Radio Signal Strength Indicator (RSSI) [6] or Angle of Arrival (AOA) [7], etc. In spite of critical connectivity [8], the range-based schemes typically have higher location accuracy than the range-free schemes, but need additional hardware to get distances or angles and have weakness in the noisy environments.

In contrast, the range-free schemes do not need the distance or angle information to the sensor nodes from the anchor nodes for their localization [9-15]. The range-free schemes provide more economic and simpler estimation than the range-based ones, but their results are not as precise as those of the range-based methods. Nowadays, the range-free schemes have gained more popularity than the range-based methods.

In Yun et al. [15] new range-free localization schemes based on RSS information are shown. They employ soft computing techniques to overcome the limitations of the previous range-free localization methods such as Centroid localization. Yun et al. [15] have only considered the genetic algorithm to optimize the fuzzy system with five trapezoidal membership functions. Also they have not examined their system in different environment noises. In this research, two different hybrid soft-computing techniques, genetic fuzzy and neuro-fuzzy systems with eight various types of membership functions that each type including different number of membership functions such as five, seven and nine are used to achieve more accuracy and error resilience. The achieved new methods for more realistic evaluating are examined in three different environmental noises.

In this paper, our vision for localization by soft computing is outlined. The technical background is considered in Section 2. In Section 3, the design of the proposed localization is sketched and described. The simulation and its results are discussed directly in section 4. Finally, Section 5 concludes our discussion.

II. TECHNICAL BACKGROUND

Bulusu et al. proposed a range-free, proximity-based and coarse-grained localization algorithm [10], which uses anchor nodes, location information (X_i, Y_i), to estimate node location. The anchor nodes are placed at known positions (X_i, Y_i) that send periodic beacon signals containing their positions. Each sensor node computes its position as a centroid of the positions of all the connected anchor nodes to itself by

$$(X_{est}, Y_{est}) = \left(\frac{(X_1 + \ldots + X_N)}{N}, \frac{(Y_1 + \ldots + Y_N)}{N} \right) \qquad (1)$$

|where (X_{est}, Y_{est}) represents the estimated position of the sensor node and N is the number of the connected anchor nodes to the sensor node. The main advantage of the Centroid localization method is its simplicity and ease of implementation but exhibits large amount of error [12].

For improving the Centroid algorithm, weighted

Centroid localizations [9-15] have been proposed. In this method, anchor nodes are weighted according to their closeness to the sensor nodes, and each sensor node computes its position by

$$(X_{est}, Y_{est})= \left(\frac{(w_1.X_1 + \ldots + w_N.X_N)}{\sum_{i=1}^{N} w_i}, \frac{(w_1.Y_1 + \ldots + w_N.Y_N)}{\sum_{i=1}^{N} w_i} \right) \quad (2)$$

where N is the number of adjacent anchor nodes. This method has the weakness that the determining of the weights ($w_1, w_2, \ldots, w_n$) is very dynamic and heuristic, and the performance highly depends on the choosing of the weights.

Soft computing such as fuzzy logic, neural networks, genetic-fuzzy and neuro-fuzzy systems became a formal computer science area of study in the early 1990's. Soft computing deals with imprecision, uncertainty, and approximation to achieve tractability, robustness, and low solution cost [16].

Genetic algorithms have demonstrated to be a powerful tool to perform tasks such as generation of fuzzy rule base, optimization of fuzzy rule bases, generation of membership functions, and tuning of membership functions [17]. Fuzzy systems generated or adapted by genetic algorithms are called Genetic Fuzzy Systems (GFS) [18]. The combination of fuzzy systems with genetic algorithms have great acceptance in the scientific community, once these algorithms are robust and can search efficiently large solution spaces [19].

Neural networks and fuzzy logic so-called neuro-fuzzy are used to solve for uncertain and nonlinear problems. A neural network can approximate to a function, but it is impossible to translate the result in terms of natural language. The fusion of neural networks and fuzzy logic in neuro-fuzzy models provide learning as well as readability [20].

Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy systems incorporate the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to request interpretable IF-THEN rules [20].

The strength of neuro-fuzzy systems involves two opposite requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of these properties prevails. The neuro-fuzzy in fuzzy modeling research field is divided into two sections: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model [20].

III. METHOD

There are n anchor nodes with overlapping coverage region. They know their positions $(X_1, Y_2), (X_2, Y_2), \ldots, (X_n, Y_n)$. In addition they send periodic beacon signals containing their positions to help nodes to locate themselves. Each node listens for a fixed time period and collects the RSS information of all beacon signals that it receives from adjacent anchor nodes. This is illustrated in Figure 1.

In this environment, each sensor node collects the positions of anchor nodes and measures its RSSs. Then, it calculates the edge weight of each anchor node. The edge weight should already be modeled by genetic- fuzzy system and neuro-fuzzy system. Finally, it uses the edge weights of all anchor nodes to determine the position of sensor node using Equation 2, as shown in Figure 2.

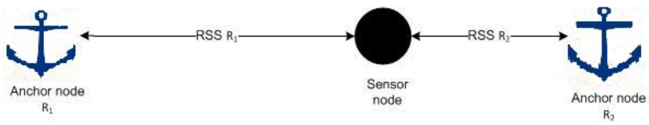

Figure 1. Simple example of connectivity and RSS information.

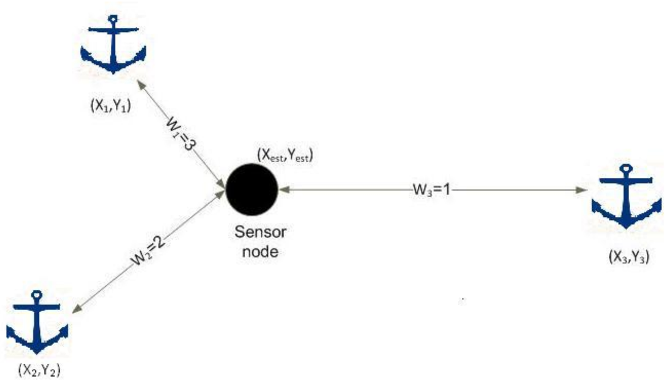

Figure 2. Simple example of weighted Centroid method.

The RSS is the signal strength from the anchor node, not a distance measurement. However, there is a non-linear relationship between RSS and distance. To overcome the uncertainty of the RSS and the nonlinearity between the RSS and the distance, the fuzzy logic system is utilized and the none-linear relationship between the weight of an anchor node and its RSS is modeled. The fuzzy model has the following form,

$$R^l: \text{IF } x \text{ is } A^l \text{ THEN } y \text{ is } B^l \quad (3)$$

The input variable x is the RSS from anchor node and takes a value in the interval $[0, RSS_{max}]$, where RSS_{max} is the maximum RSS value. In embedded devices, the received signal strength is converted to the RSSI [15].

Consequently, to design more precise fuzzy systems, eight various types of membership functions that each type including different number of membership functions such as five, seven and nine are examined. For this reason, the input space of RSSI can be decomposed into five, seven and nine trapezoidal, difference between two sigmoidal, Gaussian combination, Gaussian, generalized bell, product of two sigmoidally, π- shaped and triangular membership functions.

The output variable y is the edge weight of each anchor node for a given sensor node and takes a value in the interval [0, w_{max}], where w_{max} is the maximum weight. As in *x*, the output space of the weight is decomposed into five, seven and nine triangular membership functions for mamdani fuzzy inference system and linear membership functions for TSK fuzzy inference system. For instance, Figure 3 shows that the input space of RSSI is decomposed into seven generalized bell-shape membership functions: Very Low, Low, Mild-low, Medium, Mild-high, High, and Very High.

Now, the rules are considered for the fuzzy logic system. If an anchor node emits high powered signal, the anchor node is likely to be close to a given sensor node and it should have a high weight. Conversely, if an anchor node is connected to the sensor node but emits low powered signal, the anchor node is likely to be far from the given sensor node and should have a low weight.

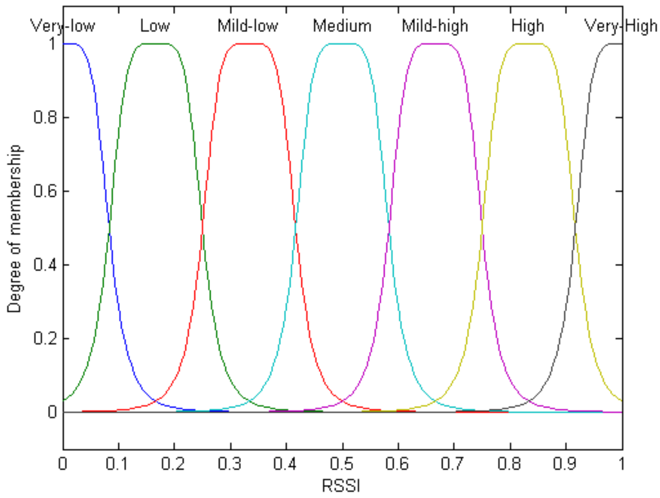

Figure 3. Fuzzy membership functions of RSSI.

To achieve more precise weight for WCL, we have trained the fuzzy logic system with genetic algorithms and neural networks. For this reason we used standard genetic algorithm and standard ANFIS with hybrid optimization method.

IV. Simulation and Results

In this section, Yun et al. [15] proposed Weighted Centroid Localization (WCL) and the new proposed optimized WCL with the genetic fuzzy system and the neuro-fuzzy system are simulated and their results are collected. The algorithm is coded in Matlab environment. In this simulation, a 100 * 100 m^2 region is considered. One hundred and twenty one anchor nodes are placed regularly which each one 10 m apart and 60 sensor nodes are placed randomly.

The transmission range of all anchor nodes is assumed 8.94 m [15]. For the simulation of the RSS the following model is used which also takes into account noise [21]:

$$R_{ij} = (k d_{ij}^{-\alpha}) + (AWGN) \qquad (4)$$

where R_{ij} is the RSS value between the i^{th} sensor node and the j^{th} neighbor anchor node, *k* is a constant which takes into account carrier frequency and transmitted power (equal for each beacon) [21], d_{ij} is the distance between the ith sensor node and the j^{th} neighbor anchor node and α is the attenuation coefficient [21]. Here, we assume k=50 and α=-1 [15]. The AWGN (additive white Gaussian noise) is used to mimic more realistic environment. AWGN is considered as a zero-mean Gaussian distributed random variable with known variance 0.5.

For evaluating the accuracy of estimate, location error and average location error as following are used,

$$\text{Location Error} = \sqrt{(X_{est} - X_a)^2 + (Y_{est} - Y_a)^2} \qquad (5)$$

Average Location Error=

$$\sqrt{(X_{est} - X_a)^2 + (Y_{est} - Y_a)^2} / \text{number of sensor nodes} \qquad (6)$$

To compare, Weighted Centroid Localization (WCL) proposed by Yun et al. and the new proposed optimized WCL with the genetic fuzzy system and the neuro-fuzzy system are implemented. In this comparison, we place sensor nodes randomly and run the localization algorithms through 100 different additives white Gaussian noises. To yield more precise evaluation, we repeat the evaluation 400 times. The averages of these runs are considered as the simulation results for each localization method.

In this simulation, eight fuzzy systems are built with eight different membership functions, triangular, trapezoidal, Gaussian, Gaussian combination, generalized bell-shaped, π-shaped, difference between two sigmoidal and product of two sigmoidally shaped. Genetic- fuzzy and neuro-fuzzy are used to optimize the eight fuzzy systems with five, seven and nine membership functions. To better evaluate the methods, each localization algorithm is examined with three different signals to noise ratio, 0, -5, and -10 dB.

Figure 4 shows the result of one specific run. The black dotes denote the actual position of sensor nodes and the red dotes denote the estimated position of sensor nodes.

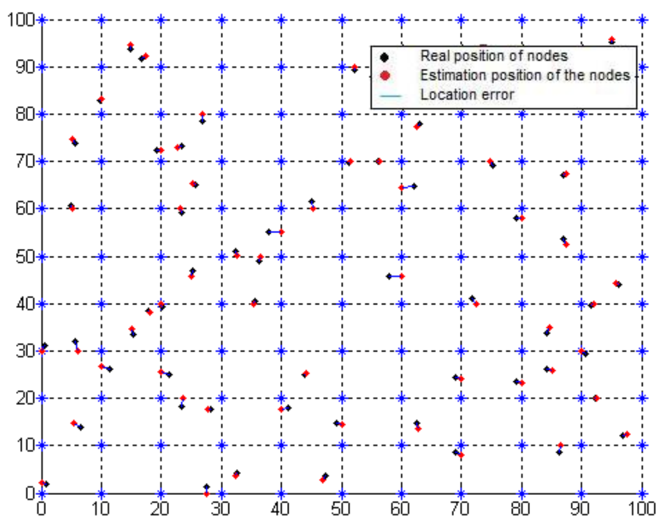

Figure 4. Simulation results of one specific run.

According the simulation achievements, the most reasonable result for the trained fuzzy systems with neural networks and genetic algorithms is Gaussian with five membership functions as illustrated in table 1, 2, and 3.

TABLE I. THE SIMULATION RESULTS WITH 0 DB SNR.

Method	Average Error (m.)	Maximum Error (m.)	Minimum Error (m.)
YUN ET AL. WCL	1.4291	1.7040	1.0285
GENETIC-FUZZY + GAUSSIAN MFS	0.9501	1.5946	0.5846
NEURO-FUZZY + GAUSSIAN MFS	0.9014	1.2236	0.7004

TABLE II. THE SIMULATION RESULT WITH -5 DB SNR.

Method	Average Error (m.)	Maximum Error (m.)	Minimum Error (m.)
YUN ET AL. WCL	1.4310	2.0634	0.7209
GENETIC-FUZZY + GAUSSIAN MFS	1.0997	2.2318	0.5626
NEURO-FUZZY + GAUSSIAN MFS	0.9459	1.5815	0.6161

TABLE III. THE SIMULATION RESULT WITH -10 DB SNR.

Method	Average Error (m.)	Maximum Error (m.)	Minimum Error (m.)
YUN ET AL. WCL	1.5001	2.6740	0.6285
GENETIC-FUZZY + GAUSSIAN MFS	1.3771	3.0789	0.5752
NEURO-FUZZY + GAUSSIAN MFS	1.0826	2.3057	0.5781

As shown in simulation results, the trained fuzzy systems with neural networks yield better localization than that of Yun et al. WCL and the trained fuzzy system by the genetic algorithm.

V. CONCLUSION

Wireless sensor networks have broad applications, and self-organization technology is the basis of wireless sensor network applications. So, localization in WSNs has become a very important research topic. In this research, an enhanced Centroid localization method is simulated and its performance is shown in different noisy environments. This method is a type of distributed algorithm. Therefore, it can be applied to applications of a large scale network.

From the results in this paper, neuro-fuzzy systems can choose more precise weights than genetic fuzzy systems, which mean that the WCL localization methods with optimized fuzzy systems by neural networks are more accurate. Although the localization results from fuzzy systems with seven and nine membership functions are more precise, the optimized fuzzy system with five Gaussian membership functions by neural networks are suggested due to their implementation complexity, limited processor and power energy of senor nodes.

As mentioned above, in this research a localization method has been developed and its performance is calculated considering different types of noise. The future work could be the implementation of related algorithms in three dimensional environments considering noisy and asymmetric conditions that result in non-sphere patterns and also improve the algorithms and results by adding hop-count policy.

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