A Probabilistic Fuzzy Approach for Sensor Location Estimation in Wireless Sensor Networks

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***Abstract*—Nowadays, wireless sensor networks are widely used in a variety of applications such as in military, vehicle tracking, disaster management and environmental monitoring. Accurate estimation of the sensor position can be crucial in many of these applications. In this research, we propose a localization algorithm based on probabilistic fuzzy logic systems (PFLS) for range-free localization. The algorithm utilizes received signal strength (RSS) from the anchor nodes embedded with variant degrees of environmental noise. The proposed system is compared with another algorithm based on Fuzzy Logic Systems (FLS) against variant amount of noise. Simulation results demonstrate that FLS can be much more accurate than PFLS method if the environment is noise-free. However, as the environmental noise increases, the PFLS reaches better performance.**

I. Introduction

WIRLESS sensor network is a network consisting of thousands of sensors within a particular area. These sensors are able to communicate with each other. They can detect different objects, collect information, and transmit messages. Nowadays, sensor network technologies have become very important especially for applications such as environmental monitoring, military systems, and disaster management.

Despite many advantages, these sensors are usually small in size and have many physical limitations. For instance, In many applications it is crucial to know a node's location. Clearly, the most accurate and reliable way to obtain this information is to equip each node with a GPS receiver. However, this method is expensive and not feasible for sensor nodes due to the power constraint. To solve this constraint, researchers have developed many localization methods in which instead of requiring every node to have GPS installed, only a few nodes are equipped with GPS hardware. These nodes are called *anchor nodes* and they know their exact positions. Other normal sensors then obtain distance information through talking to each other and derive their positions based on the information. Two main methodologies of distributed localization are range-based and range-free localization. Range-based localization [1],[2],[3] are hardware intensive methods which localize a sensor node using techniques such as time of arrival(TOA), time difference of arrival of two different signals (TDOA), and angle of arrival (AOA).

Although the range-free approaches [4],[5],[6] normally produce less accurate location results than the range-based approaches, they are more economic and provide simpler estimates. Bulusu et al. presented a range-free, proximity-based localization algorithm [1]. In his method, the anchor nodes broadcast their position and each sensor node computes its position as a centroid of the positions of all the connected anchor nodes to itself. This method is simple and economic but it contains a large amount of error. Kim and Kwon [5] proposed an improved version of [1]. In their method, anchor nodes are weighted according to their proximity to the sensor nodes, and each sensor node computes its position as a weighted centroid of the positions of all connected anchor nodes to itself. This method has less error than the previous one but its performance is highly related to the design of the weights while the choice of the weights is heuristic. Sukhyun Yun et al. [7] presented some intelligent localization approaches to improve accuracy of position estimation.

In this paper, localization is considered as a complex real world system and for the first time it is modeled by a Probabilistic Fuzzy System. The novel concept of Probabilistic Fuzzy Logic (PFLS) was first introduced by Meghdadi and Akbarzadehin [8] in 2001 as a way of representing and/or modeling existing uncertainty in many real world systems. The approach is actually based on combining both the concepts of probability of truth and degree of truth in a unique framework. Later in 2005, Liu and Li presented a formal mathematical framework for handling this hybrid paradigm of uncertainty. In this research, the behavior of simulation with FLS and PLFS in both static and dynamic environments is examined and compared. Unlike static environment that has little or no noise; dynamic environment may contain a variant amount of noise which can be created by some defenses.

After a general introduction in Section I, Section II of this article reviews some basic concepts that are used in the

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paper. In Section III, the environmental setup needed for simulation is explained. Section IV presents two intelligent localization algorithms using Fuzzy and Probabilistic Fuzzy Logic systems. In the next section, localization is simulated by PFLS, FLS in dynamic environments and findings of the experiments are presented. The paper is then concluded in the last Section.

II. PRELIMINARIES

Fuzzy modeling techniques are well established and are extensively used for modeling complex and nonlinear deterministic systems [9].The fuzzy logic system (FLS) is an inference system that imitates the human thinking and consists of a fuzzifier, some fuzzy IF–THEN rules, a fuzzy inference engine and a defuzzifier.

A simple conventional fuzzy if-then rule with multiple inputs and single output can be shown in the following form:

Rule i: If x_1 is $A_{1,i}$ and x_2 is $A_{2,i}$ and …. x_n is $A_{n,i}$
Then τ is B_i (1)

Where $A_{j,i}(j = 1, \dots, n)$ **and** B_i $(i = 1, \dots, I)$ corresponds to the fuzzy sets in the antecedent and consequent part. I is the number of rules and n is the number of input variables.

Fuzzy modeling techniques are not suitable in their conventional form for probabilistic modeling of randomized and stochastic systems. Consequently, the need for a probabilistic fuzzy modeling approach is inevitable because many of the real world complex systems may exhibit randomness in their behavior as well [10].

The following is a summary of the PFLS formulation by Liu and Li [11] that included here for completeness: "Similar to the ordinary FLS, a PFLS includes fuzzification, fuzzy rules, fuzzy inference engine and defuzzification .The significant difference of PFLS to FLS is that the fuzzification and defuzzification procedure are based on probabilistic fuzzy sets instead of ordinary fuzzy sets. The concept of probabilistic fuzzy set is defined as follows:

Probabilistic Fuzzy Set:

For an input variable $x \in X$, and its fuzzy membership grade $u \in [0,1]$, then the probabilistic fuzzy set $\tilde{A}$ can be expressed by a probability space(U_x, ξ, P) , where U_x is the set of all possible events $\{u \in [0,1]\}$, ξ is a σ-field.The probability P is defined onξ. For all element event E_i's in U_x

$$P(E_i) \geq 0\ ,\ P(\sum E_i)=\sum P(E_i) \quad P(U_x)=1 \tag{2}$$

where E_i corresponds to an event that u= $u_i \subseteq [0,1]$, $u_i=(1,\dots,S)$is a certain value of fuzzy membership grade, and $P(E_i)$is the probability for the event E_i. S is the number of the element event in the set $\{u \in [0,1]\}$. The probabilistic fuzzy set can be expressed as the union of finite subprobability space as follows:

$$\tilde{A} \equiv \cup_{x \in X} (U_x, \xi, P) \tag{3}$$

If the crisp input is determined, the corresponding fuzzy membership grade of an ordinary FLS is a single value. However, in the PFLS, the fuzzy membership grade is a random variable with a certain probabilistic distribution function (PDF).

The inference engine of PFLS is similar to that of the ordinary FLS which gives a mapping from input fuzzy set to output fuzzy set. The inference process is based on the operation methods of PFS including union, intersection and complete operation.

The ith rule of the PFLS is expressed as

Rule i: If x_1 is $\tilde{A}_{1,i}$ and x_x is $\tilde{A}_{2,i}$ …and x_n is $\tilde{A}_{n,i}$
Then τ is $\tilde{B}_i$ (4)

Where $\tilde{A}_{j,i}(j = 1, \dots, \bar{J})$,$(\bar{J} = n)$ and $\tilde{B}_i$ $(i = 1, \dots, I)$ is called as the probabilistic fuzzy set of antecedent and consequent part, $\bar{J}$ is the number of input variables and I is the number of fuzzy rules.

The above rule presents a probabilistic fuzzy relation between the input space and the output space of the PFLS. The probabilistic fuzzy relation between the input space $X_1 \times X_2 \times \dots \times X_{\bar{J}}$ and the output space τ is denoted as $\tilde{R}_{\tilde{A}_{1,i} \times \dots \times \tilde{A}_{\bar{J},i} \to \tilde{B}_i}(x, \tau)$, where $\tilde{A}_{1,i} \times \dots \times \tilde{A}_{\bar{J},i} \to \tilde{B}_i$ denotes the Cartersian product of $\tilde{A}_{1,i}, \dots, \tilde{A}_{\bar{J},i}$and $\tilde{A}_{i,j} \equiv \cup_{x_j \in X_j}\left(U_{\tilde{A}_{j,i}}, \xi_{\tilde{A}_{j,i}}, P\right), \tilde{B}_i \equiv \cup_{\tau \in Y}(U_{\tilde{B}_i}, \xi_{\tilde{B}_i}, P)$."

III. SIMULATION SETUP

The conditions used for simulation in this paper are identical to the ones applied by Yun et al [7]. In this simulation, a 100*100 m^2 region with one hundred and twenty one anchor nodes has been used. As shown in Fig.1 anchor nodes are placed regularly within 10m distance from each other, and 60 sensor nodes are randomly placed in the region. A sensor node can receive signal from the adjacent anchor node if it stands at a distance smaller than the transmission range. The transmission range of all anchor nodes is considered to be 8.94m.

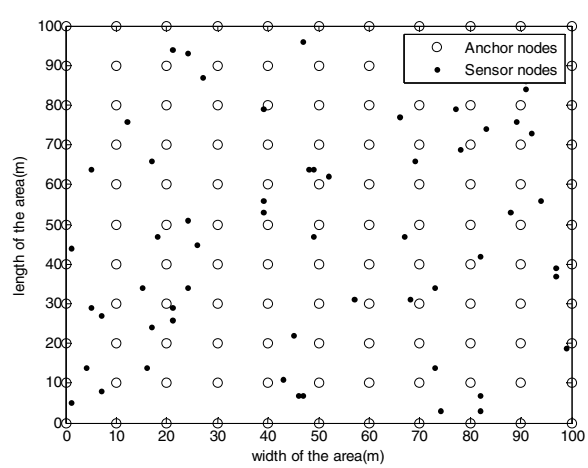

Fig. 1. Distribution of nodes in the simulated area

While anchor nodes send out beacon signals, each sensor node listens for a fixed time period and collects the RSS information of all those beacon signals from adjacent anchor nodes in order to locate itself. In this environment, we have considered that not only each anchor node knows its position, through GPS or by other means such as pre-configuration but the radio propagation is perfectly spherical and also the transmission ranges for all radios are identical. For the simulation, the following RSS model is used which also takes into account noise:

$$R_{ij} = \left(kd_{ij}^{-\alpha}\right) + (AWGN * Var) \quad (5)$$

where R_{ij} is the RSS value between the *i*th sensor node and the *j*th adjacent anchor node, k is a constant which takes into account carrier frequency and transmitted power, d_{ij} is the distance between the *i*th sensor node and the *j*th adjacent anchor node and a is the attenuation exponent. Here, we use $k = 50$ and $a = 1$ and AWGN (additive white Gaussian noise) to simulate more realistic environment.

To evaluate the proposed approaches, the two following performance criteria are considered: Location Error (LE) and Average Location Error (ALE).

$$Location\ Error = \sqrt{(X_{est} - X_a)^2 + (Y_{est} - Y_a)^2} \quad (6)$$

$$Averrage\ Location\ Error = \frac{\sum \sqrt{(X_{est} - X_a)^2 + (Y_{est} - Y_a)^2}}{number\ of\ sensor\ nodes} \quad (7)$$

IV. LOCALIZATION ALGORITHMS

Localization algorithms consist of two sets of nodes: anchor nodes and sensor nodes. Sensor nodes are distributed randomly in the environment and they receive messages from anchor nodes.

For completeness the following localization algorithm, as in [7], for each sensor node is summarized below:

1- The adjacent anchor nodes are discovered using connectivity.
2- The IDs and positions of anchor nodes and their RSSs are computed.
3- The edge weight of each anchor node is calculated by either FLS or PFLS, as explained shortly.
4- The position of sensor node are computed by

$$(X_{est}, Y_{est}) = \left(\frac{w_1.X_1 + \cdots + w_k.X_k}{\sum_{i=1}^{k} w_i}, \frac{w_1.Y_1 + \cdots + w_k.Y_k}{\sum_{i=1}^{k} w_i}\right) \quad (8)$$

Where $(X_1, Y_1), (X_2, Y_2). . . (X_k, Y_k)$ are the positions of the anchor nodes and k is the number of adjacent anchor nodes and w_i is the weight of each anchor node.

A. Localization with FLS

In this research, the weight of each anchor node is computed using received signal strength (RSS). Although this method is not precise, but it can be a cue, as obviously if an anchor node sends out high powered signal, the anchor node is probably close to a given sensor node and it should have a higher weight. Conversely, if an anchor node sends out low powered signal, it is likely to be far from the given sensor node and should have a low weight. To overcome the uncertainty of the RSS and the nonlinearity between the RSS and the distance, we use FLS to model the relationship between the weight of an anchor node and its RSS.

The proposed fuzzy If Then rule is in the following form:

$$R^l : IF\ x\ is\ A^l\ THEN\ y\ is\ B^l \quad (9)$$

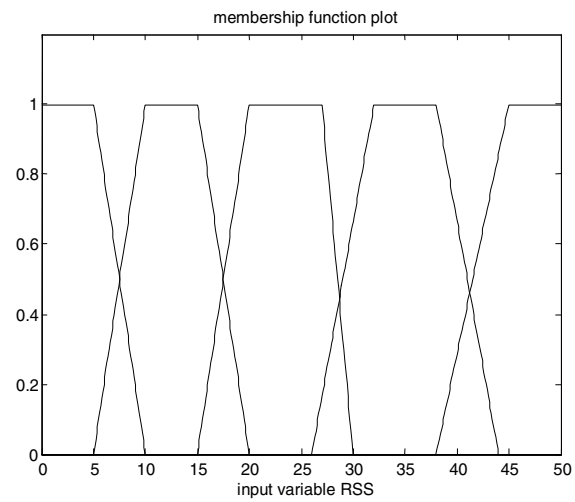

Fig.2 Fuzzy membership function of input

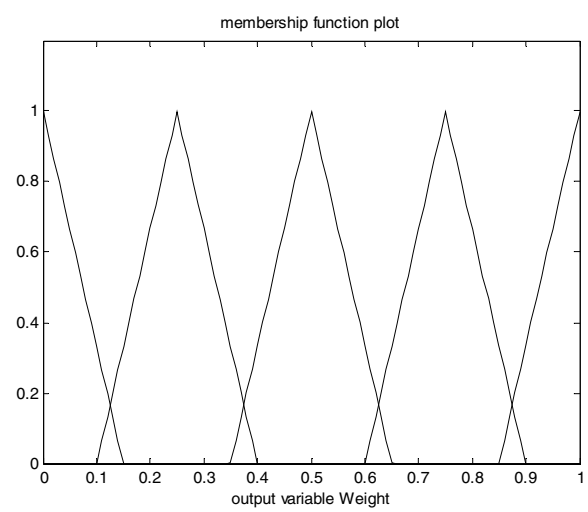

Fig.3 Fuzzy membership function of output

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. 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. The input and output spaces consist of five membership functions: VL, L, M, H, and VH, as shown in Fig.2 and fig.3. Table I presents fuzzy rule base used in this research.

TABLEI
FUZZY RULL BASE FOR EDGE WEIGHT

Rule	If RSS is	Then weight is
Rule 1	Very Low	Very Low
Rule 2	Low	Low
Rule 3	Medium	Medium
Rule 4	High	High
Rule 5	Very high	Very high

A. Localization by PFLS

Probabilistic fuzzy logic is a new approach for incorporating probability in fuzzy logic in order to better represent non_deterministic real world systems [10]. In order to model the existing uncertainty in the localization, in defining the optimal rule set, each conventional rule is substituted with a probabilistic fuzzy rule with output probability vector *P* defined such that the only output sets of the conventional rules are the most probable output sets of the probabilistic fuzzy rules. For example, rule R2 in the above rule set may be modified as follows:

If RSS is low then weight is very-low with probability %10 and weight is low with probability %80 and weight is medium with probability %10

The consequent part of the PFR can be thus expressed in a compact form using the output probabilities vector *P*. the sample probabilistic fuzzy rule set that used in the simulation as follows:

Rule 1: if RSS is *very_low* *P*= [0.9 0.1 0.0 0.0 0.0]
Rule 2: if RSS is *low* *P*= [0.1 0.8 0.1 0.0 0.0]
Rule 3: if RSS is *medium* *P*= [0.0 0.1 0.8 0.1 0.0]
Rule 4: if RSS is *high* *P*= [0.0 0.0 0.1 0.8 0.1]
Rule 5: if RSS is *very_high* *P*= [0.0 0.0 0.0 0.1 0.9]

It is obvious that probabilistic fuzzy system can be regarded as an extension of conventional one. If the statistical parameters are selected such that degree of randomness tends to zero, then probabilistic fuzzy system is converted to conventional form. In other words, conventional fuzzy logic is a special case of the probabilistic fuzzy logic with zero degree of randomness [8].

V. SIMULATION RESULTS

In this section, we want to examine the behaviors of modeling by two approaches of FLS and PFLS within a dynamic environment with variant amount of noise. Simulation is repeated for 60 times such that in each iteration both the number of sensors that have noise and the amount of noise have been increased gradually. Average location error in each iteration of simulation for two approaches has been depicted in Fig.4.

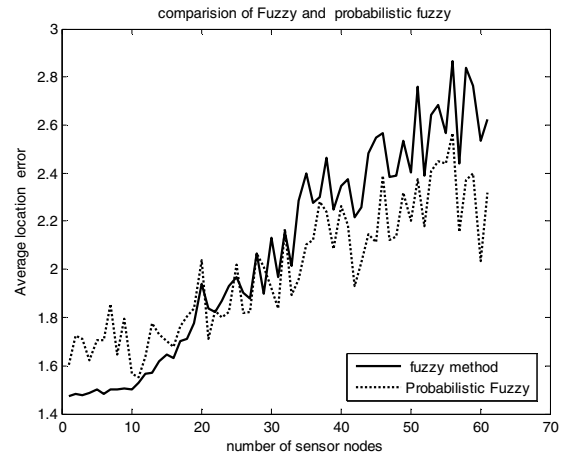

Fig. 4. Comparison of Average Location Error in Fuzzy and Probabilistic fuzzy

The results demonstrate that in the beginning, when the fewer sensors are noisy, FLS has a better performance. However, as more sensors transmit noisy signals, the performance of PFLS obviously gets better. In other words, PFLS has a better performance in the very noisy conditions.

TABLEII
AVERAGE ERROR OF SIMULATIONS

Method	Average Error
Fuzzy	2.2716
Probabilistic Fuzzy	1.9928

Also, Table II shows the average of ALEs during 60 simulations. As the results present, the average error of system simulated by PFLS is less than FLS approach.

VI. CONCLUSION AND FUTURE WORK

Probabilistic fuzzy logic is recommended here as a general framework for a combination of fuzzy logic and probability theory and hence a better handling of cases where both sources are uncertainty exist. In this research, for the first time, localization in wireless sensor networks is modeled by Probabilistic Fuzzy Logic System.

Localization is a non-deterministic problem; hence it can be modeled by PLFS. In this paper, localization with variant amount of noise is solved by FLS, PLFS.

Based on the results of simulation, FLS approach yields a better performance in the static environment; but under noisy conditions, PFLS seems to be much more effective than FLS approach. Although the results of the simulation presented in this paper are very positive; but there are still

ways to improve the system. For instance, the probabilities vector *P,* used in the PFLS simulation is constant in this research. In future, determining this vector by considering the conditions of real environment or by computing with evolutionary approaches might dramatically affect general performance.

REFERENCES

[1] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-less low cost outdoor localization for very small devices," *IEEE Personal communications Magazine*, Vol. 7, pp. 28–34, Oct.2000.

[2] N. Patwari, and A. O. Hero, "Using Proximity and Quantized RSS for Sensor Localization in Wireless Networks," *IEEE/ACM 2nd Workshop on Wireless Sensor Networks and Applications*,USA, sep. 2003.

[3] M. McGuire, K. N. Plataniotis and A. N. Venetsanopoulos, "Location of mobile terminals using time measurements and survey points," *IEEE Transactions on Vehicular Technology*, Vol. 52, pp. 999–1011, July 2003.

[4] S. Yun, J. Lee, W. Chung E. Kim, "Centroid localization method in wireless sensor networks using TSK fuzzy modeling," *International symposium on advanced intelligent systems*, pp. 971–974, 2008.

[5] S. Y. Kim, O. H. Kwon, "Location estimation based on edge weights in wireless sensor networks," *Journal of Korea Information and Communication Society*, Vol. 30, 2005.

[6] D. Niculescu, B. Nath, "DV based positioning in ad hoc networks," *Journal of Telecommunication Systems*, 2003.

[7] Y. Sukhyun, L. Jaehun, and Wooyong, "A soft computing approach to localization in wireless sensor networks," *Expert Systems with Applications*, Vol. 36, pp. 7552–7561, 2009.

[8] A. H. Meghdadi, M-R. Akbarzadeh-T, "Probabilistic fuzzy logic and probabilistic fuzzy systems," *The 10th IEEE International Conference on Fuzzy Systems.* Vol. 2, pp. 1127-1130, 2001.

[9] L. -X. Wang, C. Wei, "Approximation Accuracy of Some Neuro-Fuzzy Approaches," *IEEE Trans. Fuzzy Systems*, Vol. 9, 2000.

[10] A.H. Meghdadi, M-R. Akbarzadeh-T, "Uncertainty Modeling through Probabilistic Fuzzy Systems," *Proceedings of the Fourth International Symposium on Uncertainty Modeling and Analysis* (ISUMA'03), 2003.

[11] Zhi Liu, Han-Xiong Li, "A Probabilistic Fuzzy Logic System for Modeling and Control," *IEEE Trans. Fuzzy Systems*, Vol. 13, pp. 848-859, 2005.