Performance of Improved Fuzzy Indoor Zone Positioning Systems in Wireless Sensor Networks

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Abstract

This paper proposes a zone-based indoor positioning scheme using a wireless sensor networks (WSNs) in conjunction with a fuzzy-based algorithm. We propose using the received signal strength indicator (RSSI) to determine the distance between the target node and reference nodes in indoor environments. This propagation characteristic has previously been used to construct a signal propagation channel model. We divide the RSSI into several power levels based on the rate of signal attenuation over distance, and the indoor environment is splitting up into zones. A fuzzy inference system (FIS) algorithm is used to improve the accuracy of localization. The RSSI values from several reference nodes are used as inputs in the FIS to estimate the location of the target node within the zone. Simulation results show that the fuzzy rectangular splitting method is the most suitable approach to splitting up the zone.

Keywords: Wireless sensor networks, Fuzzy inference system, Received signal strength indicator, Zone-based location method

1 Introduction

Developments in the Internet of things (IoT) [1] will soon make it possible to build smart cities in which traffic congestion, parking, street lighting, and urban noise are monitored and managed in real time. Wireless sensor networks (WSNs) are expected to be a key technology in the IoT. The benefits of connecting both WSN and other IoT elements extends beyond remote access. Heterogeneous information systems can be used for environmental monitoring, military surveillance, and object tracking [2-3]. However, the above applications require accurate positioning information.

Indoor or outdoor location-based services (LBSs) are expanding rapidly [4]. The global positioning system (GPS) is widely used outdoors [5]; however, it does not perform well indoors, due to the blocking of radio waves from satellites. Furthermore, indoor environments are prone to interference from moving bodies, multi-path effects and shadowing, which has necessitated the development of positioning systems especially for indoor environments [6-7].

Most existing indoor localization methods can be categorized as coordinate-based or zone-based. Coordinate-based localization methods include the angle of arrival (AOA) [8], time of arrival (TOA) [9], time difference of arrival (TDOA) [10], and trilateration [11]. These techniques rely on the relationship between the signal and distance. Distance information can then be used to obtain location coordinates. Existing zone-based methods make use of received signal strength indicator (RSSI) information collected from reference nodes to create a database for estimating the location of target nodes [12]. However, we adopted zone-based localization in this study because it is simpler and less expensive. In [13], we presented a two-stage indoor positioning scheme using a fuzzy-based algorithm for coordinate-based localization method. However, we focus on the further application of fuzzy algorithm to zone-based positioning system, in this article.

The main contribution of this paper is a novel fuzzy-based algorithm to enable indoor zone positioning in wireless sensor networks. We implemented the RSSI method in conjunction with a novel fuzzy algorithm to overcome the inaccuracies found in conventional RSSI positioning methods, associated with signal multi-path transmission and obstructions in indoor environments. The proposed positioning system is able to determine locations without the need for training. Furthermore, unlike existing systems based on fingerprinting algorithms, the proposed system does not require numerous measurement points to construct a radio map [14-15].

The remainder of this paper is organized as follows. Section 2 describes related works. Section 3 details the fuzzy inference system used for zone-based localization. Section 4 provides simulation results and discusses the performance of indoor zone positioning system using various zone-splitting methods.

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Conclusions are drawn in Section 5.

2 Related Works

2.1 Signal Propagation Model

The most common approach to indoor localization uses a signal propagation model to estimate distances based on RSSI data. In [15], the authors used the log-distance path loss model, in which the propagation model is represented as follows:

$$\overline{PL}(\mathrm{dB}) = \overline{PL}(d_0) + 10\gamma \times \log\left(\frac{d}{d_0}\right) \quad (\mathrm{dB}) \qquad \textbf{(1)}$$

where $\overline{PL}$(dB) is the received power and d_0 is within the close-in distance. "Close-in distance" is a reference point for radio field strength measurements. It is generally close to the transmitter. $\overline{PL}(d_0)$ is the received power when d is within the close-in distance, γ is the path loss exponent, and d is the distance between the reference and target nodes.

Furthermore, in an ideal space, the path loss exponent γ is 2. Table 1 shows the values of the path loss exponent in various real environments.

Table 1. Value of path loss exponent in various environments

The path loss exponent	
Environment	Value
Open space	2
In the building	1.6 to 1.8
In the factory	2 to 3

It is necessary to take into account the effects of shadowing in order to improve simulations in actual indoor environments. Thus, we combined the log-distance path loss model with the log-normal distribution used in [16]. This resulted in the following propagation model:

$$\overline{PL}(\mathrm{dB}) = \overline{PL}(d_0) + 10\gamma \times \log\left(\frac{d}{d_0}\right) + X_\sigma \quad (\mathrm{dB}) \qquad \textbf{(2)}$$

where X_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB).

2.2 Basic Positioning Schemes for Indoor Environments

Most indoor positioning systems use triangulation based on distance measurements, and distance conversion results have a direct effect on trilateral positioning. RSSI measuresthe distance directly, whereas TOA and TDOA measure distances by computing the attenuation of the emitted signal strength or by multiplying the velocity of the radio signal by the travel time. The RSSI method is the most commonly used due to cost considerations. Thus, we adopted the RSSI method to enhance localization performance.

2.3 Fuzzy Inference System

Fuzzy logic (FL) is widely used in inference systems to imitate human behavior and make decisions. These systems are referred to as Fuzzy Inference Systems (FISs) [17]. There are two common types of FIS: (1) Mamdani-type for capturing expert knowledge and (2) Sugeno-type for control problems in dynamic nonlinear systems. The Mamdani scheme uses output membership functions, whereas the Sugeno scheme does not [18].

FIS has been used to improve the accuracy in WSN localization. In [19], the authors proposed a fuzzy logic-based approach to mobile node localization in sparse networks with few available anchors. They achieved a 24-40% improvement in localization accuracy. In [20], a fuzzy system for collaborative feedback communication in wireless sensor networks reduced error in the localization estimates to less than 5%. In [21], the authors proposed a novel algorithm for localization in WSNs using fuzzy distance measurements based on RSSI, which resulted in error of approximately 7%. In [17], the authors presented a localization method based on an FIS estimator in a wearable wristband, which achieved accuracy of approximately 95%.

2.4 Zone-based Positioning

Zone-based positioning is generally used for passageways or indoor environments, such as office spaces and hospitals. The fingerprinting process can be divided into two phases: training and online positioning [22]. A novel Wi-Fi RSSI fingerprinting scheme for zone localization was presented in [17]. In the positioning phase, RSSI data is trained using the FIS in order to estimate the location of the user within a zone. In [23], the authors presented an indoor localization scheme based on a wireless local area network with multiple zones. The RSSI in each zone, the range of each AP, and the distance to each zone are set in the offline phase. In the online phase, the zone is identified using RSSI in real time. The zone-based localization methods in [17, 23] regard zones as their final localization result.

Many researchers have adopted a third localization process based on machine learning [24-25]. K-nearest neighbor (KNN) classification and neural networks (NNs) are widely used in fingerprinting algorithms [14, 15, 25-26]. These schemes provide adequate estimation accuracy; however, they require a considerable quantity of training data. Computation cost is high and distance-based learning lacks specificity.

Mamdani-type FIS is a simple, intuitive approach to dealing with simple problems. Figure 1 presents the

Mamdani-type fuzzy inference system adopted in this study. The proposed system comprises an input, a fuzzifier, a fuzzy rule-based inference engine, a defuzzifier, and an output. We used the RSSI method in conjunction with a fuzzy algorithm to enhance localization performance. We compare the pros and cons of these localization methods in Table 2.

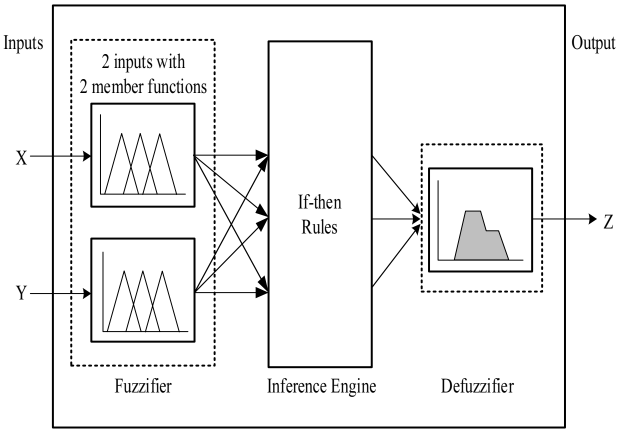

Figure 1. Mamdani-type fuzzy inference system

Table 2. Pros and cons of various localization schemes

Localization method	Strengths	Weaknesses
KNN	Simple classifier	Requires more training data and measurement points; slow convergence; not robust to noisy data
NN	Applicable to a variety of classification and forecast problems	Requires more training data and measurement points; high computational burden; prone to overfitting
Fuzzy	Requires only a small set of data and measurement points for training; interpretable; and simple	Requires development of fuzzy rules and membership functions

3 Application of Fuzzy Algorithm to Zone-based Positioning System

In indoor environments, the position of reference nodes affects the accuracy of positioning. Locating reference nodes in four corners (as a square) can improve positioning accuracy [27]. In this paper, we included an additional reference node in the center of the square to overcome uncertainty. The proposed positioning topology based on five reference nodes is shown in Figure 2.

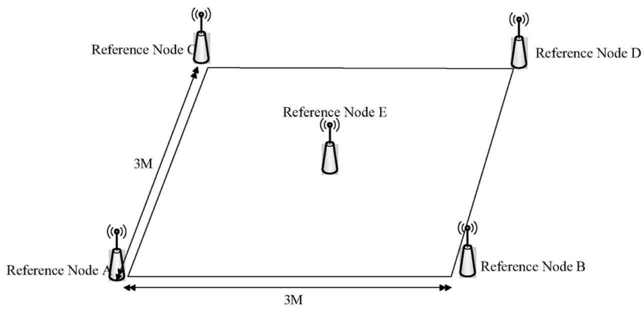

Figure 2. Topology of reference nodes

We employed a zone-based positioning system in this study. The RSSI value from the reference node is simulated using signal propagation model. The model of signal attenuation can be divided over distance into several power levels. In this manner, the indoor area is divided into multiple zones under the assumption that the RSSI power levels are identical at each reference node. We use the FIS to construct a fuzzy rule base in order to identify the zone of the target node. The processing flow of the system is presented in Figure 3.

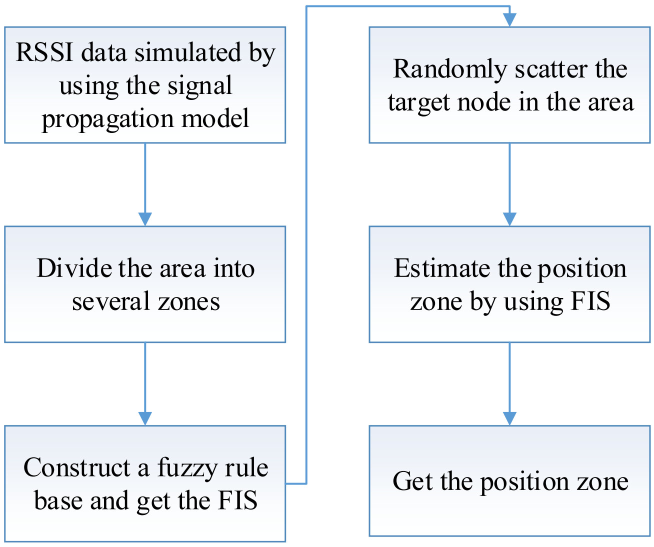

Figure 3. Processing flow of proposed system

The FIS structure of the zone-based positioning system is presented in Figure 4. The FIS is a Mamdani-type fuzzy inference system with five inputs and one output. The inputs (RSSI_a, RSSI_b, RSSI_c, RSSI_d, RSSI_e) are the values simulated utilizing the signal propagation model and the output (zone localization) is estimated using FIS. The fuzzifier section converts RSSI values into fuzzy values using a 6-triangular membership function for use in the if-then rule section.

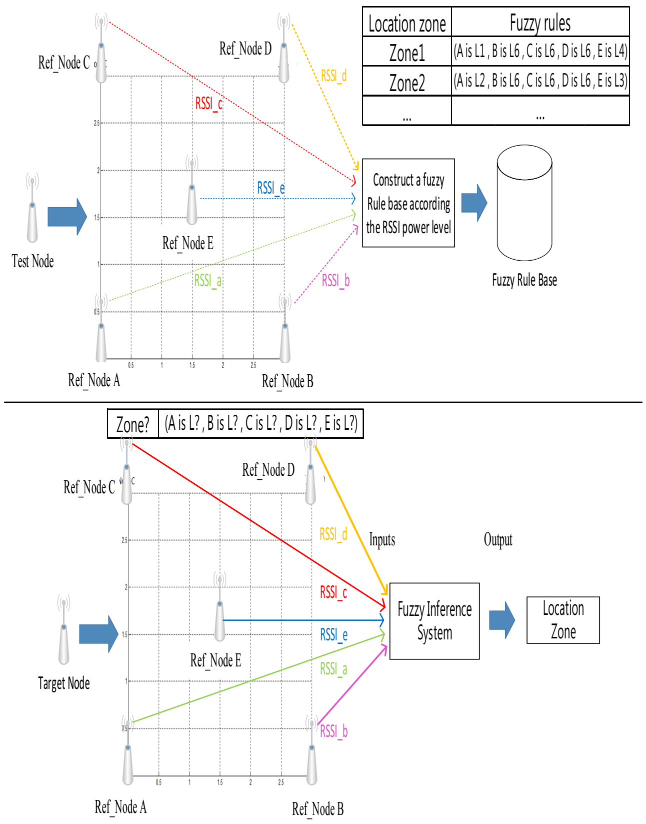

Figure 4. FIS structure of proposed zone-based positioning system

The number of membership functions is determined by the input RSSI power levels, which are defined as six fuzzy sets (L1, L2, L3, L4, L5 and L6), as shown in Table 3. We did not observe obvious changes in the RSSI power levels for S6 and S7; therefore, we placed these two power levels within the same fuzzy set (L6).

Table 3. fuzzy membership function for RSSI power level [13]

Fuzzy Set	RSSI Power Level	RSSI Range (dBm)
L1	S1	0 to -11
L2	S2	-9 to -16
L3	S3	-13 to -19
L4	S4	-17 to -21
L5	S5	-20 to -23
L6	S6, S7	-24 to -26

The triangular membership function is presented in Figure 5. The RSSI power level from the corner reference node (A) and the center reference node (E) are shown in Figure 6 and Figure 7 respectively.

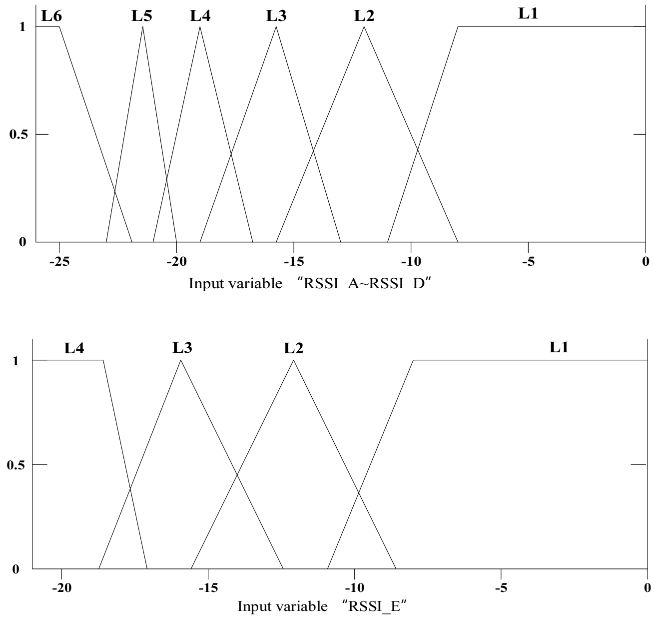

Figure 5. RSSI triangular membership function [13]

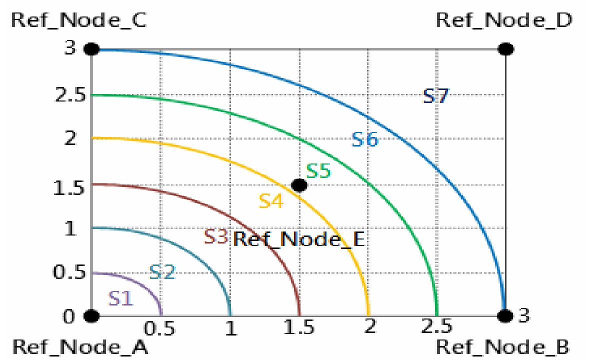

Figure 6. RSSI power level from reference node A [13]

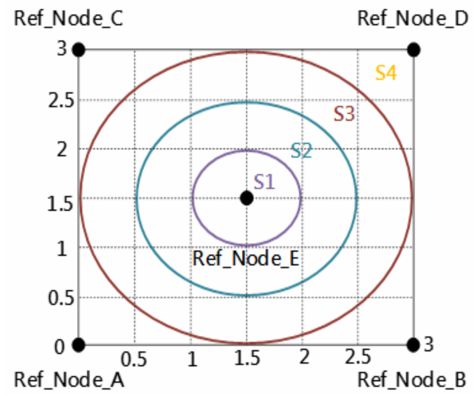

Figure 7. RSSI power level from reference node E [13]

In this paper, we probe various methods by which to splitting up the zones in accordance with the topology of the reference node in the 3M x 3M simulation area, as follows:

3.1 Triangular Splitting Method

Figure 8 presents the triangular splitting method, wherein the simulation area is divided into four equal triangular zones. Despite the wide usage of triangular splitting, there remains considerable room for improvement. In reference to the two splitting methods, the area of the triangular splitting zone is large and the positioning resolution is not very high. However, if we the area were split into more a larger number of zones, the judgment of zone can be judged erroneously zone identification could be compromised due to the instability of the RSSI at the boundary of the splitting zone.

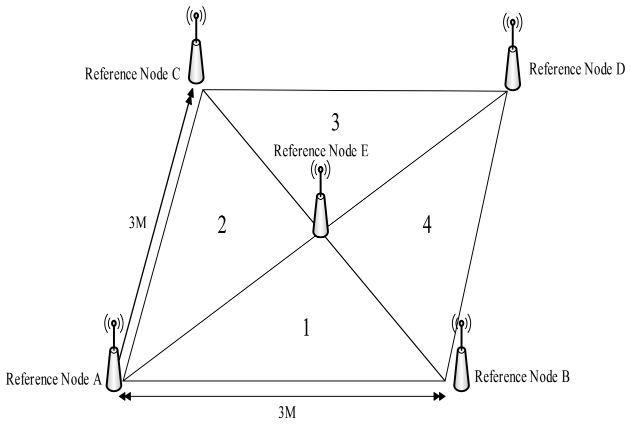

Figure 8. Triangular splitting method [13]

3.2 Fuzzy Triangular Splitting Method

Figure 9 depicts another method that includes an additional zone near the border between the triangles. This zone is meant to improve analysis in the zone and increase the likelihood of obtaining accurate positioning data.

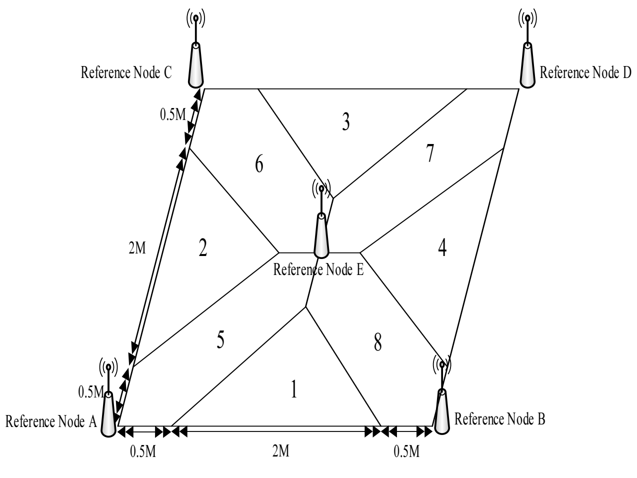

Figure 9. Fuzzy triangular splitting method [13]

3.3 Fuzzy Rectangular Splitting Method

This method involves re-splitting the simulation area into nine square zones, as shown in Figure 10. This helps to improve positioning in cases where the target node is in the central area.

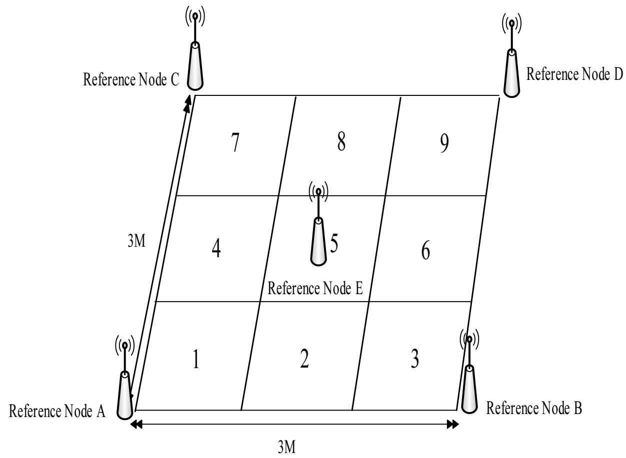

Figure 10. Fuzzy rectangular splitting method [13]

4 Simulation Results

In this section, we present our simulation results using the proposed zone-based indoor positioning system. We used standard as well as several custom MATLAB® functions in the simulations. We established a channel model and then simulated the received RSSI value using a mathematical model. Gaussian random variable X_σ was added to the channel model to simulate the effects of shadowing, path loss, multipath, noise and interference, which are typical of actual indoor environments. These effects destabilized the received RSSI values. The standard deviation parameters were set to 3dBm, 5dBm, 7dBm, and 9dBm to estimate positioning efficiency in indoor environments. In (2), the value of X_σ parameter was adjusted to simulate various indoor environments, as shown in Figure 11 to Figure 14. The X-axis indicates the distance between reference node and target node; the Y-axis indicates the RSSI.

The simulation results in Figure 11 to Figure 14 indicate that when the standard deviation (σ) is larger, the influence of RSSI value in the channel model is large. However, from the perspective of the receiver observing this phenomenon, it is not possible to tell whether changes in the RSSI value are due to shadowing, path loss, multipath effects, noise, interference, or other factors. We therefore added a Gaussian random variable to the path loss model to simulate the impact of environmental factors in actual indoor environments. We defined various indoor environments by adjusting the standard deviation of the parameters. A smaller standard deviation (representative of an indoor environment without obstacles) produces a stable model, whereas a larger standard deviation (representative of a complex indoor environment) produces an unstable model.

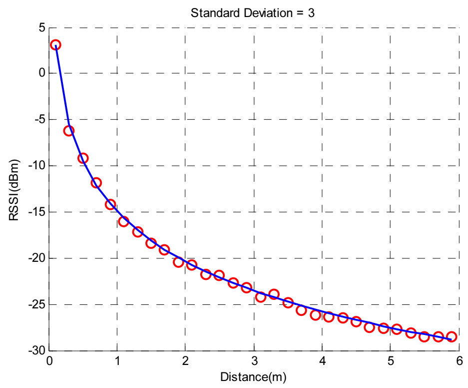

Figure 11. Signal propagation model with σ=3

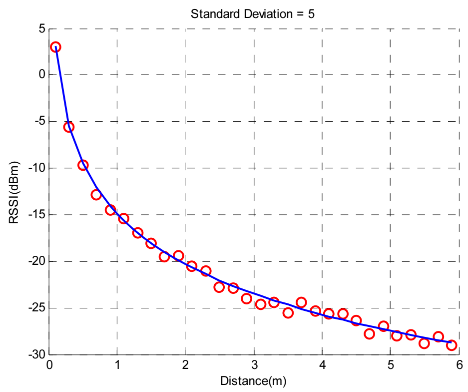

Figure 12. Signal propagation model with σ=5

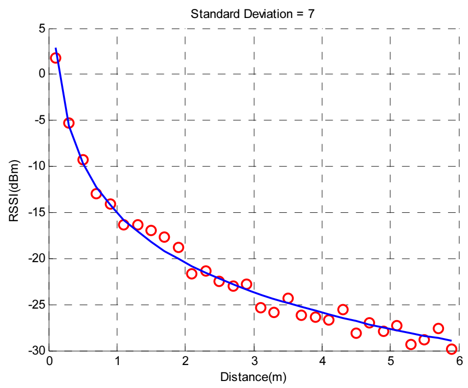

Figure 13. Signal propagation model with σ=7

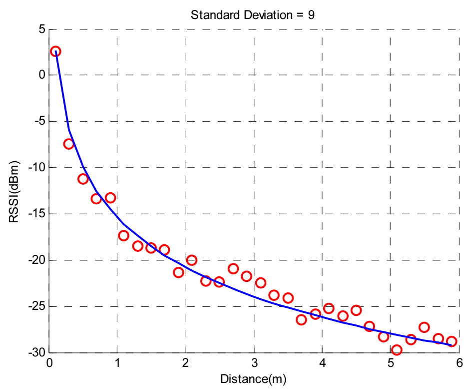

Figure 14. Signal propagation model with σ=9

In this paper, we implemented FIS-based zone positioning using the fuzzy triangular splitting method as well as the fuzzy rectangular splitting method in order to enhance the accuracy positioning estimates. The percentage of the positioning estimates that are correct is obtained as follows:

$$E = \frac{P_{correct}}{P_{Total}} \times 100\% \quad \textbf{(3)}$$

where P_{Total} is the total number of sampling points deployed in the indoor environment; $P_{correct}$ represents the number of sampling points in correct positioning estimates; P_{Total} is set to 100 to calculate the average number of correct positioning estimates in the simulations. A performance comparison using various standard deviations is presented in Table 4 and Figure 15.

Table 4. Correct Positioning Estimates obtained using three methods with variations in standard deviations

Standard deviation	Accuracy of positioning estimates		
	Triangular splitting method	Fuzzy triangular splitting method	Fuzzy rectangular splitting method
3	82%	77%	91%
5	77%	73%	88%
7	76%	72%	81%
9	69%	66%	80%

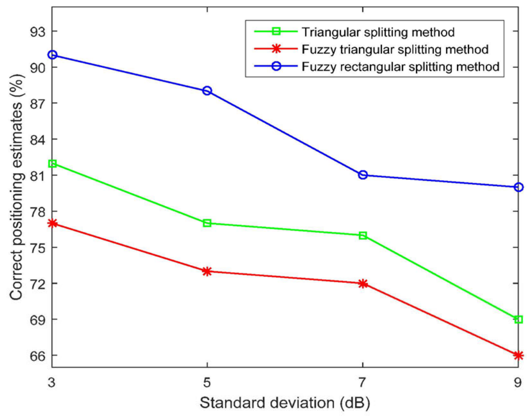

Figure 15. Average number of correct positioning estimates (percent)

As shown in Table 4 and Figure 15, an increase in the standard deviation resulted in a gradual decrease in the number of correct positioning estimates. When using the proposed fuzzy rectangular splitting method with σ = 3, 91% of the positioning estimates were correct. Even when σ was increased, more than 80% of the positioning estimates were correct. A further increase in σ reduced the number of correct positioning estimates to 66%. Overall, the fuzzy triangular splitting method was outperformed by the conventional triangular splitting method. The fuzzy rectangular splitting method outperformed the other two methods from the perspective of accuracy. As for positioning resolution, the area was divided into nine square zones of 1M × 1M, which means that as long as the zone is identified correctly, the error would be less than 1 m.

In the above simulations, the three splitting methods do not produce the same number or size of splitting areas; therefore, it would be unfair to calculate the percentage of correct positioning estimates from the results in Table 4. Nonetheless, we can see that the rectangular splitting method combined with fuzzy inference produces a larger number of splitting zones as well as a higher percentage of correct positioning estimates.

In the previous simulation, the sampling of the anchor point was randomly set to 100; however, this was not high enough to determine whether the positioning results were stable. In subsequent simulations, we gradually increased the number of sampling points from 100 to 400. Under these conditions, the percentage of correct positioning estimates achieves convergence.

Figure 16 presents the percentage of correct positioning estimates obtained using the fuzzy triangular splitting method vs. the number of sampling points. The percentage of correct positioning estimates gradually converged with an increase in the number of sampling points, regardless of the standard deviation. In simulations with 225 sampling points, the percentage of correct positioning estimates in the two zones converged as follows: $\sigma = 3$ [72%, 74%], $\sigma = 5$ [69%, 71%], $\sigma = 7$ [62%, 64%], $\sigma = 9$ [60%, 62%].

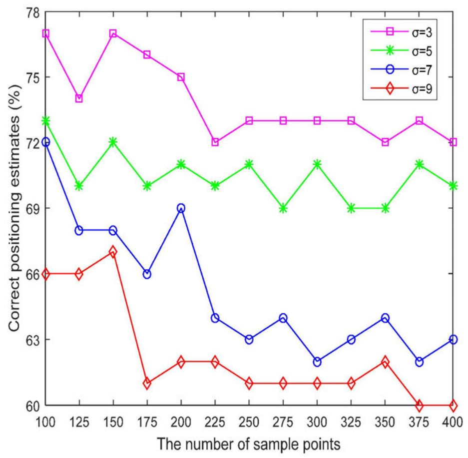

Figure 16. Percentage of correct positioning estimates obtained using fuzzy triangular splitting method

As shown in Figure 17, the rectangular splitting method combined with fuzzy inference led to a convergence in the percentage of correct positioning estimates as the number of samples was increased. In simulations with 225 sampling points, the percentage of correct positioning estimates converged as follows: $\sigma = 3$ [83%, 85%], $\sigma = 5$ [80%, 82%], $\sigma = 7$ [77%, 78%], and $\sigma = 9$ [73%, 75%].

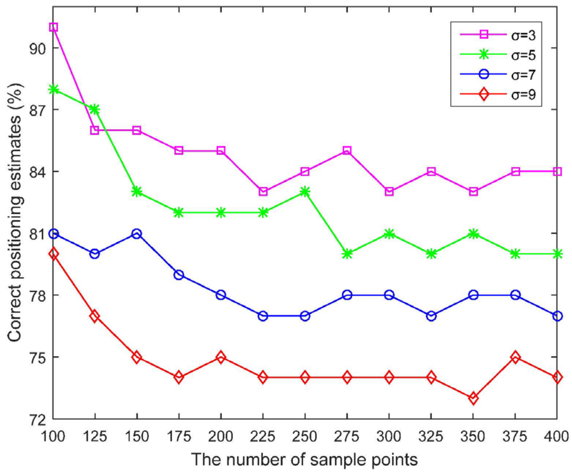

Figure 17. Percentage of correct positioning estimates obtained using fuzzy rectangular zone splitting method

When using the fuzzy inference method, increasing the number of sampling points to 225 led to convergence in the percentage of correct positioning estimates. This also means that using more than 225 sampling points makes the judgements more reliable. Figure 18 and Table 5 compare the two fuzzy zone splitting methods under four ranges of standard deviation.

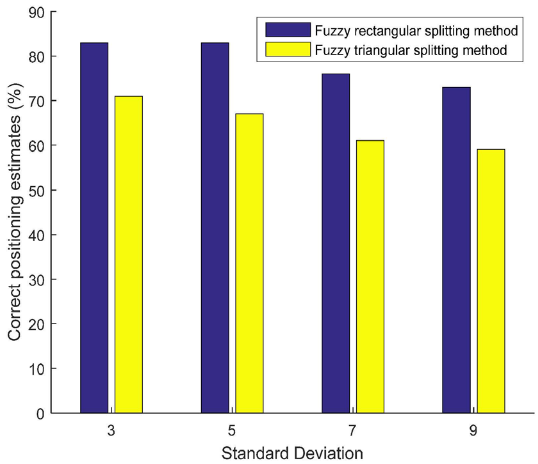

Figure 18. Comparison of two fuzzy zone splitting methods with regard to positioning performance using four ranges of standard deviation

Table 5. Comparison of two fuzzy zone splitting methods with regard to positioning performance using four ranges of standard deviation

σ	Fuzzy triangular splitting method	Fuzzy rectangular splitting method	Improvement R_i
3	73%	83%	13.7%
5	70%	82%	17.1%
7	64%	77%	20.3%
9	62%	74%	19.35%

Equation (4) below was used to calculate the improvement provided by the fuzzy triangular splitting method over the fuzzy rectangular splitting method:

$$R_i = \frac{E_{FuzzySqr} - E_{FuzzyTri}}{E_{FuzzyTri}} \times 100\% \quad \textbf{(4)}$$

where $E_{FuzzySqr}$ represents the average percentage of correct positioning estimates obtained using the fuzzy rectangular splitting method, and $E_{FuzzyTri}$ represents the average percentage of correct positioning estimates obtained using the fuzzy triangular splitting method.

As shown in Table 5 and Figure 18, the fuzzy rectangular splitting method outperformed the fuzzy triangular splitting method by 13.7% - 20.3%. The fuzzy rectangular splitting method also outperformed the fuzzy triangular splitting method from the perspective of accuracy. With regard to the stability of positioning, an increase in σ enabled the fuzzy rectangular splitting method to achieve accurate estimations in 74% to 83% of the cases.

We also sought to determine whether the proposed rectangular zone splitting method could increase the percentage of correct positioning estimates in cases where an unknown target was close to the central reference node. This was achieved by randomly deploying 200 sampling points within a radius of 0.5 meter from the central reference node. As shown in Figure 19, we compared the positioning performance of the two fuzzy zone splitting methods using various σ values. The results are presented in Figure 20 and Table 6.

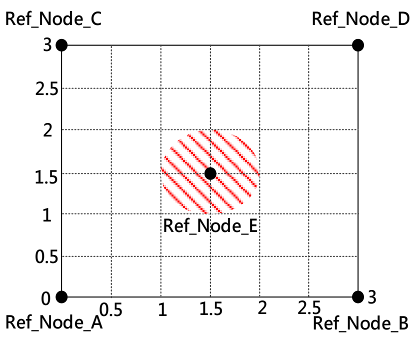

Figure 19. Area of central reference node (radius of 0.5 m)

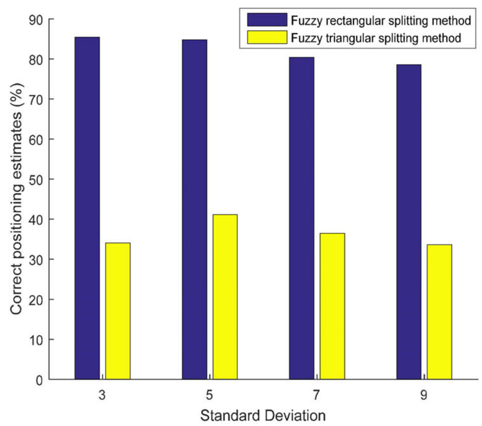

Figure 20. Positioning performance of two fuzzy zone splitting methods in region of central reference node

Table 6. Positioning performance of two fuzzy zone splitting methods in region of central reference node

σ	Method	Correct positioning estimates	Performance improvement
3	Rectangular splitting method	85.4%	51.4%
	Triangular splitting method	34%	
5	Rectangular splitting method	84.8%	43.7%
	Triangular splitting method	41.1%	
7	Rectangular splitting method	80.4%	44%
	Triangular splitting method	36.4%	
9	Rectangular splitting method	78.6%	45%
	Triangular splitting method	33.6%	

The difference in positioning performance between the two fuzzy splitting methods was calculated as follows:

$$E_{promote} = E_{FuzzySqr} - E_{FuzzyTri} \quad \textbf{(5)}$$

As shown in Table 6 and Figure 20, the fuzzy rectangular splitting method outperformed the triangular splitting method by more than 40%.

In the previous simulation, we explored two zone splitting methods based on fuzzy inference. In an indoor environment, the fuzzy rectangular splitting method has more consistent regions, higher resolution, and better positioning performance. The above results were averaged from all of the regions; therefore, we also investigated the performance of these methods in specific regions. This was achieved by deploying 50 positioning sampling points in each zone (to ensure a sufficient number of samples), and then applying the rectangular splitting method with fuzzy inference. We then identified the zones in which positioning performance was not up to par. Table 7 and Figure 21 present the average positioning performance in each zone.

Table 7. Positioning performance of fuzzy rectangular zone splitting in nine specific zones

Zone Number	Average percentage of correct positioning estimates in each zone			
	σ =3	σ =5	σ =7	σ =9
1	86.2%	82.8%	81%	76.6%
2	84.4%	81.2%	78.2%	77.6%
3	87.4%	83.2%	80.8%	77%
4	81.8%	79.4%	74.4%	65.6%
5	88.6%	85.8%	80.2%	78%
6	81.6%	80%	75.6%	65.8%
7	86.2%	83.8%	81.4%	77.8%
8	81%	83.4%	76.4%	74%
9	86.4%	83%	80.2%	75.8%

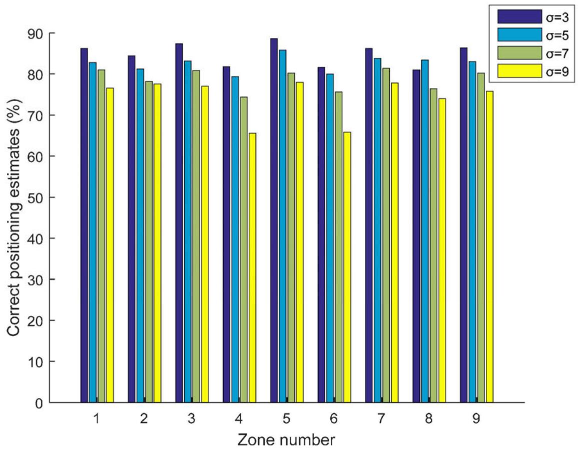

Figure 21. Positioning performance of fuzzy rectangular splitting method in nine specific zones

Table 7 shows that when σ = 3 and σ = 5, the average positioning performance in 9 zones is roughly 80%. However, in cases of large deviation in the RSSI values (σ = 7 and σ = 9), positioning performance was good in only five of the zones (1, 3, 5, 7, 9) in the vicinity of the reference nodes. In zones at a distance from the reference nodes, performance was not as good. From a theoretical perspective, there should be little difference in performance in these four areas; however, our simulation results presented a notable difference in performance between zones 4/ 6 and zones 2 /8. This may be due to inconsistencies in the fuzzy rule base. The division of the region and deployment of reference nodes clearly affects location performance.

5 Conclusion

This paper presents an efficient fuzzy-based indoor zone positioning system for wireless sensor networks. The RSSI between the reference node and target node is used to estimate the position of the zone without the need for additional hardware. The proposed method is fast and does not require training or a large number of measurement points for the formulation of a database. The shape of the regions, the location of the reference points, and the fuzzy rule base all affect location performance. Based on these constraints, we propose using fuzzy rectangular splitting as well as fuzzy triangular splitting to enhance the accuracy of zone positioning within an indoor environment. Simulation results demonstrate that the fuzzy rectangular splitting method outperforms fuzzy triangular splitting by more than 40% under four standard deviations. The proposed fuzzy rectangular splitting method is the most suitable for splitting up zones for indoor localization.

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