PREDICTION OF RECEIVED SIGNAL STRENGTH USING THE FUZZY LOGIC CONTROLLER FOR LOCALISATION OF SENSORS IN MOBILE ROBOTS

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Abstract

Improving the accuracy rate in the localisation of mobile sensor networks is challenging. Mobile localisation in mobile sensors has various applications, such as mobile robot navigation, networking taxi service for finding the nearest taxi drivers, vehicle ad hoc networks for rerouting the path during road accidents, site works, and many more. In this research work, we have adopted the experimental data from the literature by Marti *et al.* and performed a simulation to predict the location in three different environments, such as garden, classroom, and corridor. All three environments have been configured with 55 transmitters and four beacons, the localisation has been calculated with received signal strength (RSS), and the data uncertainties in RSS are addressed by implementing the fuzzy logic system using semi-elliptic membership function (SEMF), which has an improved accuracy rate compared to conventional controllers.

Key Words

Fuzzy logic controller; Received signal strength; Localisation; semi-elliptic membership function; Mobile sensor.

1. Introduction

Mobile sensor localisation is a quite active and trending research area [1]–[5], which has more scope in future technologies like driverless car, rerouting [6], [7], tracking of public transport vehicle [8], [9] for customer transparency and many more. Improving an accuracy rate in localisation is always a quite challenging task. In this research work, fuzzy logic controller has been developed to improve the accuracy rate, and it has been studied and experimented based on the research gap in the literature. Location-based service apps are widely used and rely on people's location data in indoor spaces due to the Internet of Things and the mobile Internet's rapid expansion [10]. Due to the pervasive wireless infrastructures and low prices, the WiFi fingerprint localisation method [11], [12] is now preferred. Researchers [13] have examined the complementary natures regarding localisation precision and energy consumption; WiFi fingerprint localisation and pedestrian dead reckoning on smartphones are excellent candidates for integration. The improved cuckoo search algorithm with fuzzy logic and the Gauss–Cauchy strategy, which combines the meta-heuristic algorithm with the conventional approach to reduce localisation error, have been suggested by Scholars [14]. Singh *et al.* [15] have studied in a three-dimensional environment, with one anchor node to locate unknown sensors using range-based and range-free algorithms (with fuzzy logic).

According to experiments conducted by Mishra *et al.* [16], mobile robots in structured environments now have a navigation controller that can function in reactive and deliberate ways; a neuro-fuzzy system is introduced to investigate the advantages of both intentional and reactive navigation control. A localisation approach was suggested by Chadha and Jain [17] that first determines best alternative RSS value for the unknown anchor node. Karaduman *et al.* [18] have deployed software agents with a fuzzy logic controller on ultra-wideband localisation-based mobile robots, which have enhanced the localisation accuracy rate compared to the conventional controller. Rahayu *et al.* [19] developed an inverted global sensor for studying navigation and localisation of automated guided vehicles. According to a study by Singh *et al.* [20] on the scenario put forward, to locate target nodes using

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edge weight information, received signal strength (RSS) information must be shared between the target nodes and the anchor nodes that correspond to them.

The clustering protocol studied by Bhushan *et al.* [21], fuzzy logic-based energy adequate clustering, uses fuzzy if-then rules to cluster heads on various environments. Vargheese *et al.* [22] have designed a fuzzy logic controller for quality of service routing in mobile ad hoc network, which is the system for connecting individual mobile nodes. Ranjita *et al.* [23] proposed a fuzzy logic-based on alternative rerouting during road accidents, site work in process and many more reasons for road blockage. Multispectral visual odometry (MVO), a novel technique for localisation and navigation of mobile robots, has been put out by Fahima *et al.* [24]; the suggested method entails fusing visible and infrared photos to locate the mobile robot in a variety of settings, including day, night, indoors, and outdoors. Distance matrix and estimation matrix are utilised to locate node in the Markov chain model that Bamasaq *et al.* [25] has developed as a node localisation technique. Himansu *et al.* [26] proposed a method to significantly outperform previously proposed range-free methods in target node 3D position accuracy; the technique helps in mapping for various situations, including tracking workers at various installation sites, solar plant tracking in smart cities, and mapping fire hazards in forests. Further fuzzy logic is applied in various applications, such as predictive maintenance [27], diagnosing [28], prediction of machining parameters [29], and many more applications. Zhuang *et al.* [30] developed hybrid sensing in large-scale indoor environments to localise mobile robots using two modes: omnidirectional vision and laser scanning. Savage *et al.* [31] estimated the localisation of mobile robots by vector quantisation with the combination of hidden Markov models and the Viterbi algorithm. Kraeussling [32] designed a novel method for mobile robot localisation using the tracking method based on the Kalman filter and geometrical properties. Chi Guo *et al.* [33] focussed on semantic mapping using a mobile robot with a 2D laser range and monocular camera. Bayram *et al.* [34] designed a six-axis dual-arm robot manipulator for orthopedic treatment disorders. Du Qiang Zou *et al.* [35] developed a brain-inspired cognitive map building for achieving accurate mobile robot navigation. Tapas *et al.* [36] studied stability using a force sensor for biped-robot applications with an electro-mechanical model. Further, the localisation of mobile robots indoors [37] and outdoors [38] using GPS, motion control [39], 3D mapping [40], collision free [41] and 2-D laser range sensors, respectively.

In the above literature, localisation in sensor networks has been applied in various fields such as mobile robot navigation, smart cities, automatic guided vehicles, ad hoc networks, and fuzzy logic system is a tool to find the optimal localisation in sensor networks, still research exists in predication of RSS value, this research manuscript addresses the data uncertainties in RSS.

The manuscripts are organised as follows. The problem condition of the task is illustrated in Section 2. The experimental findings are covered in Section 3. In Section 4, the architecture of fuzzy system formulation is covered. The research's findings are finally explained in the conclusion section, followed by a reference.

2. Problem Statement

In sensor networks, localisation estimation is quite a challenging task with a higher accuracy rate. Marti *et al.* [42] have performed localisation of mobile sensors in low visibility conditions. The authors have estimated the RSS using ZigBee fingerprinting approach, and found the distance of each point in the solution space of three environments, such as a garden, classroom, and corridor, and they have concluded that the error rate in RSS value prediction can be reduced by addressing the data uncertainty issue; considering this as a research gap the fuzzy logic system has been adapted using semi-elliptic membership function (SEMF) to increase the accuracy rate in the prediction. SEMF [43] remains underutilised and unexplored with real-time application. Consider this also as the second objective of the research, an attempt has been made to validate the merits of SEMF, such as reduction in computation cost, geometric parameters and faster convergence in finding an optimal point of decision. Hence, considering the above research gaps, SEMF has been adopted in this work.

3. Experimental Data

Several intriguing localisation techniques based on radio-frequency signals that can be sent in smoke are available in the sensor networks community. A few methods for locating mobile nodes using this type of signal analysis have recently been presented, including time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received [26] signal strength (RSS). Marti *et al.* [42] have performed investigation with mobile robot and they have estimated the RSS value in the following environments

3.1 Fuzzy Inference Training

The training is performed for all three environments by placing 55 transmitters with four beacons in all three scenarios; the RSS value and the distance of each point are trained with the fuzzy inference system. IF-THEN rules train the fuzzy inference system, and it has been described using a finite state machine, as shown in Fig. 1. The trained inference system predicts the RSS value with distance as the input. The fuzzy space of both input and output parameters is classified with an attempt using the SEMF [36]. An attempt has been made with SEMF to apply with actual time application.

3.2 Garden

It is one of the environments to study the prediction of RSS value; the size of the garden field (Fig. 2) is 40×40 Sq. ft. Plants along the edges have surrounded the field, and the middle space has been plotted with 55 transmitters for the experimentation of localisation. The fuzzy system has been

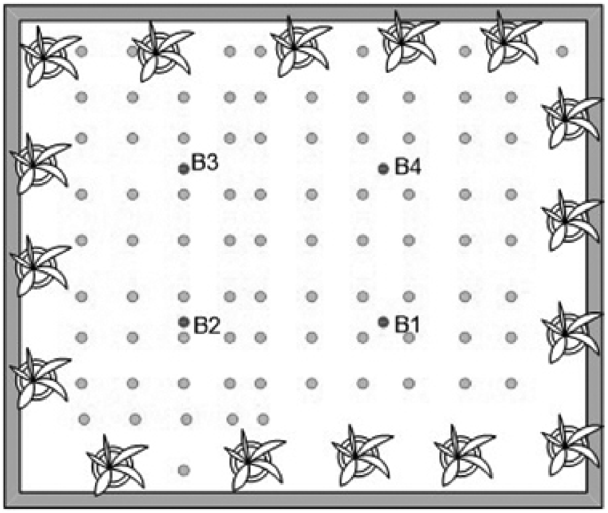


Figure 1. State transmission of all 55 points.

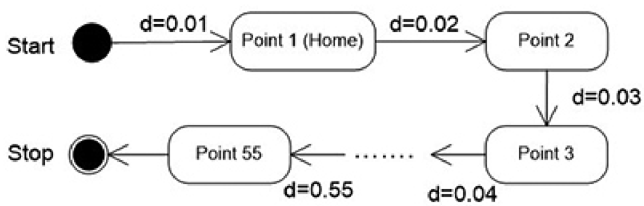


Figure 2. Garden.

designed to predict the RSS value by training the fuzzy inference system with distance and RSS value, as shown in Fig. 1. The motivation for selecting the garden environment is to automate the irrigation process in the garden; hence, the process has been imitated with the localisation of robot position in the garden field. The research has been further extended to studying plant health, diagnosing the risk state of plant diseases and many more.

3.3 Classroom

It is the other scenario considered for the testing, the application of mobile robot in education domain will also be upcoming trend for application like monitoring students during examination, and assisting the student's requirements like providing answer papers, question papers and many more. The size of the classroom is 40×40 sq. ft. (Fig. 3), and the coordinate points in the classroom are plotted with space around desks, in between area of desks, and also in dais. The class is well structured for the free movement of mobile robot in across all parts and also a ramp is provided for climbing the dais. The classroom has been plotted with 55 transmitters, and the RSS value of all the points has been trained and simulation for predication of RSS values is performed with a fuzzy logic system.

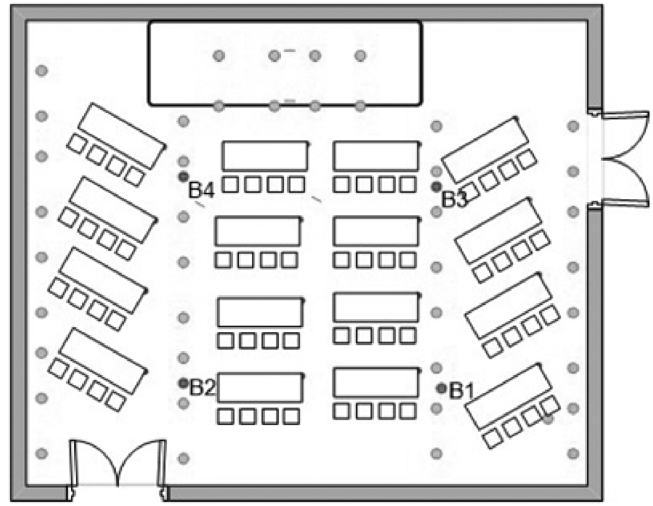


Figure 3. Classroom.

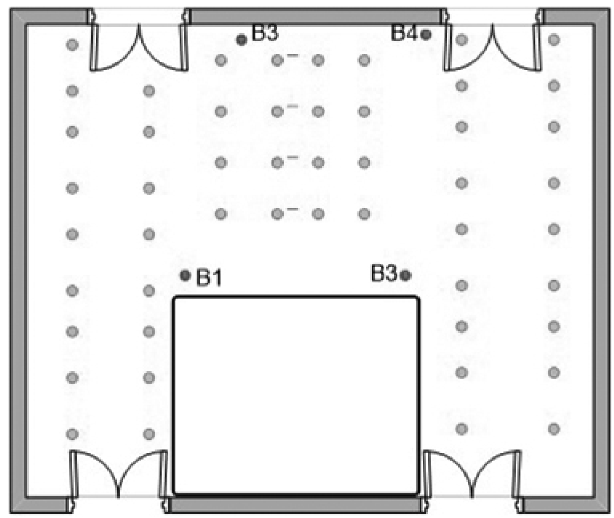


Figure 4. Corridor.

3.4 Corridor

It is a quite common and general place for testing of mobile robot localisation, because this place giving similar constraints as like public places, so this place is also considered for experimentation of localisation. The entire place is also plotted with 55 coordinate points and the size of the area is 40×40 Sq. ft. Fig. 4 also remains the same as like earlier two environments. There is a hallow gab in the center down corner for the size of 14×10 Sq. ft. which has been not considered for experimentation. The environment has quite clear space for the movement of mobile robots.

4. Estimation of RSS Values Using Fuzzy Logic

The output parameters of the mobile robot location are estimated using fuzzy logic systems, and the fuzzy controller is trained with the RSS value of each location point. The input parameters are the location of each point, and the output parameter is the RSS value. The fuzzy system has been trained in three environments: a garden,

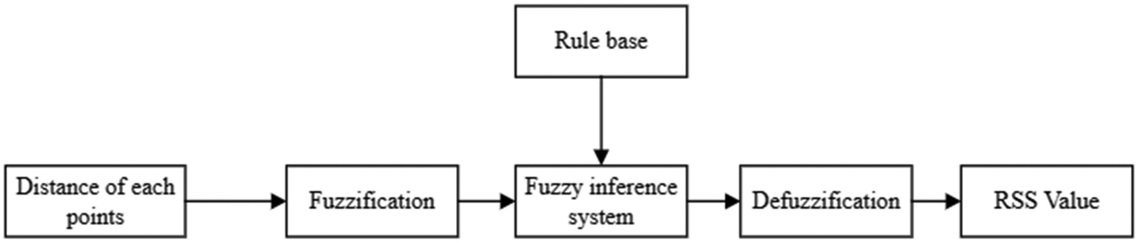
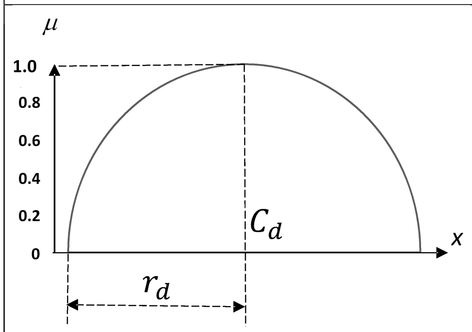


Figure 5. Architecture of fuzzy system.

Table 1
Parameters of Membership Function

Semi-elliptic	
	$SEMF((x;C_d,r_d)\mu_E(x)) = \begin{cases} \left|\sqrt{1-\frac{(C_d-x)^2}{r_d^2}}\right| & if\ C_d - r_d \leq x \leq C_d \\ 0 & otherwise \end{cases}$ C_d *&* r_d- Centre of the ellipse and radius of the ellipse

a classroom, and a corridor. The fuzzy space of all the input and output parameters is fuzzified with the SEMF. Inference in the fuzzy logic system is carried out via centroid-type fuzzification. The fuzzy inference system uses the Takagi–Sugeno–Kang (TSK) model type because it has better accuracy rate in the prediction of the values. TSK has the ability to predict the values with higher accuracy with lesser linguistic variables, and the architecture of fuzzy system is shown in Fig. 5.

4.1 Membership Function

The fuzzy logic system performs the fuzzification by categorising the fuzzy space of the input and output parameters. The mobile robot's input parameters are the distance between each point, and its output parameter is the RSS value. The parameters in this work are fuzzed using the SEMF. Inference in the fuzzy logic system is carried out via centroid-type fuzzification. Table 1 illustrates the mathematical formulation of SEMF. Table 2 displays the SEMF's coordinate points of all three environments.

5. Result and Discussion

Python 3.7, Spyder 4.2.5, and the "skfuzzy" toolkit are used to mimic fuzzy inference systems. The workstation setups consist of 16GB of RAM and Windows 10 OS.

5.1 Garden Environment

The RSS value of each location point is predicted using the fuzzy system with SEMF, as shown in Fig. 6, and the experiment results are also in the same figure for

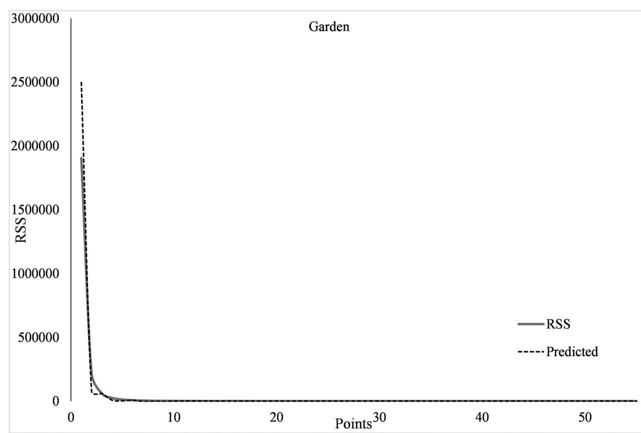


Figure 6. Comparison of RSS value predicted results with experiment values of garden environment.

comparison. The prediction of the RSS value of the garden environment has a higher accuracy rate in all 55 location points because the SEMF has accounted for the uncertainty in data which makes the fuzzy system more robust and reduces the error rate in prediction. The average error rate of RSS value prediction is 1.5% only. SEMF has unique characteristics with geometric property which has shown higher accuracy in predication and computational cost is also low by having geometric parameters like centre (C_d) and radius (r_d). The coordinates of all 55 points in the garden environment are recorded and trained with the fuzzy system. The error rate of each location point is shown in Fig. 7.

Table 2
Coordinate Points of SEMF for Garden, Classroom and Corridor

Sl. No.	Points	Garden		Classroom		Corridor	
		Parameters					
		C_d	r_d	C_d	r_d	C_d	r_d
1	Point 1	3594765.5	844652.5	613379.3	141124.1	466623892.1	113370300.1
2	Point 2	371798.9	77821.8	81801.7	16459.4	23881784.7	5369546.5
3	Point 3	96502.8	17995.5	24712	4373.9	4087137.3	841769.3
4	Point 4	36872.8	6176.1	10534.6	1659.1	1157426.4	218683.3
5	Point 5	17472.4	2652	5439.3	770.7	433698.8	75502.7
6	Point 6	9498.4	1317	3173.3	408.3	194345.8	31328.9
7	Point 7	5679.4	724.4	2014.8	237.4	98609.9	14789.8
8	Point 8	3641.6	430	1361	147.8	54817.3	7683.4
9	Point 9	2463	270.6	963.9	97.1	32679.3	4297.8
10	Point 10	1737.4	178.5	708.5	66.5	20587.5	2549.7
11	Point 11	1268	122.3	536.8	47.2	13562.7	1586.9
12	Point 12	951.8	86.5	416.9	34.5	9270.7	1027.9
13	Point 13	731.4	62.9	370	45.5	7485.7	1163.3
14	Point 14	573.4	46.7	218.6	15.3	3503.7	335.6
15	Point 15	457.3	35.4	181.5	12.1	2646.3	242.4
16	Point 16	370.2	27.3	152.4	9.7	2033.6	178.5
17	Point 17	303.7	21.4	129.4	7.9	14430.6	3344.6
18	Point 18	252	17	110.8	6.5	1255.5	101.7
19	Point 19	211.3	13.7	95.7	5.4	1005.5	78.4
20	Point 20	178.8	11.1	83.2	4.5	814.2	61.2
21	Point 21	152.6	9.1	72.8	3.8	665.9	48.4
22	Point 22	131.2	7.6	64.2	3.2	549.6	38.6
23	Point 23	113.6	6.3	56.8	2.7	457.4	31.1
24	Point 24	99	5.3	50.6	2.4	383.6	25.2
25	Point 25	86.7	4.5	45.3	2	324	20.7
26	Point 26	76.4	3.8	40.6	1.8	275.4	17.1
27	Point 27	67.6	3.3	36.7	1.5	235.5	14.2
28	Point 28	60.1	2.8	33.2	1.4	202.6	11.8
29	Point 29	53.7	2.5	30.1	1.2	175.1	10
30	Point 30	48.1	2.1	27.5	1.1	152.1	8.4
31	Point 31	43.3	1.9	25.1	0.9	132.7	7.2
32	Point 32	39.1	1.6	23	0.8	116.3	6.1
33	Point 33	35.4	1.5	21.1	0.8	102.4	5.3

Continued

Table 2
Continued

Sl. No.	Points	Garden		Classroom		Corridor	
		Parameters					
		C_d	r_d	C_d	r_d	C_d	r_d
34	Point 34	32.2	1.3	19.5	0.7	90.4	4.5
35	Point 35	29.3	1.1	18	0.6	80.1	3.9
36	Point 36	26.8	1	16.7	0.6	71.3	3.4
37	Point 37	24.5	0.9	15.4	0.5	63.6	3
38	Point 38	22.5	0.8	14.4	0.5	56.9	2.6
39	Point 39	20.7	0.7	13.4	0.4	51.1	2.3
40	Point 40	19.1	0.7	12.5	0.4	45.9	2
41	Point 41	17.6	0.6	11.6	0.3	41.5	1.8
42	Point 42	16.3	0.5	10.9	0.3	37.5	1.6
43	Point 43	15.1	0.5	10.2	0.3	34	1.4
44	Point 44	14.1	0.4	9.6	0.3	30.9	1.2
45	Point 45	13.1	0.4	9	0.2	28.1	1.1
46	Point 46	12.2	0.4	8.5	0.2	25.7	1
47	Point 47	11.4	0.3	8	0.2	23.4	0.9
48	Point 48	10.6	0.3	7.8	0.3	21.5	0.8
49	Point 49	10	0.3	7.1	0.2	19.7	0.7
50	Point 50	9.3	0.3	6.7	0.2	18.1	0.7
51	Point 51	8.8	0.2	6.4	0.2	16.7	0.6
52	Point 52	8.2	0.2	6.1	0.1	15.4	0.5
53	Point 53	7.8	0.2	5.7	0.1	14.2	0.5
54	Point 54	7.3	0.2	5.5	0.1	13.1	0.4
55	Point 55	6.9	0.2	5.2	0.1	12.2	0.4

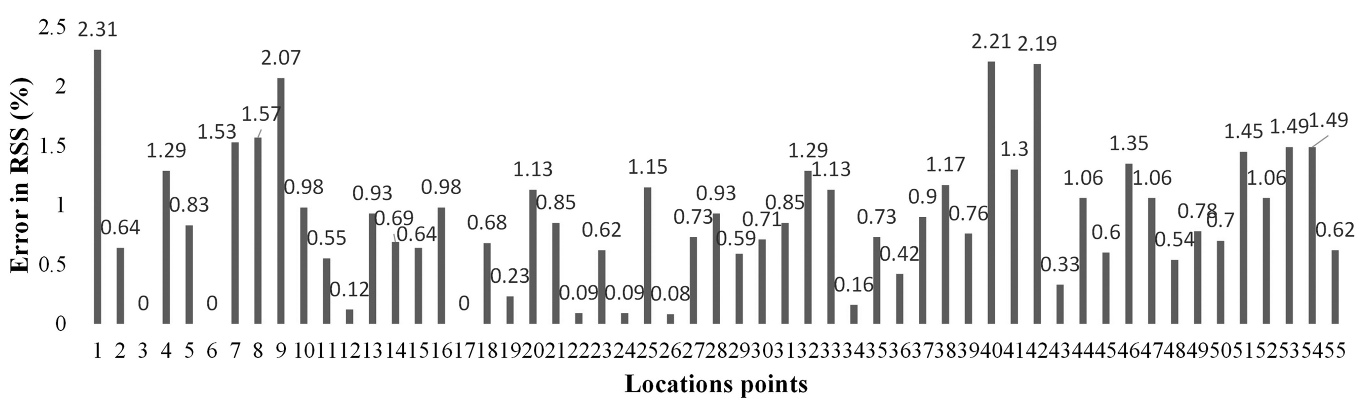


Figure 7. Error rate in prediction of location point in garden environment.

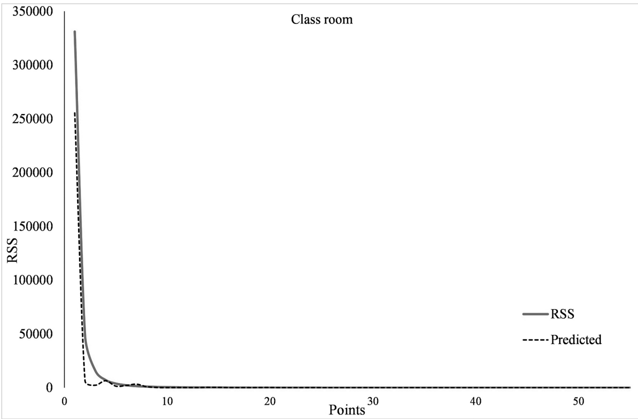


Figure 8. Comparison of RSS value predicted results with experiment values of classroom environment.

5.2 Classroom

The coordinate points of all 55 points in the classroom are predicted using a fuzzy logic system. The experiment results comparisons are also plotted in Fig. 8. The average error rate of the predicted value is 1.5%. The classroom environment has more hurdles due to more table chairs; the fuzzy system error rate in the prediction of RSS value depends on the training of the fuzzy inference system. The geometrical characteristics of SEMF can incorporate the data uncertainties in the system, and the error rate of all 55 points is shown in Fig. 9. SEMF has gained the similar advantage of the Gaussian membership function, whereas it overcomes the limitation of long tail which removes non-zero numbers in the fuzzy system and also improves the accuracy rate in prediction of RSS values. SEMF also improves the system to be more robust by improving the accuracy rate and reducing the computation load with lesser geometric parameters.

5.3 Corridor

The fuzzy logic system also predicts the RSS value of the corridor environment. The results are compared with experimental data, as shown in Fig. 10. The average error rate in predicting the coordinate points of RSS value in the corridor environment is 1.5%. The solution space in

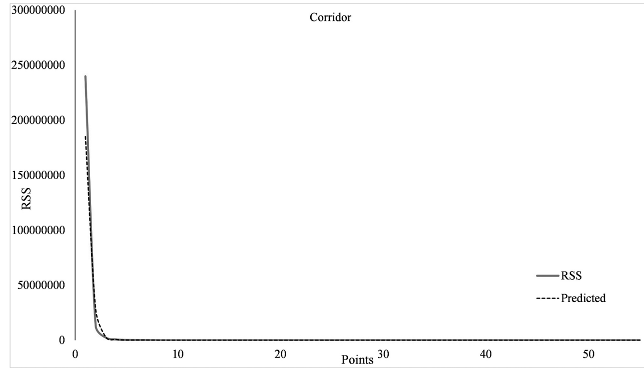


Figure 10. Comparison of RSS value predicted results with experiment values of corridor environment.

this environment has fewer hurdles than the classroom, the accuracy of predicting the RSS value for all 55 location points has equal competence compared to the other two environments, and the error rate of all the points is shown in Fig. 11. SEMF has shown faster convergence rate in prediction, the simulated results also have shown faster convergence between point 5 to point 14, and also improve the accuracy rate in further points. Hence, SEMF has given a higher accuracy rate in training the fuzzy inference system.

5.4 Comparison of Results

The RSS value of all three environments is predicted using the fuzzy logic system; the results are compared with those available in the literature by Marti *et al.* [42]. The authors have performed the prediction with four different methods: K-NN, minimum distance (MD), and neural network. Even though K-NN, MD and neural networks are advanced methods, the prediction accuracy is purely based on the training. In fuzzy logic, all the localisation points of all three environments have been trained at a higher accuracy rate. The fuzzy logic with SEMF has given greater advantage in terms of accuracy and computation. TSK model fuzzy inference system [44] has the characteristics accounting for the data uncertainties in both input and output parameters, and predicting the values in higher accuracy. Table 3 shows the mean error

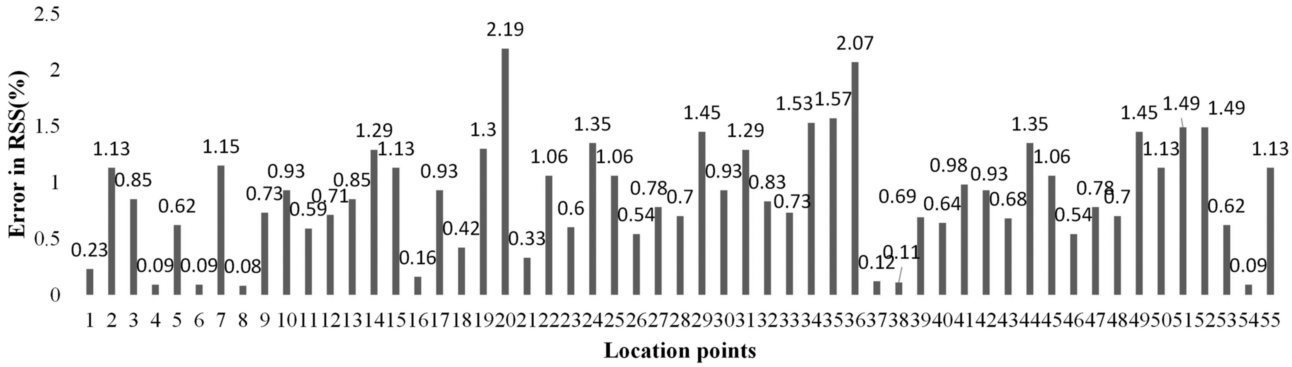


Figure 9. Error rate in prediction of location point in the classroom environment.

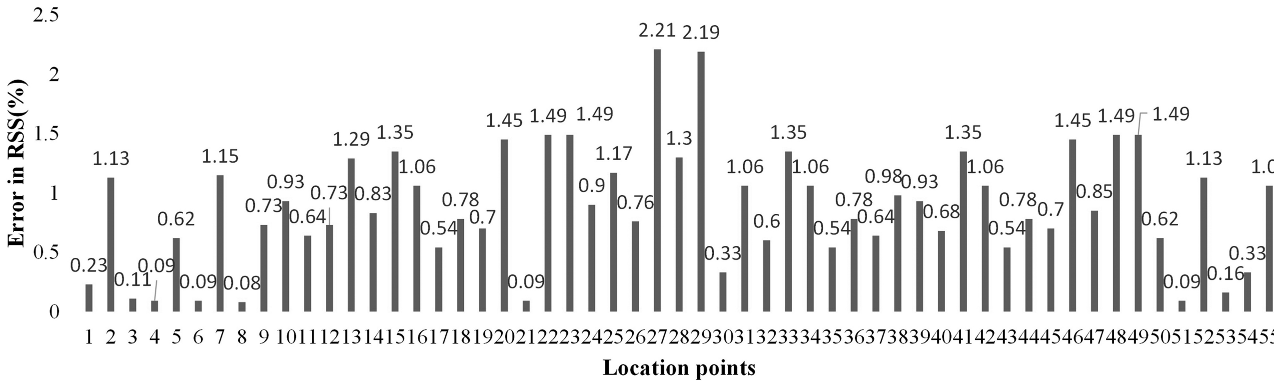


Figure 11. Error rate in prediction of location point in a corridor environment.

Table 3
Error Rate (%) of RSS Value Prediction

Sl. No.	**Prediction Methods**	**RSS Value Error Rates**
1	K-NN [42]	24.96
2	MD [42]	35.67
3	Neural network [42]	31.53
4	Fuzzy logic	1.5

rate of the methods adopted in [42] compared with the fuzzy logic system.

6. Conclusion

The error rate in the RSS value prediction is considerably reduced using a fuzzy logic system. The fuzzy system has the advantage of considering the uncertainty in both input and output parameters, the other system adapted in [42] is quite advanced, but the prediction has more error rate as per the results. The outcomes of the research are

- All the prediction system accuracy rate is based on the system training and considering the uncertainties in the training data.
- Fuzzy logic addresses the uncertainties in input parameter distance and output parameter RSS value, reducing the error rate, and also reduced the computation cost by using SEMF.
- The attempt made with fuzzy logic using SEMF for real-time localisation application has quantified the potential of SEMF.
- SEMF has greater advantage with geometric property which made faster convergence in localisation, and also reduced its computation load by having fewer parameters such as centre *(C_d)* and radius *(r_d)*.

Future research can be extended.

- The prediction system can be extended with a hybrid intelligence system with a combination like KNN with fuzzy logic to grab both sides advantages of the learning system.
- This method can also be extended with Type-2 fuzzy logic system to improve the accuracy rate further.

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