Arab J Sci Eng (2018) 43:4145–4159
https://doi.org/10.1007/s13369-017-2826-2

RESEARCH ARTICLE - SPECIAL ISSUE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Localization Based on RSSI Exploiting Gaussian and Averaging Filter in Wireless Sensor Network

Ranjan Kumar Mahapatra[1] · N. S. V. Shet[1]

Received: 3 May 2017 / Accepted: 20 August 2017 / Published online: 19 September 2017

Abstract The primary focus in this paper is on position estimation of an unknown sensor node in indoor environment. Received signal strength (RSS)-based algorithm was used for position estimation in which Gaussian filter and averaging filter were used for distance estimation, and for localization, trilateration and least square estimation were used. IRIS motes from MEMSIC were used for the experiments and were configured in real time to record the RSSI. Effect on distance estimation and localization was studied in indoor environment by conducting several experiments. Simulation results show that the proposed sensor selection, distance estimation based on RSSI as well as localization method helps in improving accuracy of position estimation in different environmental conditions.

Keywords Received signal strength indicator · Distance estimation · Localization · Line of sight · Gaussian filter · Averaging filter · Wireless sensor networks

1 Introduction

Technological advancement in sensing and computing in wireless communication, to monitor the physical activities, has put forward the growth in wireless sensor network. In present days, position-based services possess much more impact on our daily lives.

✉ Ranjan Kumar Mahapatra
mahapatra.ranjankumar@gmail.com

N. S. V. Shet
shet@nitk.ac.in

1 Department of Electronics and Communication Engineering, National Institute of Technology, Surathakal, Karnataka, India

For Location-based applications, localization of the object has become more and more challenging issue [1–3]. Location of sensor nodes must be known to make the intelligence of the data meaningful. Three well-known scenarios, where having location information of sensor nodes is an advantage, are as follows:

- Deployment of WSNs in rescue and relief troop by locating the enemy field, i.e., where the event has happened.
- Facilitation of many application service like target tracking to locate survivors in battle field has become possible.
- Geographical routing as well as network coverage can be assisted.

Advancement in wireless communication, VLSI, electronics and MEMS have helped a lot toward the development of cheap, low-power, smart as well as multi-functional sensors which can be deployed in a large scale to have the location information.

In indoor environments, GPS (Global Positioning System [4] with a accuracy of 10 m) cannot be used, as the signals get attenuated and accuracy becomes insufficient for localization in indoor environment. For decimeter level precision in indoor environment, accuracy is low as well as the cost is high [5,6]. Hence low cost, low power, high precision are essential for any positioning algorithm.

A typical comparison [7,8] of various methods which is used for distance/angle estimation between two nodes is given in Table 1.

Time-based methods as ToA, etc., are mostly dependent upon synchronization. AoA cannot be a choice as it requires extra hardware (not cost-effective). So adapting RSSI-based distance estimation for localization would be appropriate without any need of extra hardware or need for synchronization.

Table 1 Comparison of methods

Method	Precision measurement	Maximum distance	Requirement of extra hardware	Challenges
RSSI	Meters (2–4 m)	Communication ranges	None	RSSI variation, interferences
ToA	Centimeters (2–3 cm)	Communication ranges	None	Synchronization of node
TDoA	Centimeters (2–3 cm)	Few meters (2–10 m)	Ultrasound transmitter	Work distance is maximum
AoA	A few degrees	Communication ranges	Set of receivers	For small sensors

Among several approaches, RSSI-based distance estimation has become a vital approach for distance estimation as well as for localization of the object as it does not require any extra hardware for implementation.

Received signal strength is the voltage which is measured by the receiver's signal strength indicator circuit. It is often represented as measured power which is termed as square of the signal strength magnitude. Many RSSI-based localization algorithms [9,10] have already been used by several WSN community to perform efficient localization. No additional bandwidth or energy requirement is necessary for the measurement of the RSSI during the communication between the sensors.

In our previous work [11], distance estimation was the objective. The number of experiments and the number of data samples collected per experiment in that work were less for distance estimation. This resulted in a higher variance of RSS and therefore RSS vs distance curve was not very accurate. In this present work, we have extended the previous work to localize an unknown sensor node by conducting several experiments using large number of data samples. We have proposed an approach to select the sensors required for the distance estimation as well as for the localization using RSS. To mitigate abnormal RSSI fluctuation, we have incorporated the use of Gaussian filter as well as averaging filter. Here our key idea was to filter the RSS values from the fluctuated raw RSS data with the help of the Gaussian and averaging filter for distance estimation and localization.

1.1 List of Acronyms

The list of acronyms used in this paper is shown in Table 2.

Table 2 List of acronyms used

AoA	Angle of arrival
ADC	Analog to digital converter
BS	Base station
BW	Bandwidth
DSSS	Direct sequence spread spectrum
GPS	Global positioning system
IoT	Internet of things
IP	Internet protocol
LoS	Line of sight
LSE	Least square estimation
ML	Maximum likelihood
MLE	Maximum likelihood estimation
MEMS	Micro electro mechanical system
MSE	Mean square error
MMSE	Minimum mean square error
NLoS	Non line of sight
PDF	Probability density function
PLE	Path loss exponent
QoS	Quality of service
RSSI	Received signal strength indicator
Rx	Receiver
RF	Radio frequency
ToA	Time of arrival
Tx	Transmitter
TDoA	Time difference of arrival
TDMA	Time division multiple access
UDP	User datagram protocol
VLSI	Very large scale integration
WSN	Wireless sensor network

1.2 Sources of Error for the Measurement of RSSI

RSSI plays an important role in distance estimation as well as localization of an object. But variation in RSSI is much higher due to the several environmental factors. Even though target is fixed, RSS keeps changing with time [12,13]. In general, two of the major sources which affects RSSI are [14]:

– Multipath:
  Multipath signals cause frequency selective fading as multiple signals arrive at receiver with different phases and amplitudes, which constructively or destructively add as a function of frequency. This effect is mitigated by using the direct sequence spread spectrum or by frequency hopping. Also, spread spectrum helps to reduce the interference in the unlicensed band. As it is known, sum of the measured power of each multipath signal is

equivalent to the measured received power using wideband method [15].
– Shadowing:
Even if the effect of multipath is mitigated, RSS is influenced by the shadowing. It is explained in terms of the attenuation of signal due to the obstructions (furnitures, walls etc.) in indoor environment termed as medium scale fading [14].

In general, wireless communications are quite often affected by several unavoidable factors like obstacles, multipath, etc.

1.3 Research Objective

In order to achieve efficient localization, we have chosen research laboratory for indoor environment, as here, propagated signal will get reflected, may adopt multipath to reach destination. Here, it is possible to analyze the behavior of the propagated signal under various environmental factors and to use the received RSS to estimate the distance and localize the object. Hence, our objective was to select group of sensors based on RSSI variation. Then by using those selected sensors, we would create a testbed and develop a distance estimation technique based on RSS which exploits Gaussian as well as averaging filter to mitigate the abnormal RSS values. In the last phase of our work, we would be able to propose a localization algorithm which will help efficiently to localize the object.

Remainder of this paper is organized as follows: In Sect. 2, relevant research on RSSI is briefly reviewed. Section 3 explains the experiments and results and finally conclusions are drawn in Sect. 4.

2 Literature Review

In this section, relevant research on range-based position technique for wireless sensor network is reviewed. Several measurement techniques have already been discussed in [16,17]. To measure the distance and to localize the object, there are four generic algorithms such as:

– ToA based [18]
ToA technique is mostly based upon accurate time measurements of transmitted and received signals between two sensor nodes. Based on propagation time and the speed of the signal, distance between the sensor nodes is calculated by the multiplication of time difference and the speed of the propagated signal. These approaches usually rely on synchronization. To calculate ToA for propagated signal between two nodes, a common clock is essential between two nodes or a protocol like two-way ranging protocol [19,20], which can give necessary exchanged time information. Here, to synchronize both the sensor nodes in time, extra hardware is required which becomes quite expensive.

– TDoA based [21,22]:
Here, estimation of time difference of arrival for two signals (i.e., signal propagating between the target sensor node and the two reference sensor nodes) is performed. Time difference of arrival measurements are nonlinear function to the coordinates of the source. TDoA estimation is performed by cross-correlating two signals which travels between target node and the reference node. Delay is calculated by the largest value of the cross-correlation values.

– AoA based [23]:
AoA mostly rely on directional antennas or on multiple antenna configuration for the estimation of the angle of arrival of the received signal, from the anchor nodes. High accuracy in AoA is dependent upon antenna arrays [24] with certain amount of spatial diversity which depicts the requirement for more powerful hardware.
– RSS based: Here shadowing model is used for distance estimation between anchor node and the unknown node with the help of received signal strength, and coordinate is calculated by trilateration method in which three or more anchor nodes are necessary.

As per the above depiction of the three methods (i.e., ToA, TDoA and AoA), it is obvious that RSS-based technique possesses much more advantages which includes no/ less requirement of extra hardware with less complexity and cost.

Indoor positioning mostly rely on RSS-based technique and has been used widely. Jeffrey Hightower and Gaetano Borriello [25] proposed 3D location sensing which was based on RSS analysis. Li [26] has proposed a RSS-based joint estimation of unknown location coordinates in changing environment. Here they have used the combination of distance-power gradient, a parameter of path loss model and RSS-based location estimation. Authors were able to eliminate the need for extensive modeling and channel measurement. Also, it optimizes the performance in different environment.

Laitinen et al. [27] used narrowband measurements at five VHF frequencies to evaluate the accuracy of RSS-based location algorithms. They have used Kalman filter on estimated coordinates to eliminate largest location errors. Tian et al. [28] proposed RSSI-based DV-hop algorithm, where they have incorporated the advantages of range-based as well as range-free methods which have improved the accuracy as compared to the previous algorithms. Zanca et al. [29] investigated the performance comparison of different localization algorithm. Here authors have focused on RSS-based measurements only for comparison.

Chen et al. [30] proposed an improved RSSI-based algorithm for a park light control and children location tracking system. Here, they have established piecewise linear path loss model, where only linear operation was required for RSSI-based range estimation. Xu et al. [31] proposed a method which illustrates the relationship function of RSSI variance and distance. Based upon this they have established the log-normal shadowing model where variance can be adjusted dynamically. Their proposed method has proved that it has self-adaptability to various environment.

Feng et al. [32] proposed an RSS-based indoor positioning system which uses compressive sensing that recover sparse signals from noisy environment by solving l_1 minimization problem. Liu et al. [33] proposed a 3D range-free localization, named as hexahedral, where space is divided into a lot of hexahedrons. Here, by simulation they were able to achieve high accuracy. Mukhopadhyay et al. [34] proposed a technique which combines (mean + filter), mode, (mode + filter), to evaluate RSS for indoor localization. El Assaf et al. [35] proposed a localization algorithm which is used for anisotropic wireless sensor network. The developed algorithm can be used for both 2D as well as 3D scenarios.

Luo et al. [36] proposed a method for improved RSSI-based localization which makes use of the uncertain data mapping. Further they determined RSS data tuples and applied a strategy which matches the data tuple patterns to RSS data vector for localization. Lee et al. [37] proposed a location tracking method which uses RSS values received from Bluetooth Low Energy beacon. A method have been imposed to reduce the noise generated in the environment by the use of double Gaussian filter.

2.1 Problem Overview

As the primary focus on this work is on wireless sensor networks operating in indoor environment, GPS cannot be used. Hence, RSS-based technique in localization is a good alternative. But, RSS is noisy, varies with several environmental factors, unstable and challenging to use in practice. Hence, intensive study is essential to understand the nature of RSS behavior and its dependencies. In reference to these, some problems with higher priority are:

– Selection of sensors from a group of sensors which have almost similar characteristic for RSS is essential for distance estimation as well as for localization.
– Detailed investigation of RSS behavior at several distances in dynamic indoor environment is not done. Hence for distance estimation and localization, thorough analysis of the RSS behavior in various environmental conditions is required.
– In general, log-normal path loss model for received signal strength-based localization excludes the influence of several factors such as T_x power level, radio channels, etc., on RSS. Hence, there is a need for specific model for wireless sensor network.
– Various published research work on RSS-based localization is simulation based rather than real-time experimented work. Simulation-based work considers the RSS uncertainty as statistical quantity instead of detailed investigation. Hence, there is a need for detailed experimental study.

Hence, investigating the above problems is of primary task to use the RSS efficiently for distance estimation as well as for localization.

3 Experiments and Results

3.1 Experimental Setup

The setup for the experimental work is defined as:

– Sensor nodes were deployed in several indoor environment.
– Maximum no. of sensor nodes were set to be 5.
– Sensor nodes were placed 1.22 m above the ground on tripod stand in some experiments.
– RSS was received by the Base Station.
– Installed architecture was 2D.
– Deployed sensor nodes were static.

3.1.1 Basic Assumptions for the Experiment

– The network area used for the experimental purpose is a fixed $M \times N$ area with length M (6 ft) and width N (3 ft) and K (5) number of sensors.
– Homogeneous sensor nodes were used as they possess the same transmission range as well as the same initial energy.
– As we are using the static model, location of the anchor sensors and the BS remained unchanged.

3.1.2 Software and Hardware Setup

In this experimental work, we have used software platform Moteview for configuring IRIS motes and MATLAB R2015a for computation. To carry out the experiment, we have used both hardware (Core i7 Intel 4790 CPU 3.60GHz processor, 64 bit for server, IRIS motes) and software (Moteview and MATLAB). The architecture used to carry out the analysis involved five nos of XM2110 IRIS (product of MEMSIC

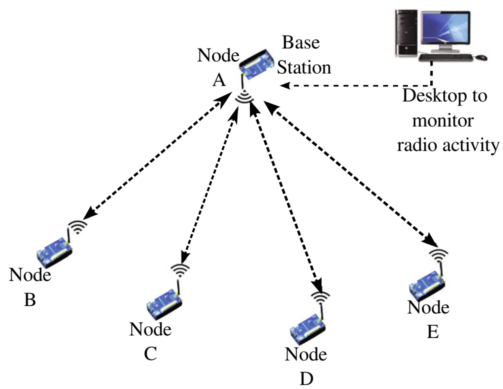

Fig. 1 Wireless sensor network setup

[38]) sensor nodes (one BS and other four communicating nodes) as shown in Fig. 1.

Base Station, i.e., node A was mounted on a MIB520 Interface Board and was connected to a PC (Core i7 Intel 4790 CPU 3.60GHz processor, 64 bit) via USB port. Base Station was programmed with XMeshBase firmware to act as a receiver. All other nodes were programmed to transmit the packets. BS had to record all the RSSI data. RF power level was set to 3.2 dBm (level 0). Antenna connected to each sensor node is of 1.2 inch omni-directional with the gain of 3 dBi. Data transmission rate was 250 kbps. The frequency of operation was kept 2.4 GHz with IEEE 802.15.4 standard for communication.

3.2 Experimental Analysis

In this paper, for our experimental setup, we have considered four phases which are as below:

- Phase-I: Selection of nodes based on the experimental results from RSSI variation.
- Phase-II: RSSI measurement in the area of interest.
- Phase-III: Use of the measured RSSI in an efficient manner for shadowing model analysis.
- Phase-IV: Localization of the unknown node.

3.2.1 Phase-I: Selection of Sensor Nodes

The flow chart to select sensors to deploy for the localization purpose is shown in Fig. 2.

Selection of T_x power level:

Here we intend to verify the fluctuations introduced due to the several sensors at different power levels. For this purpose, we have deployed 4 sensors (One BS and other communicating nodes) as shown in Fig. 3. Received values of the RSSI from 3 different nodes were recorded in the time interval of 5 min till 30 min. Then mean of the RSSI is calculated. Figure 4 shows the variation of mean RSSI to the different power

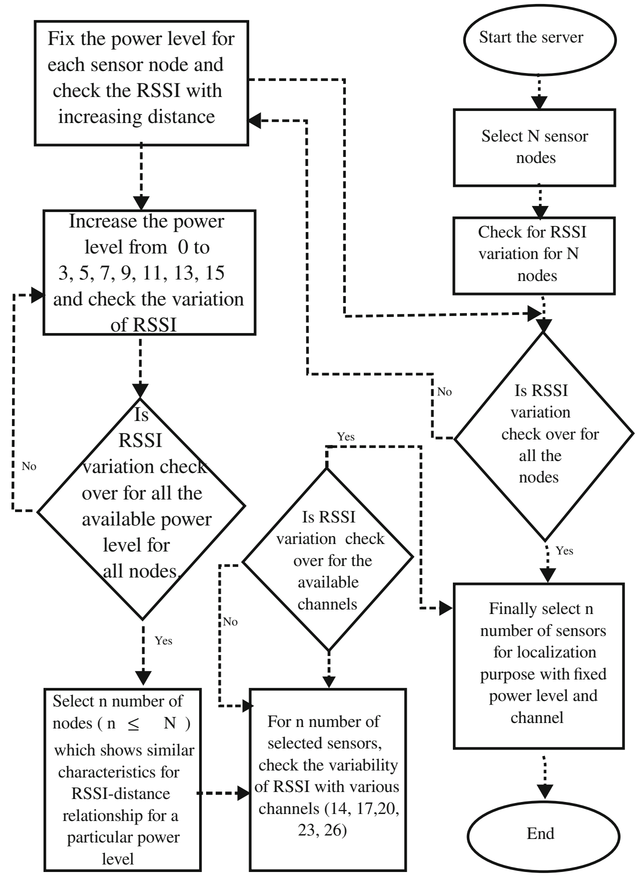

Fig. 2 Flow chart to select the sensors for localization

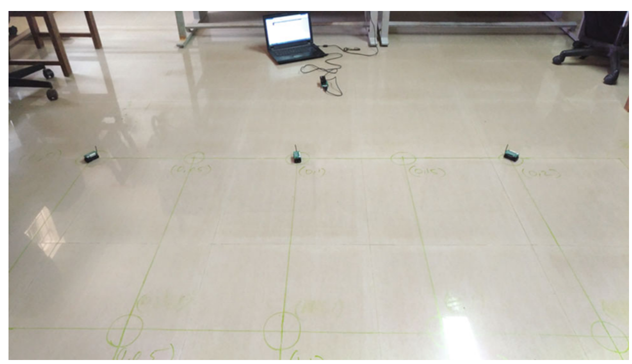

Fig. 3 Sensor network deployment

levels. Range of received power for different nodes is shown in the following Table 3:

From Fig. 4, it can be inferred that:

- With same transmitting power, Mean RSSI values for same receiver nodes were different.
- Variation between the nodes at the same position was small (approx.), except some points even if we have increased the transmitting power. We found that mean

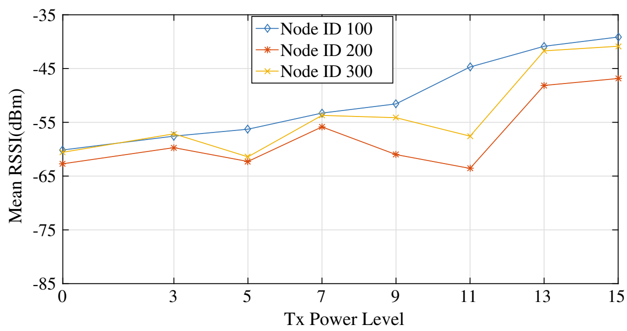

Fig. 4 Fluctuation in RSSI due to different power level

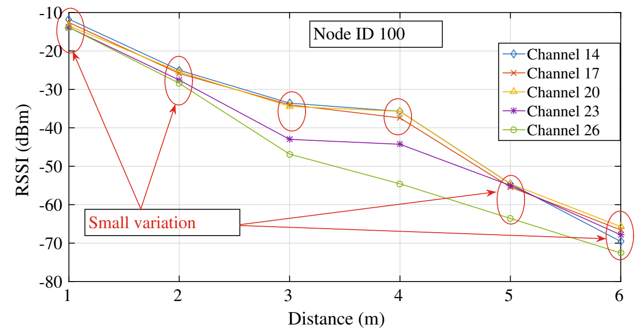

Fig. 5 RSSI measurement at Node ID 100 with various channel

Table 3 Maximum and minimum value of mean RSSI for different nodes

Node ID	Maximum mean RSSI in dBm	Minimum RSSI in dBm
100	−39.14	−60.14
200	−46.85	−63.57
300	−40.85	−61.42

RSSI value from the node id 100 was always the highest except one mean measurement.

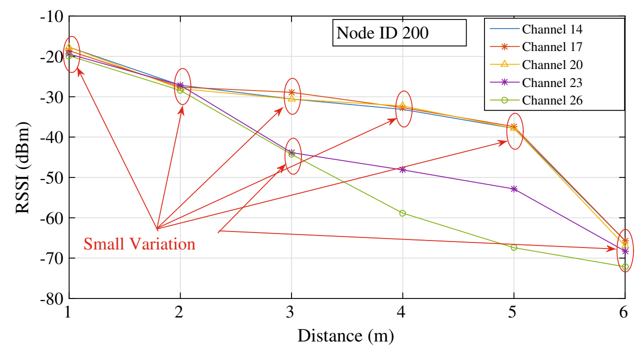

Fig. 6 RSSI measurement at Node ID 200 with various channels

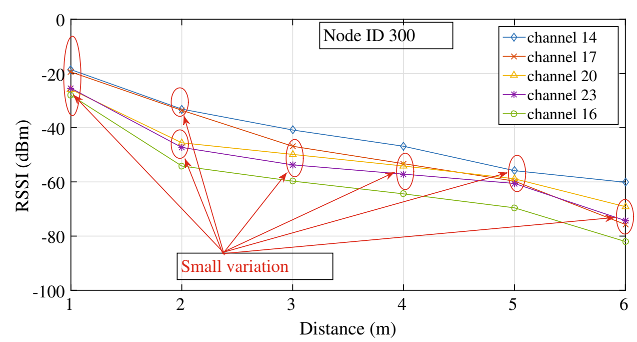

Fig. 7 RSSI measurement at Node ID 300 with various channels

For our experiments, we have chosen 0 power level, i.e., 3.2 dB for all the sensor nodes.

Selection of radio channels:

ZigBee and the IEEE 802.15.4 have divided the band of 2.4 GHz into 16 channels (i.e., 11–26). As wavelength is different for different RF channels, RSSI gets influenced with the variation in wavelength.

Here different sensor nodes were used to send RSSI and five different frequency channels (i.e., Channel 14, Channel 17, Channel 20, Channel 23, Channel 26), among 16 channels as discussed above were used as test frequency bands as shown in Figs. 5, 6 and 7. Measurements of RSSI were recorded with increasing distance from 1 to 6 m between T_x and R_x. In this experiment, mean values of RSSI are based on 7 measurements on each distance for each node at time interval of 5 min till 30 min. It was observed that:

- Using same frequency channel for each node, RSSI values kept on decreasing with increase in distance.
- Different frequency channels have shown more similar behaviors within 3 m and more deviation after that, as it is observed from Figs. 8, 9, 10, 11, and 12. Reason being influence of multipath fading is less at the shorter distance from the transmitter.
- Due to the presence of several environmental factors, sudden changes in the value of RSSI were unexpected.

In available channels other than channel 26, rate of packet loss due to WiFi is large. Hence for our experiments, we have chosen the channel 26, as it is WiFi free.

Fluctuation in RSSI due to the movement of the Receiver with fixed Transmitter:

In this experiment, we have selected the channel 26 and wavelength of the radio used was calculated to be 4.9212598 inch which is 12.49 cms as the length of the antenna used was 1.2 inch (approx). In the above experiments as discussed earlier, receiver was fixed and measurements were recorded. Here we have moved the receiver to a maximum range of circle with the diameter of 12.49 cms as shown in Figs. 13 and 14.

Here maximum RSSI of the mobile receiver are recorded at each distance to compare with the maximum RSSI

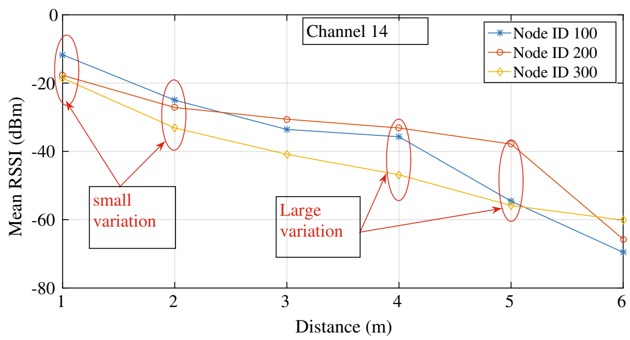

Fig. 8 RSSI measurement at channel 14 with various nodes

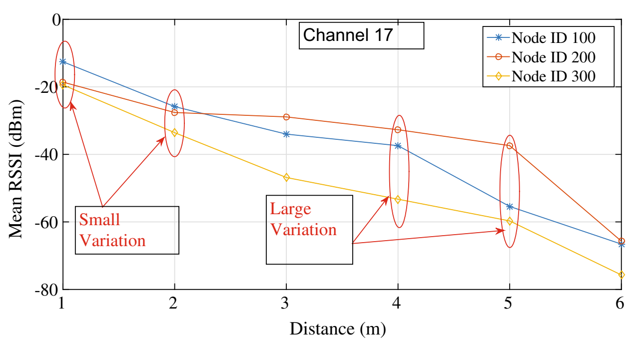

Fig. 9 RSSI measurement at channel 17 with various nodes

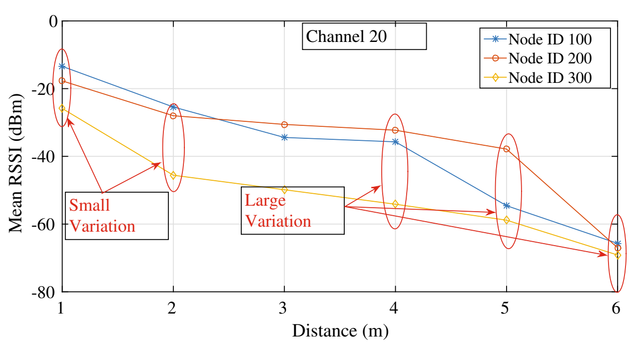

Fig. 10 RSSI measurement at channel 20 with various nodes

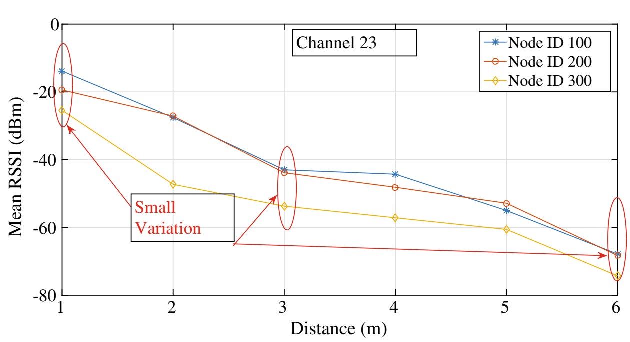

Fig. 11 RSSI measurement at channel 23 with various nodes

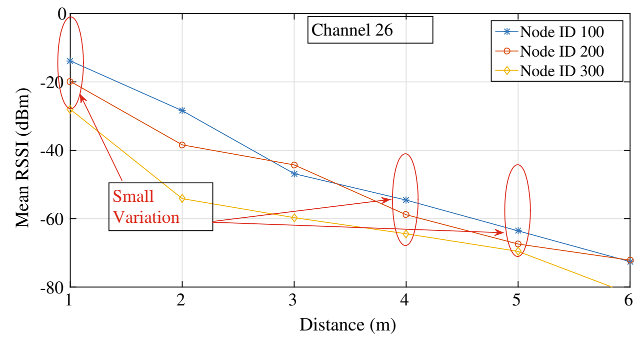

Fig. 12 RSSI measurement at channel 26 with various nodes

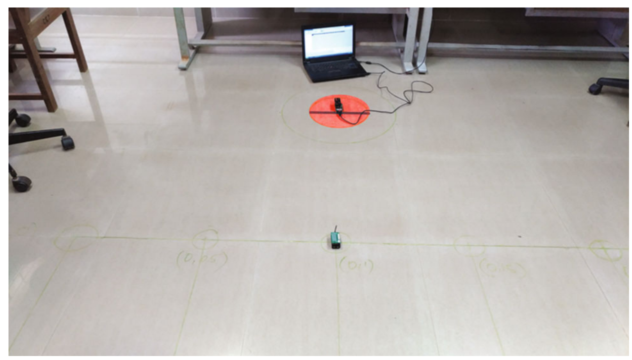

Fig. 13 Mobility of the receiver with fixed sensor node at different distances

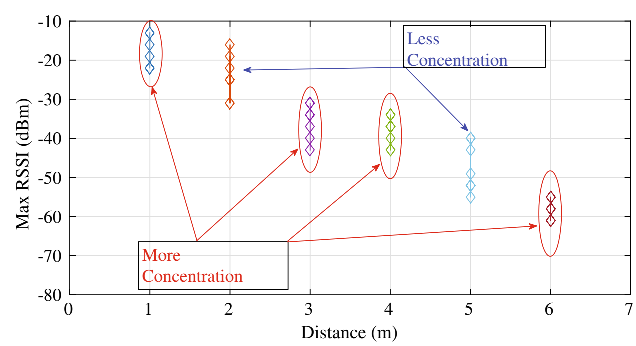

Fig. 14 Maximum RSSI with mobile receiver

recorded for the static receiver. From Fig. 15, it can be inferred that the RSSI graph shows a log-normal distribution as:

- Difference in RSSI values of the node at 1 m and at 2 m is about 15 dBm.
- Difference in RSSI values of the node at 2 m and at 3 m is about 9 dBm.
- Difference in RSSI values of the node at 4 m and at 5 m is about 3 dBm.
- Difference in RSSI values of the node at 5 m and at 6 m is about 0 dBm.

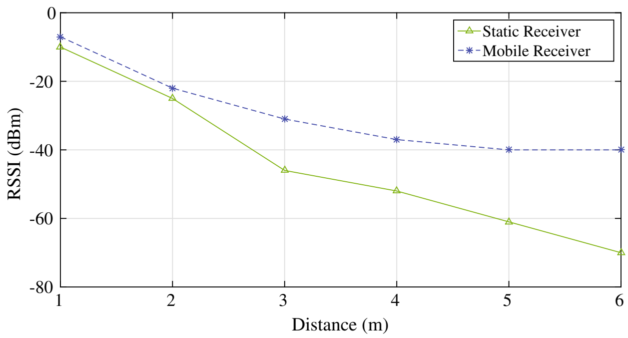

Fig. 15 RSSI-distance relationship among fixed and mobile receiver

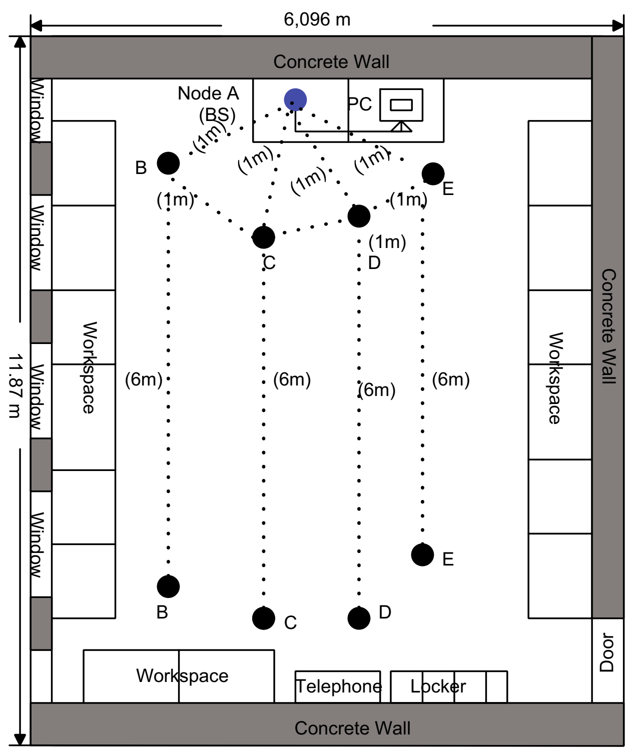

Fig. 16 Experimental model (BS and Nodes in LOS) (top-view)

which follows the log-normal signal model though it is difficult to move the receiver in practical scenarios.

3.2.2 Phase-II: RSSI Measurement

Here our first step was to analyze the RSSI data received through the experiment conducted.

With reference to Fig. 16, Sensor Node A represents the Base Station (BS) and PC is the server. Sensor Nodes B, C, D, E represent the communicating nodes.
We have taken the measurement using the architecture as shown in Fig. 16 and implemented the sensors as shown in Fig. 17. Each sensor node was placed on tripod stand for some experiments with a height of 1.2192 m.

Fig. 17 Sensor nodes installed on tripods in research lab

RSSI values were recorded at difference distances 1, 1.25, 1.5, 1.75, 2, 2.25, 2.5, 2.75, 3, 3.25, 3.5, 3.75, 4, 4.25, 4.5, 4.75, 5, 5.25, 5.5, 5.75, 6 m. Due to the presence of environmental noise, the recorded RSSI was quite fluctuating over time. Hence, we have taken 12 samples of RSSI at the same place in different time span from 0 to 30 min.

From this measured value as shown in Tables 4 and 5, we have found that some RSSI values were too large or too small as compared to other values.

Fluctuation of RSSI in time with different distances is shown in Figs. 18 and 19. To eliminate the contained error in the experimental results, we have used Gaussian filter to mitigate all the abnormal RSSI values caused by the environmental factors. The PDF (Probability Density Function) of Gaussian distribution (μ, γ^2) is formulated as

$$f(RSSI) = \frac{1}{\sqrt{2\pi}\gamma} e^{-(RSSI-\mu)^2/2\gamma^2} \tag{1}$$

where

$$\mu = \frac{1}{k}\sum_{i=1}^{k} RSSI_i \tag{2}$$

tends to be the mean of RSSI values in k no. of tests and

$$\gamma^2 = \frac{1}{k-1}\sum_{i=1}^{k}(RSSI_i - \mu)^2 \tag{3}$$

tends to be the variance.

In this paper, we have set the filter range [39,40] as $[\mu - \sqrt{3}\gamma,\ \mu + \sqrt{3}\gamma]$. The measured RSSI values outside this specified range is ignored (marked bold in Tables 4 and 5). Still the output of the Gaussian filter contains much variations in RSSI. Hence, we need to apply the averaging filter to obtain the average RSSI values for the purpose of calculation.

Table 4 Fluctuated RSSI values

RSSI/distance	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25
RSSI $_1$	−31	**−40**	**−46**	−40	−40	−43	−46	**−67**	−49	−52
RSSI $_2$	−31	−28	−40	−28	−43	−43	−46	−46	−49	−52
RSSI $_3$	**−40**	−34	−28	**−46**	−46	−28	−40	−46	−52	−49
RSSI $_4$	−34	−31	−34	−31	−40	−31	−64	−40	−52	−49
RSSI $_5$	−28	−28	−34	−34	−37	−40	**−67**	−64	−46	−46
RSSI $_6$	−28	−31	−31	−34	−37	−40	−46	−46	−55	−49
RSSI $_7$	−34	−28	−34	−28	−31	−40	−52	−46	−49	−49
RSSI $_8$	−28	−34	−28	**−46**	−31	−46	−46	−52	−49	−55
RSSI $_9$	−31	−28	**−46**	−28	−52	−52	−46	−46	**−40**	−43
RSSI $_{10}$	−34	−31	−31	−28	−40	−52	−28	−28	−55	−40
RSSI $_{11}$	−31	−31	−28	−34	−52	−46	−31	−40	−49	−55
RSSI $_{12}$	−28	−28	−28	−31	−31	**−58**	−40	−31	−43	−49
μ	−31.5	−31	−34	−34	−40	−43	−46	−46	−49	−49
γ	3.57	3.61	6.64	6.64	7.34	8.53	11.36	11.36	4.39	4.39
$\mu - \sqrt{3}\gamma$	−37.68	−37.25	−45.50	−45.50	−52.71	−57.77	−65.67	−65.67	−56.60	−56.60
$\mu + \sqrt{3}\gamma$	−25.31	−24.74	−22.5	−22.5	−27.28	−28.23	−26.33	−26.33	−41.39	−41.39

Table 5 Fluctuated RSSI values

RSSI/distance	3.5	3.75	4	4.25	4.5	4.75	5	5.25	5.5	5.75	6
RSSI $_1$	−55	−52	−55	−58	−58	−64	−70	−76	−82	**−94**	−88
RSSI $_2$	−55	−52	−55	−58	−58	−64	−70	−76	−82	−88	−88
RSSI $_3$	−52	−55	−55	−55	−58	−64	−67	−76	−79	−88	−85
RSSI $_4$	−52	−58	−58	−55	−61	−61	**−64**	−79	−79	−85	−85
RSSI $_5$	−49	−55	−55	−55	−61	−73	−70	−82	−79	−82	**−94**
RSSI $_6$	−49	**−40**	−49	**−40**	−64	−70	−70	−82	−76	−82	−82
RSSI $_7$	−49	−52	−46	−46	−49	−70	−73	−79	−76	−82	−82
RSSI $_8$	−43	−52	**−40**	−49	−49	−61	**−76**	−73	−76	−79	−76
RSSI $_9$	−49	**−40**	−52	−52	−73	−64	−73	**−67**	−73	−79	−79
RSSI $_{10}$	−46	−55	−67	−55	−70	−61	−70	−70	−73	−76	−79
RSSI $_{11}$	−52	**−70**	−67	−67	−73	−70	−73	−70	−76	−76	−76
RSSI $_{12}$	**−40**	−61	−58	**−70**	**−28**	**−43**	−67	−79	**−67**	−73	−73
μ	−49	−52	−55	−55	−58	−64	−70	−76	−76	−82	−82
γ	4.39	6.20	8.19	8.19	10.84	7.98	3.13	4.61	4.61	6	6
$\mu - \sqrt{3}\gamma$	−56.60	−62.73	−69.18	−69.18	−76.77	−77.82	−75.42	−83.98	−83.98	−92.39	−92.39
$\mu + \sqrt{3}\gamma$	−41.4	−41.27	−40.81	−40.82	−39.23	−50.17	−64.58	−68.02	−68.02	−71.61	−71.61

Equation used for estimation purpose is given as:

$$RSSI_{(avg)} = \frac{1}{m}\sum_{i=1}^{m} RSSI_i \quad (4)$$

The relationship of RSSI with increase in distance is represented in Fig. 20.

3.2.3 Phase-III: Shadowing Model Analysis

As discussed above, RSSI indicated the received signal strength when the reference distance is d_0 and n indicated the path loss index. Here RSSI indicated the received power of the sensor node in dBm, where 12 major data were continuously measured. Hence, at 1m distance, we have taken 12 samples received the RSSI as −31 dBm (approx) value.

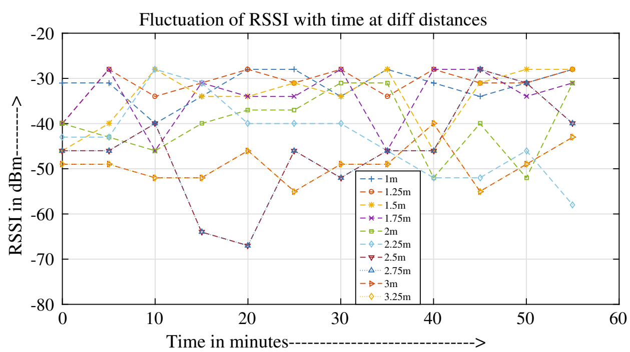

Fig. 18 Fluctuation

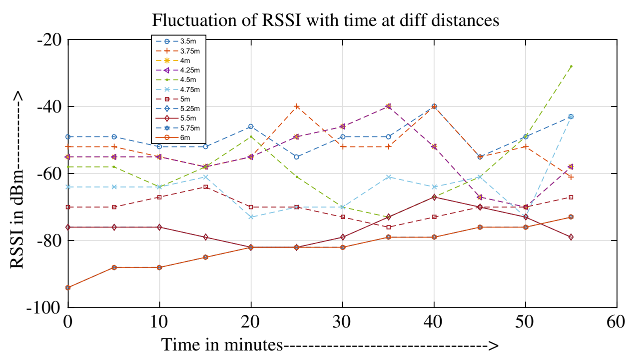

Fig. 19 Fluctuation

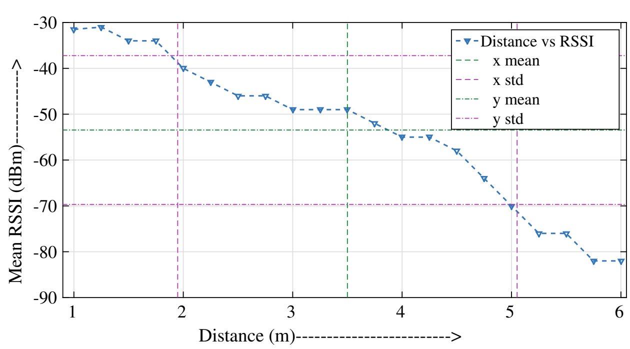

Fig. 20 Distance versus mean RSSI

Path loss exponent n with increase in distance is satisfied with the relation given as:

$$RSSI = -10 - 10 * n * \log\left[\frac{1}{d_0}\right] \tag{5}$$

$$\Rightarrow n = \frac{10 + RSSI}{10 * \log\left[\frac{1}{d_0}\right]} \tag{6}$$

$$\Rightarrow J(n) = 2657.575n^2 - 21606.434n + 45360 \tag{7}$$

Now n can be obtained by taking derivative of the equation (7) which is:

$$5315.15n - 21606.434 = 0 \tag{8}$$

$$\Rightarrow n = 4.06 \tag{9}$$

So path loss exponent for this test experiment was found to be 4.06.

With the above obtained parameter, Shadowing model for our experiment is as follows:

$$\mathrm{P_r(d)} = -31 - 10 * 4.06 * \log\left(\frac{d}{d_0}\right) + X_\gamma \tag{10}$$

$$\mathrm{RSSI_d} = B - 10 * n * \log d_{e_i} \tag{11}$$

where X_γ is the Gaussian distributed random variable with zero mean in dB and with standard deviation γ ranging from 4 to 10. n is the path loss exponent. Hence, fitting curve of Probability density of RSSI = −31 dBm is given as follows:

$$f(RSSI) = A * e^{-(RSSI-53.44)^2/2\gamma^2} \tag{12}$$

where A = 0.04812. So the fitting curve of probability becomes as:

$$f(RSSI) = 0.04812 * e^{-(RSSI-53.44)^2/2\gamma^2} \tag{13}$$

3.2.4 Phase-IV: Localization of Unknown Node

The approach to position estimation is given in the flow chart as shown in Fig. 21.

The experiment was conducted in the indoor (2D) region (research lab), with area of width 2m × length 6m. It was divided into 65 points with origin point at the bottom left corner. Four red dots represent the position of the anchor nodes, and blue dots represent the test points for the unknown node. Figures 22 and 23 show the architecture and real-time placement of sensor nodes in lab environment. Placement of four Anchor Nodes J, K, L, M with the coordinates (0,0), (0,2), (6,0), (6,2) and test points for the unknown node having the coordinates (x, y) which has to be determined, is shown in Fig. 24. The pseudocode for location estimation is presented in Algorithm 1. The input to the algorithm comprises of k RSSI values at n different distances. At first we record 12 RSSI values at different time interval and then compute the mean and variance of all the 12 RSSI at each distance l_i {i equals 1, 1.25, 1.5 …6m} (lines 3–10). To eliminate the abnormal values received at each distances, we need to compute $[\mu - \sqrt{3}\gamma, \mu + \sqrt{3}\gamma]$(Gaussian Filtering) (lines 11 and

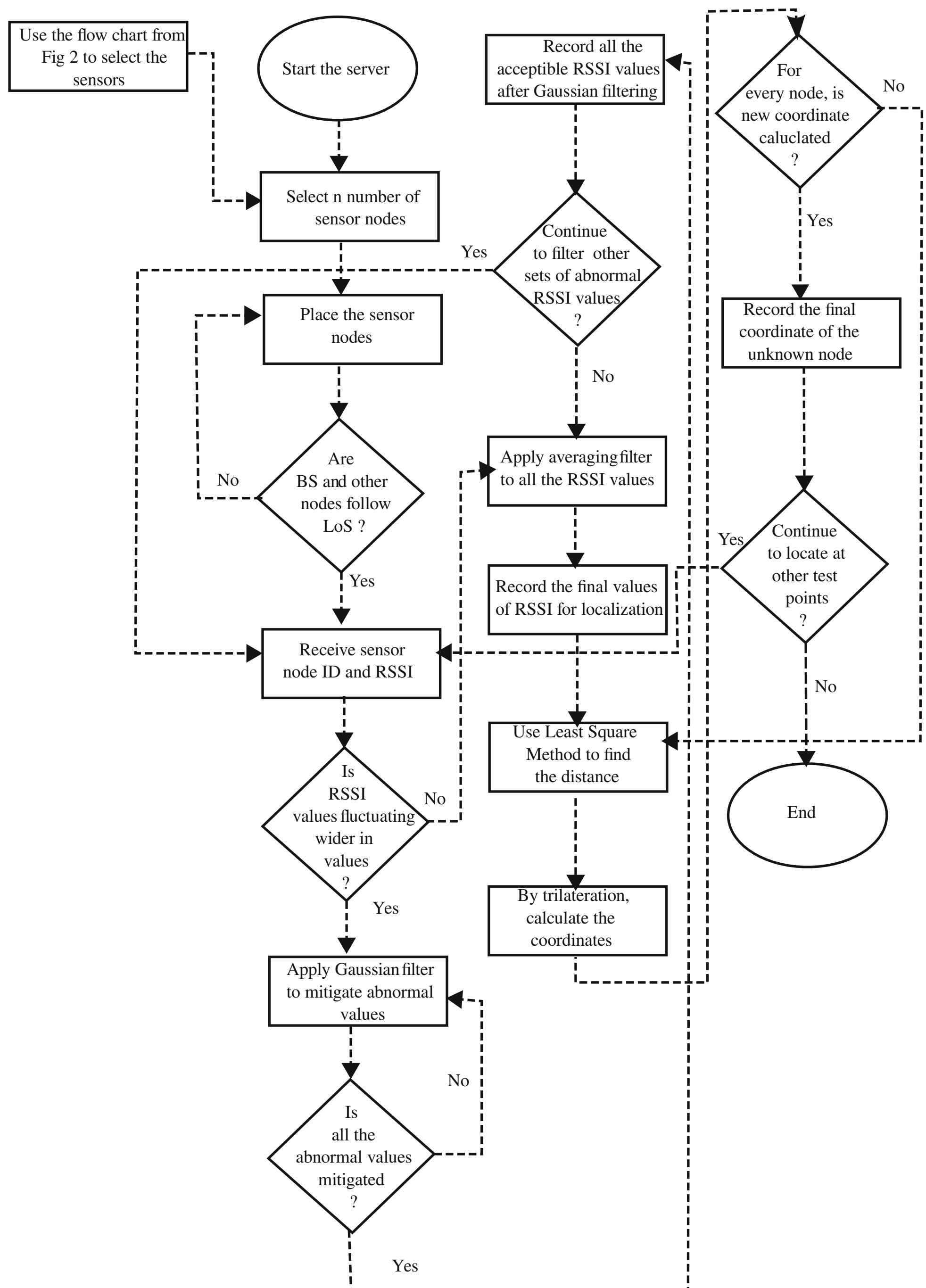

Fig. 21 Flow chart for localization

12). To refine the received RSSI values, we use averaging filter (lines 14–18). Now distance is estimated by $d_e(i)$ (lines 19 and 20). At last location is computed (line 21).

Let $RSSI_i$ be the received signal strength measured between the unknown node Q and the anchor nodes. Received RSSI was optimized using Gaussian and averaging filter. d_{e_i} is the estimated distance between the unknown node Q and the anchor nodes, which is calculated by a group of nonlinear equations as:

$$\begin{aligned} (x_Q - x_J)^2 + (y_Q - y_J)^2 &= d_{e1}^2 \\ (x_Q - x_K)^2 + (y_Q - y_K)^2 &= d_{e_2}^2 \\ (x_Q - x_L)^2 + (y_Q - y_L)^2 &= d_{e3}^2 \\ (x_Q - x_M)^2 + (y_Q - y_M)^2 &= d_{e4}^2 \end{aligned} \tag{14}$$

By subtracting fourth equation from first, second and third equation of Eq. (14), we get

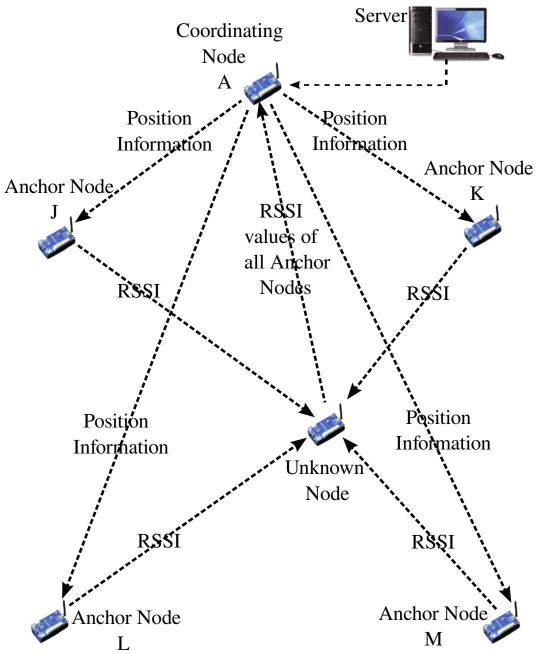

Fig. 22 Architecture for distance estimation experiment

Fig. 23 Real-time placement of sensors for location Estimation

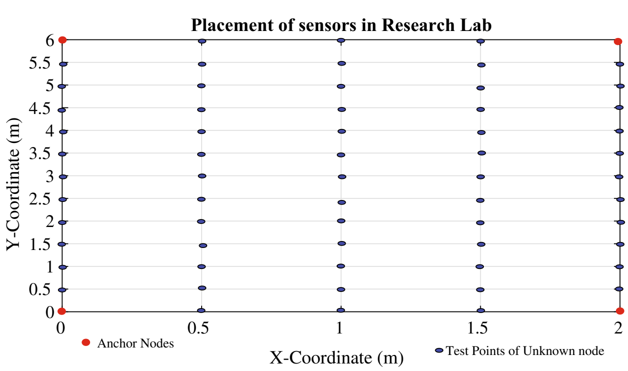

Fig. 24 Sensor placement for localization experiment

$$x_J^2 - x_M^2 - 2(x_J - x_M)x_Q + y_J^2 - y_M^2 - 2(y_J - y_M)y_Q = d_{e_1}^2 - d_{e_4}^2 \quad (15)$$

Algorithm 1 Location Estimation

INPUT: k no of RSSI samples at l no of distances.
OUTPUT: Estimated coordinates of test points.
for $i = 1 : l$ **do**
  Initialize $\mu(i) = 0$
  for $j = 1 : k$ **do**
    Compute the mean μ.

$$\mu(i) = \mu(i) + \frac{1}{k} RSSI(j)$$

  end for
  for $j = 1 : k$ **do**
    Compute the variance γ.

$$\gamma^2(i) = \gamma^2(i) + \frac{1}{k-1}(RSSI(j) - \mu(i))^2$$

  end for
  Compute $\mu(i) - \sqrt{3}\gamma(i), \mu(i) + \sqrt{3}\gamma(i)$
  Eliminate the RSSI values which are out of the range of $[\mu(i) - \sqrt{3}\gamma(i), \mu(i) + \sqrt{3}\gamma(i)]$ and recompute mean μ and variance γ
end for
for $i = 1 : l$ **do**
  Initialize $RSSI_{avg}(i) = 0$
  for $j = 1 : m$ **do**
    Compute RSSI by using averaging filter

$$RSSI_{avg}(i) = RSSI_{avg}(i) + \frac{1}{m} RSSI(j)$$

  end for
  Estimate the distance $d_e(i)$ by LS

$$d_e(i) = 10^{\frac{B + RSSI_{avg}(i)}{10n}}$$

end for
Compute the estimated location

$$X = p^{-1}q$$

$$x_K^2 - x_M^2 - 2(x_K - x_M)x_Q + y_K^2 - y_M^2 - 2(y_K - y_M)y_Q = d_{e_2}^2 - d_{e_4}^2 \quad (16)$$

$$x_L^2 - x_M^2 - 2(x_L - x_M)x_Q + y_L^2 - y_M^2 - 2(y_L - y_M)y_Q = d_{e_3}^2 - d_{e_4}^2 \quad (17)$$

Equations (15)–(17) can be shown as $pX = q$, where

$$p = \begin{pmatrix} 2(x_J - x_M) & 2(y_J - y_M) \\ 2(x_K - x_M) & 2(y_K - y_M) \\ 2(x_L - x_M) & 2(y_L - y_M) \end{pmatrix} \quad (18)$$

$$q = \begin{pmatrix} x_J^2 - x_M^2 + y_J^2 - y_M^2 - d_{e_1}^2 + d_{e_4}^2 \\ x_K^2 - x_M^2 + y_K^2 - y_M^2 - d_{e_2}^2 + d_{e_4}^2 \\ x_L^2 - x_M^2 + y_L^2 - y_M^2 - d_{e_3}^2 + d_{e_4}^2 \end{pmatrix} \quad (19)$$

and

$$X = \begin{pmatrix} x_Q \\ y_Q \end{pmatrix} \quad (20)$$

$$\begin{pmatrix} x_Q \\ y_Q \end{pmatrix} = \begin{pmatrix} 2(x_J - x_M) & 2(y_J - y_M) \\ 2(x_K - x_M) & 2(y_K - y_M) \\ 2(x_L - x_M) & 2(y_L - y_M) \end{pmatrix}^{-1} \cdot \begin{pmatrix} x_J^2 - x_M^2 + y_J^2 - y_M^2 - d_{e_1}^2 + d_{e_4}^2 \\ x_K^2 - x_M^2 + y_K^2 - y_M^2 - d_{e_2}^2 + d_{e_4}^2 \\ x_L^2 - x_M^2 + y_L^2 - y_M^2 - d_{e_3}^2 + d_{e_4}^2 \end{pmatrix} \quad (21)$$

In our experimental environment, signal propagation is affected by wall, building material even by movement of the human being. Hence it is difficult to estimate the parameter accurately in these environment. RSSI in general gets affected by multipath and shadowing which tends to the inaccuracy in the distance estimation which in turn affect the localization procedure. So, we have introduced noise in the distance estimation. Let the new noisy estimation be $\tilde{d}$, then Eq. (14) can be rewritten as:

$$\begin{aligned} (\tilde{x}_Q - x_J)^2 + (\tilde{y}_Q - y_J)^2 &= \tilde{d}_{e_1}^2 \\ (\tilde{x}_Q - x_K)^2 + (\tilde{y}_Q - y_K)^2 &= \tilde{d}_{e_2}^2 \\ (\tilde{x}_Q - x_L)^2 + (\tilde{y}_Q - y_L)^2 &= \tilde{d}_{e_3}^2 \\ (\tilde{x}_Q - x_M)^2 + (\tilde{y}_Q - y_M)^2 &= \tilde{d}_{e_4}^2 \end{aligned} \quad (22)$$

where $(\tilde{x}, \tilde{y})$ is estimated coordinate of the unknown node Q. Hence, the equation can be written as:

$$\begin{pmatrix} \tilde{x_Q} \\ \tilde{y_Q} \end{pmatrix} = \begin{pmatrix} 2(x_J - x_M) & 2(y_J - y_M) \\ 2(x_K - x_M) & 2(y_K - y_M) \\ 2(x_L - x_M) & 2(y_L - y_M) \end{pmatrix}^{-1} \cdot \begin{pmatrix} x_J^2 - x_M^2 + y_J^2 - y_M^2 - \tilde{d}_{e_1}^2 + \tilde{d}_{e_4}^2 \\ x_K^2 - x_M^2 + y_K^2 - y_M^2 - \tilde{d}_{e_2}^2 + \tilde{d}_{e_4}^2 \\ x_L^2 - x_M^2 + y_L^2 - y_M^2 - \tilde{d}_{e_3}^2 + \tilde{d}_{e_4}^2 \end{pmatrix} \quad (23)$$

By subtracting Eq. (23) from Eq. (21), we get the range error to be

$$\begin{pmatrix} \tilde{x_Q} - x_Q \\ \tilde{y_Q} - y_Q \end{pmatrix} = \begin{pmatrix} 2(x_J - x_M) & 2(y_J - y_M) \\ 2(x_K - x_M) & 2(y_K - y_M) \\ 2(x_L - x_M) & 2(y_L - y_M) \end{pmatrix}^{-1} \cdot \begin{pmatrix} (\tilde{d}_{e_1}^2 - d_{e_1}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \\ (\tilde{d}_{e_2}^2 - d_{e_2}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \\ (\tilde{d}_{e_3}^2 - d_{e_3}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \end{pmatrix} \quad (24)$$

$$Z = \begin{pmatrix} (\tilde{d}_{e_1}^2 - d_{e_1}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \\ (\tilde{d}_{e_2}^2 - d_{e_2}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \\ (\tilde{d}_{e_3}^2 - d_{e_3}^2) - (\tilde{d}_{e_4}^2 - d_{e_4}^2) \end{pmatrix} \quad (25)$$

$$= \begin{pmatrix} (10^{(10+RSSI_1)/10n_1} - 10^{(10+RSSI_1)/10n_{PL_1}}) - (10^{(10+RSSI_4)/10n_4} - 10^{(10+RSSI_4)/10n_{PL_4}}) \\ (10^{(10+RSSI_2)/10n_2} - 10^{(10+RSSI_2)/10n_{PL_2}}) - (10^{(10+RSSI_4)/10n_4} - 10^{(10+RSSI_4)/10n_{PL_4}}) \\ (10^{(10+RSSI_3)/10n_3} - 10^{(10+RSSI_3)/10n_{PL_3}}) - (10^{(10+RSSI_4)/10n_4} - 10^{(10+RSSI_4)/10n_{PL_4}}) \end{pmatrix} \quad (26)$$

At each test point, we have estimated the coordinates several times. we have considered the average of all the coordinates as the final estimated coordinates. Let

$$\tilde{x_Q}_j = \frac{1}{m}\sum_{l=1}^{m} x_{Q_l} \quad \text{and} \quad \tilde{y_Q}_j = \frac{1}{m}\sum_{l=1}^{m} y_{Q_l} \quad (27)$$

where $l \Rightarrow$ no. of times coordinates are estimated, $m = 7$ for our experiment and $j \Rightarrow$ different test point location. As $(\tilde{x_j}, \tilde{y_j})$ is estimated coordinate of the unknown node Q, hence, error-based performance evaluation between real and estimated coordinates [16,41–44] is given as:

$$E_{RSSI} = \frac{1}{k}\sum_{j=1}^{k} \sqrt{(x_{Q_j} - \tilde{x_Q}_j)^2 + (y_{Q_j} - \tilde{y_Q}_j)^2} \quad (28)$$

4 Conclusion and Future Work

In this paper, we have experimented on RSSI-based location technique in wireless sensor network. To get the optimum RSSI values, we have conducted several experiments which carried large amount of experimented data. We have also estimated the related RSSI influencing parameters and have efficiently used Gaussian filtering for optimizing the RSSI values. Analysis of RSSI variation due to power, frequency as well as movement of receiver was done extensively. The proposed position estimation algorithm combined the use of sensor selection process as well as the Gaussian filtering and average filtering with the implementation of trilateration, which helped to estimate the position of the unknown nodes.

Some of the significant contributions of this paper are as follows:

- Implementation of a wireless sensor localization network for distance estimation and localization of deployed unknown node.
- Experimental analysis of small wireless sensors for distance estimation and physical movement monitoring.
- RSSI values have been optimized with the help of Gaussian filtering at different distances.
- Proposed localization algorithm for location estimation of the unknown node.

In accord with the results obtained in our research, we contemplate to conduct the studies on these following issues in future.

- When anchor nodes are replaced, the mean and variance values of the RSS changed significantly. So, we intend to repeat our experiments with more number of samples as well as with the presence of more number of obstacles in various environmental conditions and analyze the new results.
- As shadowing effect possesses much influential role in location accuracy, we intend to improvise the accuracy by conducting some experiments.
- Number of anchor nodes play an important role in accuracy, we intend to increase the number of anchor nodes in our future work.
- In future, we intend to extend the proposed approach to comply with other several localization approach such as global positioning system, Wireless Fidelity etc.

References

1. Abowd, G.D.; Atkeson, C.G.; Hong, J.; Long, S.; Kooper, R.; Pinkerton, M.: Cyberguide: a mobile context-aware tour guide. Wirel. Netw. **3**(5), 421–433 (1997)
2. Sumi, Y.; Etani, T.; Fels, S.; Simonet, N.; Kobayashi, K.; Mase, K.: C-map: building a context-aware mobile assistant for exhibition tours. In: Community Computing and Support Systems, pp. 137–154. Springer, Berlin (1998)
3. Want, R.; Hopper, A.; Falcao, V.; Gibbons, J.: The active badge location system. ACM Trans. Inf. Syst. **10**(1), 91–102 (1992)
4. Masumoto, Y.: Global positioning system (1993). US Patent 5,210,540
5. Sayed, A.H.; Tarighat, A.; Khajehnouri, N.: Network-based wireless location: challenges faced in developing techniques for accurate wireless location information. IEEE Signal Process. Mag. **22**(4), 24–40 (2005)
6. Watson, R.; Lachapelle, G.; Klukas, R.; Turunen, S.; Pietilä, S.; Halivaara, I.: Investigating GPS signals indoors with extreme high-sensitivity detection techniques. Navigation **52**(4), 199–213 (2005)
7. Boukerche, A.: Algorithms and Protocols for Wireless Sensor Networks, vol. 62. Wiley, London (2008)
8. Boukerche, A.; Oliveira, H.A.; Nakamura, E.F.; Loureiro, A.A.: Localization systems for wireless sensor networks. IEEE Wirel. Commun. **14**(6) (2007)
9. Huang, H.; Luo, B.: A received signal strength indication adaptive algorithm for wireless sensor network. In: Applied Mechanics and Materials, vol. 273, pp. 505–509. Trans Tech Publications (2013)
10. Kaemarungsi, K.; Ranron, R.; Pongsoon, P.: Study of received signal strength indication in zigbee location cluster for indoor localization. In: Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2013 10th International Conference on, pp. 1–6. IEEE (2013)
11. Mahapatra, R.K.; Shet, N.: Experimental analysis of RSSI-based distance estimation for wireless sensor networks. In: Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), IEEE, pp. 211–215. IEEE (2016)
12. Martin, P.; Ho, B.J.; Grupen, N.; Muñoz, S.; Srivastava, M.: An ibeacon primer for indoor localization: demo abstract. In: Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings, pp. 190–191. ACM (2014)
13. Yang, J.; Wang, Z.; Zhang, X.: An ibeacon-based indoor positioning systems for hospitals. Int. J. Smart Home **9**(7), 161–168 (2015)
14. Hashemi, H.: The indoor radio propagation channel. Proc. IEEE **81**(7), 943–968 (1993)
15. Durgin, G.D.: Space-time wireless channels. Prentice Hall Professional, Englewood Cliffs (2003)
16. Liu, Y.; Yang, Z.; Wang, X.; Jian, L.: Location, localization, and localizability. J. Comput. Sci. Technol. **25**(2), 274–297 (2010)
17. Mao, G.; Fidan, B.; Anderson, B.D.: Wireless sensor network localization techniques. Comput. Netw. **51**(10), 2529–2553 (2007)
18. Razul, S.G.; Lim, C.H.; See, C.M.S.: Bayesian method for NLOS mitigation in single moving sensor geo-location. Signal Process. **91**(7), 1613–1621 (2011)
19. Lee, J.Y.; Scholtz, R.A.: Ranging in a dense multipath environment using an UWB radio link. IEEE J. Sel. Areas Commun. **20**(9), 1677–1683 (2002)
20. Sahinoglu, Z.; Gezici, S.: Ranging in the IEEE 802.15. 4a standard. In: Wireless and Microwave Technology Conference, 2006. WAMICON'06. IEEE Annual, pp. 1–5. IEEE (2006)
21. Lin, L.; So, H.C.; Chan, F.K.; Chan, Y.T.; Ho, K.: A new constrained weighted least squares algorithm for tdoa-based localization. Sig. Process. **93**(11), 2872–2878 (2013)
22. Sun, Z.; Qie, X.; Liu, M.; Cao, D.; Wang, D.: Lightning vhf radiation location system based on short-baseline tdoa technique-validation in rocket-triggered lightning. Atmos. Res. **129**, 58–66 (2013)
23. Doğançay, K.; Hmam, H.: Optimal angular sensor separation for aoa localization. Signal Process. **88**(5), 1248–1260 (2008)
24. Visser, H.J.: Array and Phased Array Antenna Basics. Wiley, London (2006)
25. Hightower, J.; Want, R.; Borriello, G.: Spoton: an indoor 3D location sensing technology based on RF signal strength (2000)
26. Li, X.: RSS-based location estimation with unknown pathloss model. IEEE Trans. Wirel. Commun. **5**(12) (2006)
27. Laitinen, H.; Juurakko, S.; Lahti, T.; Korhonen, R.; Lahteenmaki, J.: Experimental evaluation of location methods based on signal-strength measurements. IEEE Trans. Veh. Technol. **56**(1), 287–296 (2007)
28. Tian, S.; Zhang, X.; Liu, P.; Sun, P.; Wang, X.: A RSSI-based DV-hop algorithm for wireless sensor networks. In: Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on, pp. 2555–2558. IEEE (2007)
29. Zanca, G.; Zorzi, F.; Zanella, A.; Zorzi, M.: Experimental comparison of RSSI-based localization algorithms for indoor wireless sensor networks. In: Proceedings of the Workshop on Real-World Wireless Sensor Networks, pp. 1–5. ACM (2008)
30. Chen, J.; Wu, X.j.; Ye, F.; Song, P.; Liu, J.w.: Improved rssi-based localization algorithm for park lighting control and child location tracking. In: Information and Automation, 2009. ICIA'09. International Conference on, pp. 1526–1531. IEEE (2009)
31. Xu, J.; Liu, W.; Lang, F.; Zhang, Y.; Wang, C.; et al.: Distance measurement model based on rssi in wsn. Wirel. Sens. Netw. **2**(8), 606–611 (2010)
32. Feng, C.; Au, W.S.A.; Valaee, S.; Tan, Z.: Received-signal-strength-based indoor positioning using compressive sensing. IEEE Trans. Mob. Comput. **11**(12), 1983–1993 (2012)
33. Liu, L.; Zhang, H.; Geng, X.; Shu, X.: Hexahedral localization (hl): a three-dimensional hexahedron localization based on mobile beacons. Sci. World J. **2013** (2013)
34. Mukhopadhyay, B.; Sarangi, S.; Kar, S.: Novel RSSI evaluation models for accurate indoor localization with sensor networks. In: Communications (NCC), 2014 Twentieth National Conference on, pp. 1–6. IEEE (2014)

35. El Assaf, A.; Zaidi, S.; Affes, S.; Kandil, N.: Accurate nodes localization in anisotropic wireless sensor networks. Int. J. Distrib. Sens. Netw. (2015)
36. Luo, Q.; Peng, Y.; Li, J.; Peng, X.: Rssi-based localization through uncertain data mapping for wireless sensor networks. IEEE Sens. J. **16**(9), 3155–3162 (2016)
37. Lee, J.G.; Kim, J.; Lee, S.W.; Ko, Y.W.: A location tracking system using ble beacon exploiting a double-gaussian filter. KSII Trans. Internet Inf. Syst. **11**(2) (2017)
38. MEMSIC: Memsic:powerful sensing solutions. http://www.memsic.com/support/technical-documentation.cfm (2012)
39. Holtzman, J.M.: A simple, accurate method to calculate spread-spectrum multiple-access error probabilities. IEEE Trans. Commun. **40**(3), 461–464 (1992)
40. Holtzmann, J.: On using perturbation analysis to do sensitivity analysis: derivatives versus differences. IEEE Trans. Autom. Control **37**(2), 243–247 (1992)
41. Bachrach, J.; Taylor, C.: Localization in sensor networks. Handbook of sensor networks: algorithms and architectures **1** (2005)
42. Danielsson, P.E.: Euclidean distance mapping. Comput. Graph. Image Process. **14**(3), 227–248 (1980)
43. He, T.; Huang, C.; Blum, B.M.; Stankovic, J.A.; Abdelzaher, T.: Range-free localization schemes for large scale sensor networks. In: Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, pp. 81–95. ACM (2003)
44. Patwari, N.; Ash, J.N.; Kyperountas, S.; Hero, A.O.; Moses, R.L.; Correal, N.S.: Locating the nodes: cooperative localization in wireless sensor networks. IEEE Signal Process. Mag. **22**(4), 54–69 (2005)