ZigBee RF Signal Strength for Indoor Location Sensing – Experiments and Results

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Abstract -This paper discusses about the variation of signal strength due to the presence of obstacles in an indoor environment. An experimental analysis of impact of various obstacles on ZigBee RF signals strength has been done. The results obtained by the analysis have been used to locate a user inside a smart home. The parameters like Received Signal Strength (RSSI), Link Quality Indication (LQI) and Packet Error Rate (PER) has been measured and analyzed. The location of the user is an important context, based on which various controls and services can be rendered. The objective of finding out the location is to provide various services and controls like location based luminance, personalized HVAC systems. In this paper k mean clustering algorithm has been implemented to predict the location of the user. The results show that 3 to 5 m of location accuracy has been achieved.

Index Terms — ZigBee, RSSI, Packet Error Rate, Localization, Fingerprinting

I. INTRODUCTION

This paper discusses in detail about how RF signal strength is affected due to various obstacles that are generally found in indoor environments. The usual obstacles are materials like glass, wood, walls in addition to human activity. The analysis has been done in order to find out if signal strength alone can be used to find out the location of the user in order to provide various controls and services in indoor environment like smart home and buildings. The experiments have been done using two different radios RF230 and CC2430. The presence of human activity also affects the signal strength to a greater extent. All these effects on the RF signal strength have to be taken.

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Received signal strength indicator (RSSI) is a measure of the signal strength at the receiver expressed in dBm. It is usually five, eight or ten bit value depending on the hardware used. This RF signal strength parameter has been widely used for localization and tracking in indoors as it eliminates the requirement of additional hardware which in turn reduces the cost. Other measurements like Time of Arrival (ToA), Angle of Arrival (AoA) are also used. But time based methods have a disadvantage that line of sight is required for them to give a

good level of accuracy which is not possible in indoor environments because of which RSSI is being preferred. More over according to our measurements round trip time of flight method did not give accurate results when the distance was small. Using RSSI means we don't need any extra hardware. But the biggest challenge is mapping of the signal strength to distance in presence of obstacles such as walls, human activity etc. The relation between the two has to be modeled as accurately as possible for developing a precise localization system. In a densely populated and dynamic environment where the modeling is not possible fingerprinting algorithms are used. Fingerprinting has a disadvantage that it requires a large measurement database that needs to be frequently calibrated. Now days to overcome the difficulty of large database compressive sensing techniques are being used. The next section discusses the related work which is followed by other sections that explains the experiments and results obtained.

II. RELATED WORK

Many location tracking systems have been developed based on various measurements of the RF signal. Of these Received signal strength is widely used for location sensing. There are two different types of localization based on RSSI measurement. They are range based and fingerprinting localization. In range based location sensing a relation between the signal strength and distance is derived. The relation ship is used for locating the unknown node by methods like Trilateration and Min-Max. Fingerprinting based methods have two phases. One is offline or training and the second is online phase. In this method the nodes are located by using algorithms like k nearest neighbor, Support vector machines etc... The signal strength has to be analyzed using probability distribution and models like kalman filters for improving the accuracy of location.

RSSI and Link quality indicator (LQI) are the two parameters well known for link quality estimation. In [2] it has been mentioned that reflection, scattering and other physical properties have an extreme impact on the RSSI measurement. There are three models for describing the distance – path loss. They are free space model, two ray ground model which adds reflection to free space model and log-normal model. The lognormal model has to be derived experimentally. The authors of [2] have done experiments on three different radios and compared the results. They have concluded that RSSI is a bad estimator of link quality.

A survey of wireless indoor positioning techniques has been presented in detail in [3].various measuring principles and algorithms has been presented in this paper. It has been mentioned that the time based location methods are not suitable in Non Line Of Sight (NLOS) conditions and RSSI is preferred in NLOS conditions. If fingerprinting based location sensing has to be done algorithms like k Nearest Neighbors, neural networks, probabilistic methods, Support vector machines have to be used for location estimation. A comparison of localization systems such as UWB, GPS, Bluetooth, WLAN, and GSM has been presented.

Reference [4] proposes a virtual calibration procedure instead of doing a training phase for fingerprinting based location sensing methods. This method is not manual and makes use of measurements between the anchors. In our paper though the experiments are manual the measurements have been done using only the anchors and unknown node.

Paper [5] illustrates a technique to extract an estimate of velocity from signal strength. The characteristic footprints left by the motion of nodes in the network or motion of bodies external to the network have been exploited for movement detection. Experimental results have been presented using Micaz motes. The results are focused how signal strength is affected by motion of the motes. RSSI has been measured at different times and at different velocities. Our paper discusses how RSSI is varying due to obstacles inside a room. Results of [5] focus more on motion detection but our experiments focus on how to improve the location accuracy.

The authors of [6] discuss about the three techniques for automatic location sensing namely triangulation, scene analysis and proximity.

The authors of [7] have discussed about the various measurements, models and algorithms that are commonly used for device free localization. It has been suggested that device free localization is being developed which can be used to improve the existing Real Time Location Systems (RTLs). These methods use the fading characteristics of the RF signal strength for finding out the presence and location of the user. These are termed as sensor less localization as the user need not carry any radio for being localized.

It has been mentioned in [8] that fingerprinting algorithm cannot be used to track more than one user simultaneously. The impact of human presence on RF signal strength due to reflection, diffraction and scattering has been presented. Different models for establishing the relation between distance and signal strength has been described.

In the paper [9] experimental results how signal strength is affected by human presence and sensor node height has been presented. The variations in signal strength with and with out movement has been discussed in detail. Using the results an approach has been proposed for intrusion detection. A threshold has been defined to detect the motion. It has been concluded that the proposed system can be used along with other surveillance system for better accuracy

It has been proved in [10] that the location can be estimated in indoor environments up to accuracy of 1m using RSSI and ToA measurements which means the signal strength can modeled to get that level of accuracy.

In paper [12] the effect of ZigBee RSSI on crowd in an indoor environment has been discussed. Density, velocity and disorder are considered as measures to separate crowd behavior. A 25 pattern of crowd behavior in indoor space with the above measures has been defined. Data is analyzed using both time and frequency series analysis. Average RSSI, variance and median are considered for time series analysis and discrete Fourier analysis for frequency series analysis. A graph plotted between density per experimental area against velocity and disorder shows that with no crowd the RSSI value hardly changes and with crowd the RSSI fluctuates to a greater extent. This is due to the difference of electromagnetic wave absorption rate on the human body, rate of screening electromagnetic wave path and change in environment.

In [13] the RSSI values from WSN nodes are used for the real-time localization of transceiver-free objects. A customized classification approach based on support vector machine has been followed to determine location. The feasibility and effectiveness of the proposed approach has been assessed by experimental test cases.

The performance evaluation of IEEE802.15.4 wireless networks has been presented in [14]. The effect of direct and indirect data transmissions, CSMA-CA mechanisms, data payload size and non beacon enabled mode has been observed through several practical experiments. The data throughput, delivery ratio, and received signal strength indication (RSSI) are investigated as the performance metrics. It has been concluded that IEEE 802.15.4 has better performance in non-beacon mode. Through experiments the authors had achieved an average of 153.02 kbps for direct data transfer and 65.69 kbps for indirect data transfer. It had been concluded that the decrease in data rate for indirect transfer is due to the network device's polling rate. The results for the effects of CSMA-CA mechanism conclude that both the effective data rate and delivery ratio was decreased due to the presence of collisions and random back off. It has been observed that with the increase of payload size, the data rate also increased since the effect of overhead was reduced

leading to a raise of data coding efficiency. From the experiment, the authors of this paper found that the non beacon-enabled network would have larger data rate than the beacon-enabled one.

Statistical Mean Value Model, Distance Between the Fixed-nodes based Model and Gauss Model are the three experimental data processing models that have been discussed in [15]. In "Statistical Mean Value Model", unknown node receives a group of RSSI values and then computers their mean value. In "Distance Between the Fixed-nodes Model", the distance from unknown node to fixed node is computed by taking the distance and signal strength information between fixed nodes as the reference. Principle of "Gauss model" is that when an unknown node receives n RSSI values, there must be some values which are small probability events. ZigBee-based hardware platform and MATLAB are used to test the measurement error of the three methods. This paper concludes that the measurement error of Gauss model is 2 meters within 20 meters.

III. EXPERIMENTAL ANALYSIS

This section describes the measurement setup that has been used for taking the RSSI measurements. A set of measurements has been taken separately for each obstacle. The obstacles such as wood, glass, wall and human presence have been considered for these measurements.

A. Experimental setup

A set of two Crossbow's ZigBee motes (Micaz & IRIS) has been used. Micaz has an eight bit Received signal strength indicator (RSSI) and IRIS has a five bit RSSI. The motes have been programmed using TinyOS 2.x and NesC language. One node acts as a transmitter and the base station connected to PC acts a as a receiver which forwards the received packets to the serial port of the PC. Further packet processing is done at the PC using JAVA programming language. The transmitter and receiver were both kept at a height of 1m above the ground level. These measurements were taken inside a 15 m x 3 m x 2.6m C-DAC's Ubiquitous Computing Lab.

B. Measurements

One mote was programmed as transmitter that sends a packet every 1 second. The other was programmed in such a way that it receives the packet sent by the transmitter, appends the RSSI value and its Node Id, then forwards it to the serial port. The distance between the transmitter and receiver is known. The received packet is parsed and the RSSI and distance value is stored in the database. The above procedure was repeated for different distances between the transmitter and receiver. The measurements were taken initially in Line of Sight condition and later repeated by placing glass, wood and wall obstacle between the transmitter and receiver. The parameters that have been measured are Received Signal Strength Indication (RSSI), LQI and Packet Delivery Rate (PDR). The RSSI values are recorded as

signed 2s complement form of the actual value. Later these hex values recorded were converted to actual dBm values according to the datasheets of the CC2420 and RF230 radios. Every packet transmitted is assigned a packet number to check for packet losses at the receiving end. After the measurements a simple localization system has been tested by fingerprinting method with a single reference node and also with multiple reference nodes.

IV. MEASUREMENT RESULTS

In this section the results obtained for various obstacles have been discussed. The measurements have been taken for both Line of Sight and Non Line of Sight conditions. The relationship between distance and RSSI has been obtained for each obstacle. The packet error rate has also been monitored along with RSSI in order to ensure that PER does not fall below 2%.

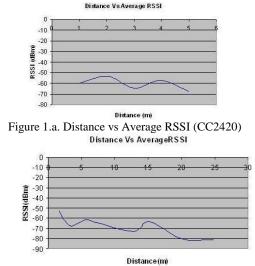


Figure 1.b. Distance vs Average RSSI (RF230)

A. Line of Sight

 $\beta = 1 - \dot{\alpha}$

These measurements were taken without any obstacle or human activity between the transmitter and receiver. Fig.1a and 1b represents a plot of the distance and average RSSI for CC2420 and RF230 radios. At each distance 50 samples of RSSI have been recorded and an average has been taken.

The relationship between the distance and RSSI was obtained by interpolating and fitting a logarithmic curve using the data obtained. Equation (1) gives the relationship between distance and RSSI for RF230 radio.

$$r = -2.503*Ln(d) - 56.978$$
 (1)

(2)

Where r is the RSSI value in dBm and d is distance in meters. The packet error rate at different distances between the transmitter and receiver has also been estimated. The maximum allowed packet error rate is 2%.

Where $\dot{\alpha}$ is the packet delivery rate and β is the packet error rate. Fig. 2 shows the packet count versus average RSSI at different distances.

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PacketCount Vs RSSI at different distances in m

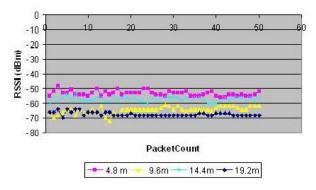


Figure 2. PacketCount vs Average RSSI at different distance between the Tx and Rx.

As long as the packet error rate is less than 2% the communication between the nodes is acceptable. If it is more than 2% the communication is no longer reliable. The RSSI value of the packets also should not fall below the receiver sensitivity for reliable communication. The PER was 0 % even when the distance between the transmitter and receiver was 25m.

The results in Fig. 2 were observed when there was no obstacle or movement between the transmitter and receiver. It can be observed that all the packets were received without any loss when there is no obstacle. The PER was 0% upto a range of 40m.The next section discusses results obtained for various obstacles.

B. Non line of sight

These measurements were taken by placing a glass, glass-wood and partial wall partitions in between the transmitter and receiver. The properties of the obstacles are shown in table I.

S.No	Obstacle type	Thickness (mm)
1.	Glass (Glazed Door)	10
2.	Glass + Wood (Compressed Wood)	Wood: 120 Glass: 6.35
3.	Partial Wall (Brick + Gypsum board)	35

TABLE I PROPERTIES OF OBSTACLES

Location estimation has to be done in lab environment with these obstacles. So to model the lab environment the above obstacles have been chosen. Fig 3.a, 3.b, 3.c shows the measurement results obtained when the obstacles where placed in between transmitter and receiver.

Distance Vs average RSSI - GassWood Obstacle

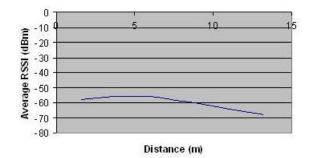


Figure 3.a. Distance vs Average RSSI (glass-wood partition)

When there is an obstacle the packet error rate is also an important parameter to be noted. The obstacles attenuate the signal, so chances for packet loss are more. It is very important to note that the packet error rate should not be above 2%.

Distance Vs average RSSI - Gass Obstacle

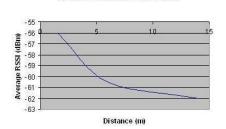


Figure 3.b. Distance vs Average RSSI (glass partition)

Distance Vs average RSSI - PartialWall Obstacle

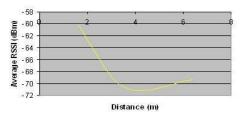


Figure 3.c. Distance vs Average RSSI (partial wall)

Fig 4.a, 4.b and 4.c show the PER results observed for different obstacles. When the measurement was taken through walls the range was reduced to 6.4m. If the distance between the transmitter and receiver was increased beyond 6.4 m, the PER was more than 2 %. So measurements results up to 6.4m are shown in the figure.

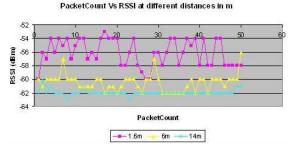
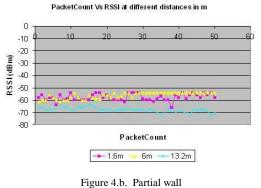


Figure 4.a. Glass wood partition



PacketCount Vs RSSI at different distances in m

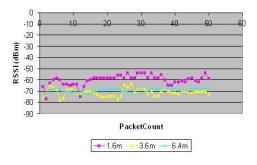


Figure 4.c. Glass door

But for the glass and glass wood obstacles the PER was less than 2% up to a range of 20m.

C. Human Presence

This section discusses about the impact of human presence on the received signal strength values. The measurements have been done for different crowd density by transmitting 1000 packets at the rate of 2 packets per second. The Fig 5.a and 5.b show how the RSSI and LQI values are affected by human presence.

The measurements had been taken by increasing the human count between the transmitter and receiver. It can be noted from Fig 5.a that the RSSI was having the maximum value (-75dBm) when no human was present between the transmitter and receiver.

With increase in human count the RSSI value decreased due to absorption and fading. When the person count was more than 2 the graph (Fig5.a) shows an increase in RSSI value due to reflection and scattering of RF signal. It was observed that the Link Quality remained at 255 through out

the experiment up to a distance of 40m. Person count vs Avg RSSI(dBm)

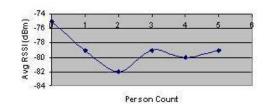


Figure 5.a. Person count vs. Average RSSI

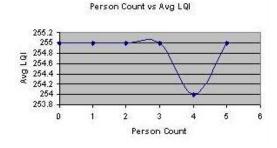


Figure 5.b. Person count vs. Average LQI

V. LOCALIZATION SENSING

After the measurement and analysis a localization algorithm has been implemented and tested inside the UBICOMP Lab of C-DAC Chennai. The location was estimated by fingerprinting method. Since the accuracy was less when simple fingerprinting was used clustering algorithm has been implemented to improve the location accuracy.

A. Location setup

The location sensing algorithm was implemented inside the UBICOMP Lab as shown in Fig 7. One reference or anchor mote has been placed at a known location inside the lab. AT86RF230 radio of Iris motes has been used. The transmission power was set at +0.5 dBm.



Figure 7. UBICOMP LAB L1, L2....L8 – Training points, A1 - anchor node

The reference or anchor mote (A1) has been placed at a height of 1.4 m above the ground level, so that it can receive the beacon message packet broadcasted by the unknown from any location inside the lab. The placement of reference mote has to be determined empirically. The user to be located will be carrying the unknown mote. The objective is to determine to which LED fixture the user is closer by. The location sensing involves two phases. One is offline and the second is

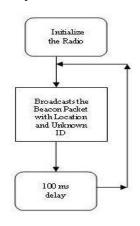


Figure 8a. Offline Phase - Unlnown Mote

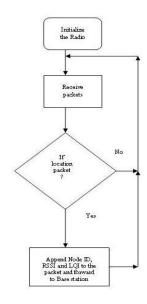


Figure 8b. Offline Phase – Anchor Mote (A1)

online phase.

B. Offline/Fingerprinting Phase

Location estimation by fingerprinting has two phases. The first phase is training phase. The different states of the motes and process involved during the offline phase are shown in Fig 8a, b, c.

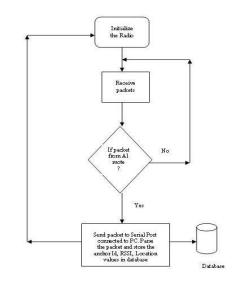


Figure 8c. Offline Phase - Base Station (BS)

The unknown node is placed at every location of interests (L1 to L8). It broadcasts a beacon packet every 100 ms which contains its Node ID and Location at which it is placed. The packet is received by the anchor mote A1. The mote A1 appends the RSSI value, LQI value and its Node ID to the packet and forwards to the Base station (BS) mote which is connected to PC. The BS forwards the packet to the serial port of the PC and the data is received and parsed. After parsing the packet, the Location, RSSI value and Anchor-Id are store in the database. The readings are taken for 1000 packets at every symbolic location in order to find out of the RSSI value that has the maximum probability at that particular location.

C. Online Phase

During the online phase, the unknown mote broadcasts a beacon every 100 ms. The anchor mote (A1) receives the broadcast packet and appends the RSSI value and forwards it to base station. At the base station the RSSI value obtained is compared with the fingerprinted values in the database and the maximum likely hood location is chosen. But the location accuracy varied from 1m to 8m. The location obtained has not been consistent for implementing in a smart home environment for Location based Lighting application.

D. Online Phase with Clustering Algorithm

In order to improve the accuracy of location, k-Mean Clustering algorithm [16] has been implemented. If a RSSI value that has not been fingerprinted (in the training phase) occurs during online phase, the location could not be identified. To overcome this issue, Nearest Neighbor identification feature has been incorporated along with the clustering.

E. k Mean Clustering

During the offline phase the unknown mote is kept at every location of interest and the corresponding RSSI values are stored in the database (in PC) that is connected to the base station node. The RSSI data stored in the database is divided into a number of clusters using k mean clustering algorithm. The number of clusters has to be decided by the user. An initial set of centroids have to be chosen. The number of centroids is equal to the number of clusters into which the RSSI data set has to be divided. Each centroid belongs to different clusters.

According to the k mean clustering the Euclidean distance between a RSSI value and the each of the centroid is calculated. After calculating the Euclidean distance between the centroids and the RSSI value, the minimum distance is found out. The RSSI value is now added to the cluster which contains the closest centroid. This step is repeated for all the RSSI data set for one time. After the first iteration, a new set of centroid values is calculated by taking the average of each cluster elements and the same process of finding the minimum distance and clustering is done. The process is repeated until two consecutive iterations result in clusters with the same elements. Fig 9 describes the steps involved in k mean clustering algorithm.

Step 1:	Get the RSSI data set (R) stored in the database during the offline phase			
Step 2:	Let the number of clusters into which R has to be divided be N			
Step 3:	Let the number of centroids be $C = N$			
	Set the values of $C_0 \dots C_n = R_0 \dots R_n$			
Step 4:	Set the value of i as zero			
2 7 32	$i = \theta$			
Step 5:	Check if (i <r.length ())<="" td=""></r.length>			
	Step 5.1: Get R.			
	Step 5.2: Calculate the Euclidean distance of R from all the centroids $C_{_0}$ to $C_{_{_N}}$			
	Step 5.3 Find the centroid to which the element R is closest and put the element $$ in the			
	cluster that contains the closest centroid.			
	Step 5.4: $i = i+1$			
Step 6:	Step 5.5: Go to Step 5 Calculate the new centroids			
owp o.	The new centroid of each cluster is the average of the elements present			
	in that cluster			
Step 7:	Repeat steps 4 to 6			
Step 8:	The steps 4 to 6 iteration has to be repeated as long as two successive			
1000	iterations results in the same set of N clusters.			
Step 9:	After completion of the iterations the clusters are stored in a new table			
200	in the database.			
Step 10:	The RSSI value, location and the number of times the RSSI value has occurred for a particular location are store in the table.			

Figure 9. Clustering Algorithm

During the online phase the average RSSI of 50 packets is taken as and identified to which cluster it belongs to. After cluster identification, the corresponding locations at which the RSSI value occurred have been retrieved. The final location is predicted based on the maximum number of times the RSSI value occurred for a location. Fig 10 explains the steps involved in predicting the location.

Step 1:	The cluster to which the current RSSI value belongs is determined by comparing the value with the cluster database table. (Result of the clustering algorithm). Let the value belong to ClusterN
Step 2:	If the current RSSI value is not present in any of the clusters: Go to Step 5
	Else Go to Step 3
Step 3:	Search for the locations at which the current RSSI value only in the ClusterN
Step 4:	If (it has occurred at only one location) Return that as the final location
	Else if (it has more than one location)
	Step 4.1: Get the number of times the RSSI value has occurred at the Locations
	Step 4.2: Find the location for which the RSSI value has occurred the Maximum number of times.
	Step 4.3: Return that value as the final location
Step 5:	Implement the Nearest Neighbor algorithm
800 - 100 - 10	Step 5. 1: Calculate the Euclidean distance of the current RSSI value from all the elements of the RSSI data set obtained during the fingerprinting phase.
	Step 5.2: Find the element which is the closest to the current RSSI values
() ()	Step 5.3: Repeat Step 3 and 4.
Skp 6:	Wait for the next packet and go back to step 1

Fig 10 Online phase with clustering and Nearest Neighbour Algorithm

If an RSSI value that has not been fingerprinted occurs then the algorithm first finds its nearest neighbor by directly finding the RSSI value that is closest to the fingerprinted data set. After getting the nearest neighbor value the previous steps of clustering and location prediction is followed.

F. Results

The location accuracy and precision has improved after using the clustering algorithm with the existing fingerprinting location sensing method. Table 2 gives the details of the accuracy obtained after using clustering and nearest neighbor algorithm.

TABLE II LOCATION ACCURACT					
S.No	Actual Location (Symboli c)	Obtained Location (Symbolic)	Average Error (m)		
1.	L1	L2, L4	5		
2.	L2	L2, L1	2		
3.	L3	L3	0.8		
4.	L4	L4, L7	4		
5.	L5	L5, L7	2		
6.	L6	L6, L7	2		
7.	L7	L6, L7	2		
8.	L8	L8, L6, L7	3		

TABLE II LOCATION ACCURACY

VI. CONCLUSION AND FUTURE WORK

The results obtained after including a data classification method, shows that the RSSI based location sensing can be used for indoor environments if the accuracy levels of 3-5 m are acceptable. The algorithm has been tested to locate multiple users simultaneously. The location of the user obtained has been integrated with lighting to control the illuminance of LED Fixtures based on the location of the user. In this method frequent fingerprinting has to be done to retain the location accuracy. In future it is proposed to explore filtering techniques to improve the location accuracy.

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