RSSI Based Position Estimation in ZigBee Sensor Networks

FATİH İLERİ
Boğaziçi University
Department of Electrical Engineering
Bebek, İstanbul
TURKEY
fatihileri@windowslive.com

MEHMET AKAR
Boğaziçi University
Department of Electrical Engineering
Bebek, İstanbul
TURKEY
mehmet.akar@boun.edu.tr

Abstract: Localization in wireless sensor networks has drawn significant research attention in recent years, since many real-life applications need to locate the source of incoming measurements as precise as possible. In this paper, two popular localization algorithms based on Trilateration and Weighted Centroid Localization are discussed. Noting that channel propagation and path loss modelling is a key in successful position estimation, we first develop an analytical indoor channel model using our experimental setup including ZigBee devices. Subsequently, the performance of the algorithms are evaluated both experimentally and via simulations with respect to the placement of beacons and channel imperfections.

Key–Words: Position estimation, RSSI, ZigBee

1 Introduction

GPS can be said to be the most popular tool against the outdoor position estimation problems. But the indoor localization problems, where no GPS signals are able to be received, require wireless sensor networks. Improvements in the processor technology makes it possible to locate multiple sensors to be used in indoor localization problems. Several distance estimation techniques, based on the communication between located sensors, are present. RSSI is the most applicable one with minimum cost [1]. And the position estimation process is performed based on the distance data derived from the RSSI measurements, as explained in Section 2. The basic problem in such a position estimation implementation is the errors in mathematical model of the propagation channel. For instance, researchers prove that a WCL based position estimation system, distance estimations of which are performed with Friis' free space transmission equation [2], yields high error rates [3]. In this paper, differently from other related researches, an empirical channel model is developed rather than implementing position estimation algorithms being dependent on the present channel models. In addition, advantages and deficiencies of the two popular position estimation methodologies, the WCL and the Trilateration, are introduced by both simulation and implementation.

2 Position Estimation Algorithms

Estimating coordinates of a node in a 2-D field requires communicating with at least three stations simultaneously. The WCL and the Trilateration algorithms, which are developed based on this idea, are briefly explained in Section 2.2 and Section 2.3, respectively. The algorithms in question are based on distance estimation between transmitter and receiver antennas, and since such a distance estimation requires path loss modelling, it is necessary to deal with path loss modelling before the position estimation algorithms in question.

2.1 Path Loss Modelling

Path loss is the power density reduction of a radio signal as it propagates through space, and mathematically, it can be explained as the difference (in dB) between the transmitted signal power and the received signal power, as in (1).

$$L = 10 \cdot \log(P_{TX}/P_{RX}) \tag{1}$$

where L is the path loss in dB, P_{TX} is the transmission power of the sender in Watts, and P_{RX} is the remaining power of a wave at the receiver in Watts.

Free space loss, multipath and fading are the leading factors causing path loss. Brief information about the complications in question is presented below.

- *Free Space Loss*: Radio signals disperse with distance, so when the distance between the receiver and the transmitter antennas increase, less signal

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power is induced at the receiver side. Even if no other impairments are present, the signal attenuates over distance since it is spread over a larger area during transmission.

- *Multipath*: Multipath problem is the arrival of a radio signal to the destination antenna by two or more paths. The problem arises from the direct and reflected signals that are often opposite in phase. These signals may cancel out each other causing data loss at the receiver antenna. Multipath problem generally occurs in environments where metallic surfaces are present.

- *Fading*: Fading is the variability of the power of a wireless signal depending on the environmental effects such as changing atmospheric conditions for fixed environments, and changing numbers and locations of the obstacles blocking wireless transmission for the mobile media.

RSSI is the information related to the received power on the antenna during the related data packet reception. RSSI can be expressed in dB using a reference signal strength P_{Ref} value (usually taken as $1mW$), as in (2):

$$RSSI = 10 \cdot \log\left(P_{RX}/P_{Ref}\right) \quad (2)$$

where P_{RX} is the remaining power of a wave at the receiver in Watts.

The RSSI value related to any received data packet is available at the physical layer in the IEEE 802.15.4 network. Signal power at the receiver antenna can be obtained by using the RSSI data captured from any ZigBee receiver in (2). Once the received signal power is obtained, then estimating the distance between the receiver and the transmitter antennas is possible by using a path loss model. Two of the commonly used path loss models are briefly explained below.

- *Log-Distance Path Loss Model*: The Log-Distance Path Loss Model is an indoor radio propagation model which estimates the attenuation of a radio signal that occurs while the signal travels in a closed area. The model is formally expressed in (3) [4].

  $$L(d) = L(d_0) + 10 \cdot \eta \cdot log(d/d_0) + X_g \quad (3)$$

  where $L(d)$ is the total path loss measured in dB at distance d, $L(d_0)$ is the path loss at the reference distance d_0 which is generally taken as 1m, η is the path loss exponent, and X_g is a zero mean Gaussian random variable, modelling the shadowing effect on the received signal power.

- *ITU Model For Indoor Attenuation*: The ITU Indoor Propagation Model, also known as ITU Model for Indoor Attenuation, is a radio propagation model that is used to estimate the path loss inside a closed area delimited by walls. As being a suitable indoor channel model, the ITU Indoor Propagation Model approximates the total path loss that an indoor link may experience. While the model is applicable only to the indoor environments, generally it uses the lower microwave bands around 2.4 GHz. However, the model is suitable to be applied to a much wider range. Mathematical formulation of this model is given by [5]

  $$L(d) = 20 \cdot \log(f) + N \cdot \log(d) + P_f(n) - 28 \quad (4)$$

  where $L(d)$ is the total path loss in dB, f is the data transmission frequency in megahertz (MHz), d is the distance between the receiver and the transmitter antennas in meters (m), N is the distance power loss coefficient, n is the number of floors or walls to be penetrated between the transmitter and the receiver, and $P_f(n)$ is the floor loss penetration factor. The distance power loss coefficient, N, is the empirically determined quantity which expresses the loss of signal power with distance. Some commonly encountered values for the distance power loss coefficient are given in Table 1 [5].

Table 1: Some commonly encountered values of the distance power loss coefficient.

Frequency	Residential	Office	Commercial
900MHz	N/A	33	20
1.2GHz	N/A	32	22
1.3GHz	N/A	32	22
1.8GHz	28	30	22
4GHz	N/A	28	22
5.2GHz	N/A	31	N/A

2.2 Weighted Centroid Localization (WCL)

The Centroid Localization (CL) algorithm estimates the unknown node coordinates simply by taking the average of the coordinates received from the transmitter antennas each of which broadcast their own position data [6]. The mathematical representation of the algorithm is given by [6]

$$P_i^{(CL)}(x,y) = (1/n)\sum_{j=1}^{n} B_j(x,y) \tag{5}$$

where $P_i^{(CL)}(x,y)$ is the estimated coordinates of the ith node, $B_j(x,y)$ is the exact coordinates of the jth beacon where the beacons are the transmitter antennas each of which continuously broadcasts its own coordinates, and n is the number of beacons, coordinates of which are received by the ith node.

The WCL, proposed by [3], is an extension of the CL algorithm. In WCL, every position data received by a node is added to the sum after being multiplied by a weight coefficient between the node and the beacon. The same procedure is implemented for each of the beacons covering the subject node. Once the sum is obtained, then it is divided by the sum of all the weight coefficients between the subject node and the communicated beacons. The mathematical expression of the method is given by

$$P_i^{(WCL)}(x,y) = \frac{\sum_{j=1}^{n}(\omega_{ij}\cdot B_j(x,y))}{\sum_{j=1}^{n}\omega_{ij}} \tag{6}$$

where $P_i^{(WCL)}(x,y)$ is the estimated coordinates of the ith node, $B_j(x,y)$ is the exact coordinates of the jth beacon, and ω_{ij} is the weight coefficient between the ith node and the jth beacon.

Note that equating $\omega_{ij} = 1$ for all i,j; we get the simple CL algorithm in (5). Considering a concentric wave expansion with a linear characteristic of the receiver and a uniform density of the beacons, researchers form the weight coefficients as [3]:

$$\omega_{ij} = \frac{1}{(d_{ij})^g} \tag{7}$$

where ω_{ij} is the weight coefficient between the ith node and the jth beacon, d_{ij} is the distance between the ith node and the jth beacon, and g is the weighting degree.

Considering (6) and (7) one can easily conclude that increasing the weighting degree decreases the effect of the far away beacons marginally, but excessively high weighting degree will make a node to estimate its coordinates nearly the same with the nearest beacon, thus increasing the error. Hence the weighting degree has to be optimized.

2.3 Trilateration

Consider a node N with an unknown location (n_x,n_y) and three beacons A, B and C, known as the positions (a_x,a_y), (b_x,b_y) and (c_x,c_y), respectively. The trilateration problem is to compute the coordinates of node N, given distances d_a, d_b and d_c, from the node to beacons A, B and C, respectively. Using the estimated distances from the node to the three beacons, the problem can be defined as in the following system of equations:

$$(n_x-a_x)^2+(n_y-a_y)^2-d_a^2=0 \tag{8}$$

$$(n_x-b_x)^2+(n_y-b_y)^2-d_b^2=0 \tag{9}$$

$$(n_x-c_x)^2+(n_y-c_y)^2-d_c^2=0 \tag{10}$$

In most cases, due to the errors in path loss measurements causing distance estimation errors, right hand sides of (8) - (10) are nonzero, thus the system does not have a solution. If this is the case, *Circle Intersections With Clustering* method can be used in estimating position of the node in question [7]. Consider the circles of radii d_a, d_b and d_c around points A, B and C, respectively. Since the circles' centers and radii, derived from path loss measurements together with the considered channel model, are obtained with measurement errors, the circles will not intersect at a single point and probably overlap in a small region, where the unknown node N is located inside. If the measurement errors are not extremely high, then each pair of circles yields two intersection points. Three of these points are clustered closely together, while the others are located far from this group. The node N is located in the middle of this cluster as shown in Fig. 1 [7].

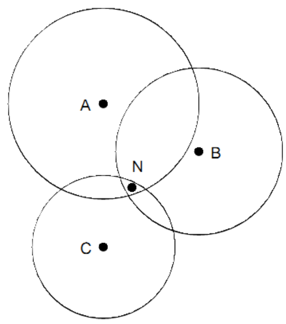


Fig. 1: Clustered regions among the three trilateration circles.

3 Simulation Based Study of Localization Techniques

As a preliminary work of indoor position estimation system design, we tested the most common two po-

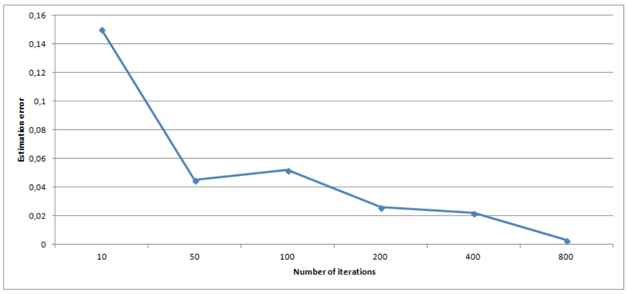


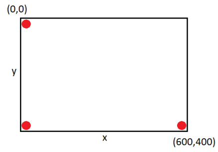
Fig. 2: Mean estimation error vs number of Monte Carlo iterations in Trilateration simulations under random noise with arbitrarily located nodes and 3 beacons.

sition estimation methodologies: WCL and Trilateration. There are two important parameters for both methods to perform successful estimations, which are the number and the position of the beacons. Besides, there is an additional crucial parameter for the WCL methodology which is the weighting degree. We developed a software program to simulate the WCL method, and a Matlab tool to simulate the Trilateration. We tested both of the methods with various beacon placements, with the aim of optimizing the position estimation setup. We implemented the algorithms for all the possible node locations on a 2-D field model of 400 units width and 600 units length, setting the weighting degree for WCL to 2.78, which is the derived path loss exponent in the empirical channel model development (see Section 4.1). We run both methods by applying the same random noise vector on the distance values to model the unreliability of RSSI data.

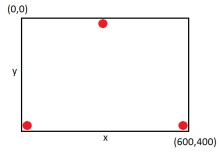
We used the circle intersections with clustering method in the Trilateration implementations. We run the Trilateration algorithm by performing Monte Carlo simulations with 400 iterations, which can be said to be a reasonable number considering the simulation results displayed in Fig.2.

3.1 Evaluation of 3 Beacons Case

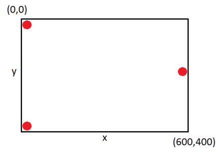
In this section we evaluate the performance of the two algorithms for the following 5 configurations as shown in Fig.3. Fig.3(a) - Fig.3(e) represent the beacon placements in each configuration. For instance, let (x, y) be any location on the 2-D simulation field, then beacons are located at $(2, 2)$, $(2, 398)$ and $(598, 398)$ on the 2-D simulation field of 400 units width and 600 units length in the beacon placement case 1 as displayed in Fig. 3(a). With these beacon placement configurations we aim to examine the performances of the Trilateration and WCL covering all the significant beacon placement variations possible with 3 beacons on a rectangular 2-D field. We simulate the algorithms for all possible node locations on the simulation field. Simulation results are shown in Fig.4 - Fig.9.



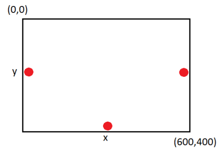
(a) Beacon placement case 1.



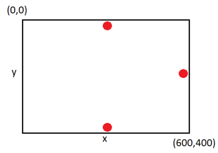
(b) Beacon placement case 2.



(c) Beacon placement case 3.



(d) Beacon placement case 4.



(e) Beacon placement case 5.

Fig. 3: Placements of the beacons in three beacons case simulations.

In the simulation results shown in Fig.4 - Fig.8 it is seen that estimation error of WCL increases excessively as the unknown node position gets out of the borders set by the beacons. Besides, mean errors of WCL estimations in cases 1 through 5 are found as 25.7%, 17.3%, 19.1%, 25.2%, and 22.3%, respectively. Thus, beacon placements in case 2 (see Fig.3(b)) can be said to be the optimal beacon deployment formation for a WCL based position estimation system with three beacons.

On the other hand, it is seen that the performance of Trilateration stays constant in all the five deployment formations in question. The estimation errors of Trilateration for the three beacons cases displayed in Fig.9 is only due to the random noise matrix applied to the distance data between the node and the beacons, duplicate of which is also applied in WCL estimations.

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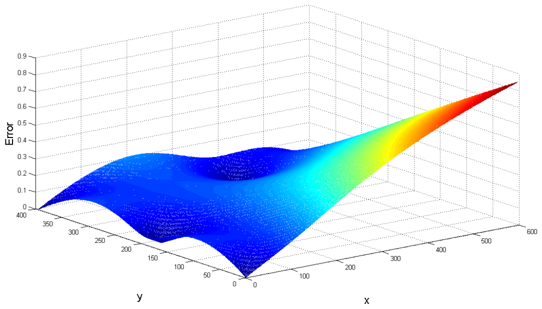

Fig. 4: WCL performance for case 1 displayed in Fig.3(a).

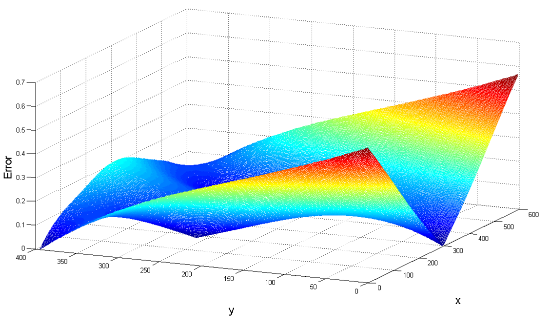

Fig. 5: WCL performance for case 2 displayed in Fig.3(b).

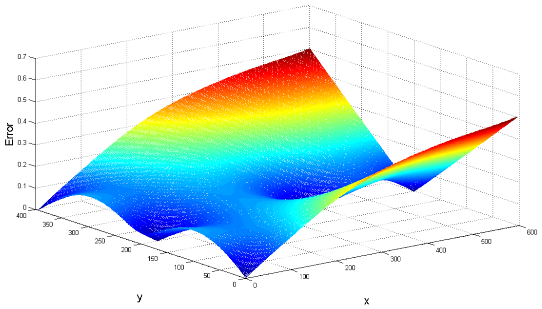

Fig. 6: WCL performance for case 3 displayed in Fig.3(c).

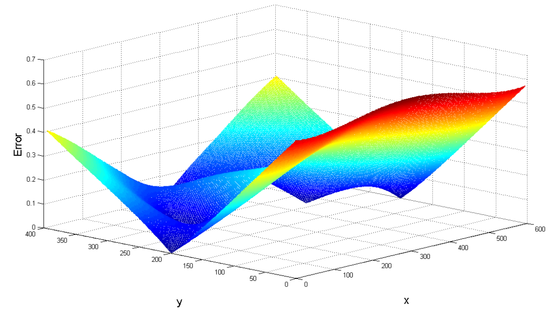

Fig. 7: WCL performance for case 4 displayed in Fig.3(d).

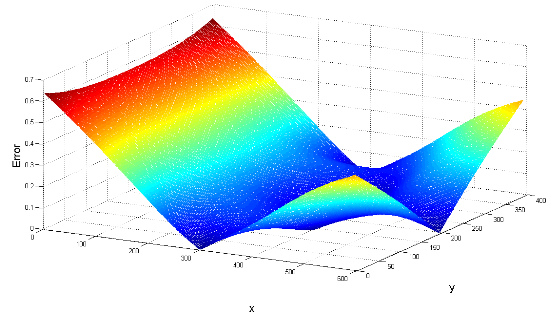

Fig. 8: WCL performance for case 5 displayed in Fig.3(e).

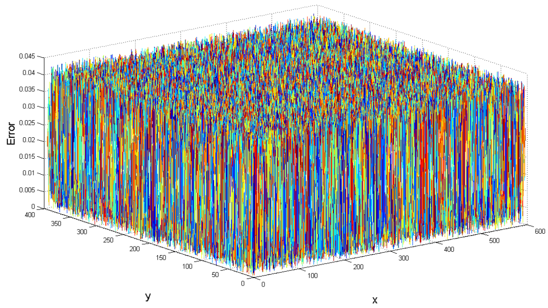

Fig. 9: Trilateration performance for all the cases displayed in Fig.3.

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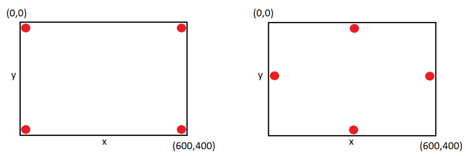
3.2 Evaluation of 4 Beacons Case

In this section, we evaluate the performance of the Trilateration and WCL algorithms for 2 different beacon placement configurations with four beacons as shown in Fig.10. Beacon placement case 6 and beacon placement case 7 are displayed in Fig.10(a) and Fig.10(b), respectively.

The Trilateration algorithm is modified such that the algorithm takes the average of the results obtained from the four different combinations built by different three beacons sets. This modification is set active for all the Trilateration simulations for the cases where the number of beacons is greater than 3. Results of the four beacons case simulations are shown in Fig.11 - Fig.13.



(a) Beacon placement case 6. (b) Beacon placement case 7.

Fig. 10: Placements of the beacons in four beacons case simulations.

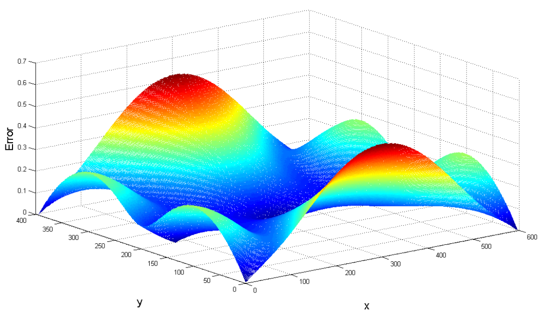


Fig. 11: WCL performance for case 6 displayed in Fig.10(a).

Simulation results displayed in Fig.11 show that performance of WCL decreases as the node gets closer to the centroid of two beacons located on a common edge of the field. On the other hand, considering the error distribution displayed in Fig.12 it is again seen that estimation error increases as the node gets out of the borders set by the beacons. Moreover mean errors of WCL in beacon placement cases 6 and

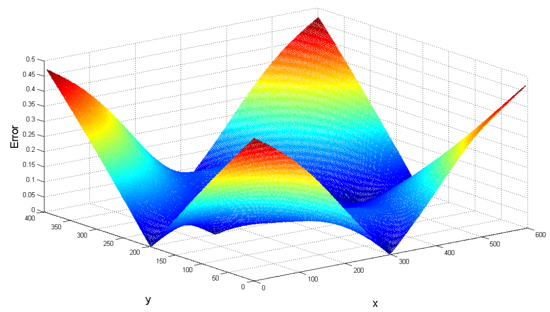


Fig. 12: WCL performance for case 7 displayed in Fig.10(b)

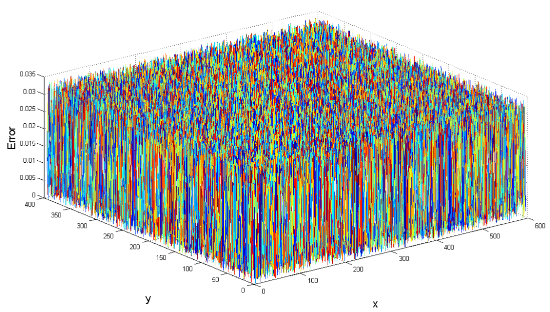


Fig. 13: Trilateration performance for the cases displayed in Fig.10.

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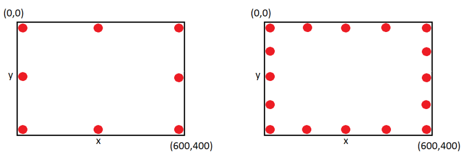
7 are found as 16.6% and 14%. Thus, beacon deployment formation displayed in Fig.10(b) can be said to be the appropriate one for a WCL based position estimation system with four beacons. Besides, Trilateration performance again stays constant independently from the beacon placements. But it is worth to note that estimation error of Trilateration decreased from 2% to 1.5% although the random noise matrix is kept constant, since the modified Trilateration algorithm takes the average of the results obtained from the four different combinations built by different three beacons sets.

3.3 Evaluation of 8 and 16 Beacons Cases

In order to examine the performances of the two methods for higher number of beacons, we run simulations for eight beacons and 16 beacons cases. Beacon placements are shown in Fig.14. Results are shown in Fig.15 - 18.



(a) Beacon placement case 8. (b) Beacon placement case 9.

Fig. 14: Placements of the beacons in eight and 16 beacons cases.

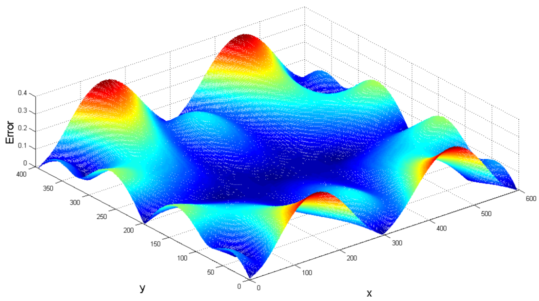


Fig. 15: WCL performance for case 8 displayed in Fig.14(a)

Also simulation results displayed in Fig.15 and Fig.16 show that WCL performance decreases as the node gets closer to the centroid of two consecutive beacons located on a common edge of the simulation

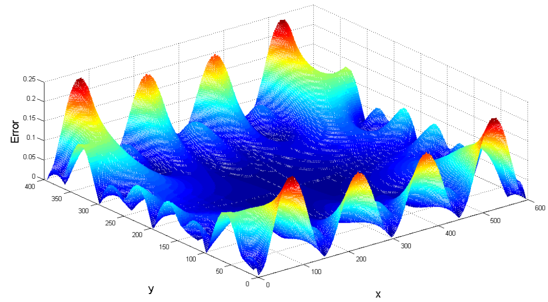


Fig. 16: WCL performance for case 9 displayed in Fig.14(b)

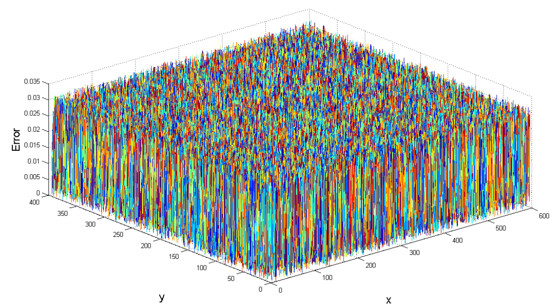


Fig. 17: Trilateration performance for case 8 displayed in Fig.14(a)

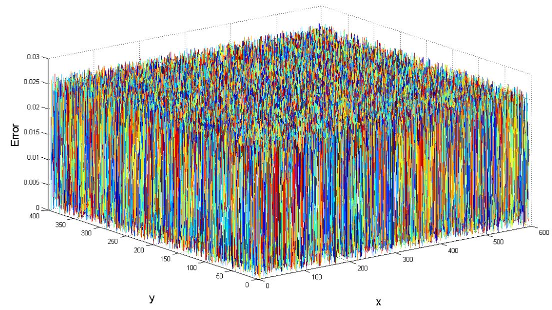


Fig. 18: Trilateration performance for case 9 displayed in Fig.14(b)

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field, as seen in the previous cases. The mean error also decreases as the number of beacons is increased, such that mean error for the eight beacons case (placement case 8 displayed in Fig.14(a)) is found as 11% while the mean error for the 16 beacons case (placement case 9 displayed in Fig.14(b)) is found as 4.3%. The mean estimation error of the Trilateration also decreased from 1.4% for the eight beacons case to 1.2% for the 16 beacons case.

3.4 Evaluation of the Trilateration and WCL with Erroneous Channel Model

All the simulations up to now are performed assuming that the estimated distances between the node and the beacons are only exposed to random noise, which could be lowered by increasing the number of Monte Carlo iterations. In order to get a better knowledge about performance of both two position estimation methodologies, we modified our simulation software in order to calculate the distances as if they are derived from the ITU Model (see Section 2.1). We assigned the floor loss penetration factor parameter ($P_f(n)$) of the ITU Model with varying error rates, and observed the performances of WCL and Trilateration methods. Simulations are run for the beacon placement case 6 (see Fig.10(a)). Results are shown in Fig.19 - Fig.22.

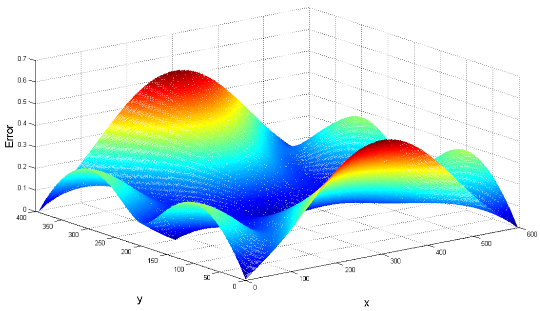

Fig. 19: WCL performance with the ITU Model, $P_f(n)$ parameter of which is provided with 20% error.

3.5 Comparison of WCL and Trilateration Based on the Implemented Simulations

To make a reasonable comparison between the WCL and the Trilateration methods, we simulated them on the same test setup with the same noise vector. Scenarios with 3, 4, 8 and 16 beacons with various placements are implemented. We also simulated the case

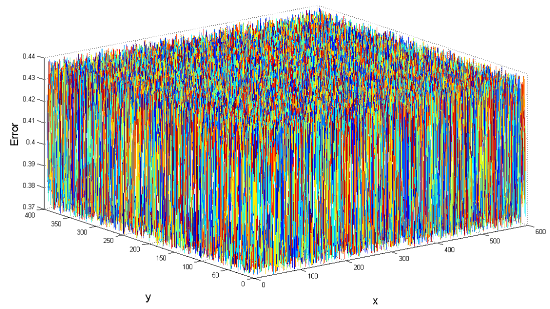

Fig. 20: Trilateration performance with the ITU Model, $P_f(n)$ parameter of which is provided with 20% error.

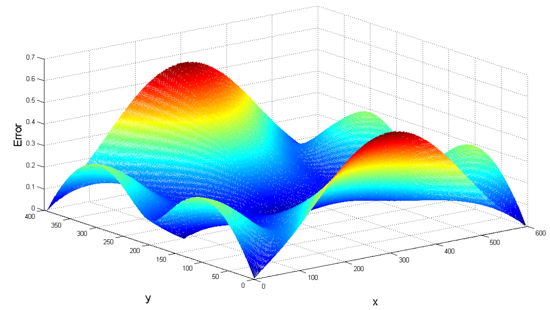

Fig. 21: WCL performance with the ITU Model, $P_f(n)$ parameter of which is provided with 100% error.

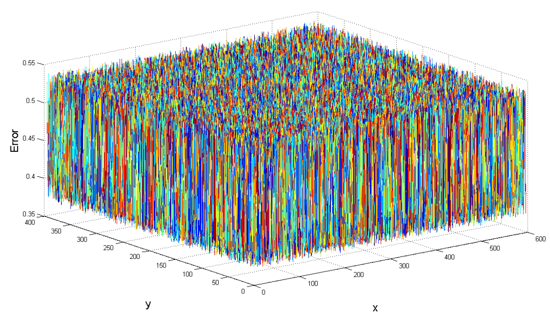

Fig. 22: Trilateration performance with the ITU Model, $P_f(n)$ parameter of which is provided with 100% error.

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where one of the channel model parameters is provided with error.

Considering the simulation results displayed in Fig.4 - Fig.8, one can easily conclude that WCL fails with high error rates with three beacons. It is also seen that WCL performs worse when the node position to be estimated is located outside of the boundaries set by the beacons. It is also seen that the region on the 2-D simulation field where the estimation error of WCL is less than 2%, expands as the number of beacons increases. Furthermore, maximum estimation error of WCL encountered decreases as the number of beacons increases. For instance the maximum error is 52% for the beacon placement case 6 (see Fig.11), while it is 23% for the beacon placement case 9 (see Fig.14(b)). On the other hand, it is seen in Fig.9, Fig.13, Fig.17 and Fig.18 that the Trilateration is quite robust against the number and placements of the beacons, such that the estimation error does not exceed 5% for any of the cases in question.

Simulation results displayed in Fig.11, Fig.12, 15 and 16 show that the position estimation performance of the WCL algorithm decreases as the node gets closer to the edges of the 2-D simulation field, especially as the node location gets closer to the centroid of two consecutive beacons. Besides, considering the simulation results displayed in Fig.19 - Fig.22, one can easily conclude that WCL method is much more robust against errors in the path loss model used in distance estimations, when compared to the Trilateration method, since the estimation error of the WCL algorithm stays nearly constant even if the parameter $P_f(n)$ is assigned with error rates up to 100%, while the Trilateration performance decreases excessively when erroneous $P_f(n)$ is provided.

Thus, it can be concluded that Trilateration is more robust against varying number and locations of the beacons, while WCL is more dependent on the beacon numbers and placements. On the other hand, WCL is much more robust against errors in channel modelling when compared to the Trilateration.

4 Experimental Evaluation of the Localization Methods

Here we introduce our position estimation system, including the design procedures and performance comparison with the ITU Indoor Channel Model. Initially we designed a ZigBee based path loss measurement system composed of a transmitter (see Fig.23) and a receiver (see Fig.24) connected to the PC, where the developed position estimation software is run. Subsequently we collected path loss data in an indoor area.

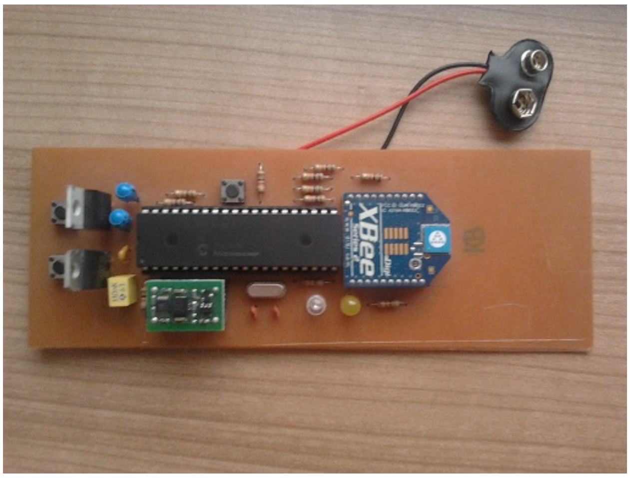

Fig. 23: RSSI transmitter.

Fig. 24: ZigBee receiver module.

Based on the collected path loss data we derived an indoor path loss model and performed position estimations with both WCL and Trilateration methods.

After completing the hardware design and software update procedures, RSSI measurements are implemented in a 20 meters x 50 meters closed industrial area as a requirement for our empirical indoor channel model design. The ZigBee receiver together with a PC are placed to a corner of the stated closed area, and then we moved RSSI transmitter along the diagonal of the area (54 meters) sending 200 RSSI samples per 1 meter. Once an RSSI byte is received by the software, it is than converted to path loss in dB as follows: The RSSI data output from the XBee module is in [dBm], hence the received power can be derived from (2) by assigning $P_{Ref} = 1mW$. Once the received power is derived, than the corresponding path loss value is generated by (1). The measurements are displayed in Fig.25.

We also tested the correlation of the ITU Model with our measurements. The corresponding ITU

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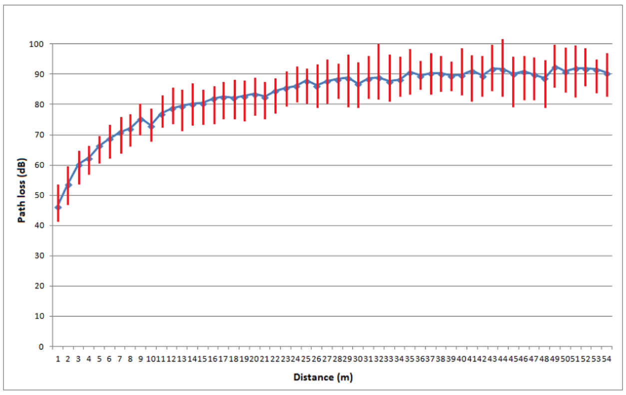

Fig. 25: Path loss vs distance (The blue dots and the red bars represent the average path loss and the variation of the path loss measurements at the related distances, respectively).

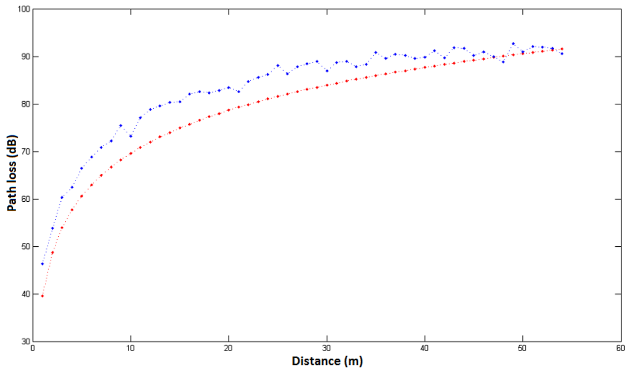

Fig. 26: ITU Model path loss estimations vs our measurements (The red curve and the blue plot represent the theoretical path loss estimations of the ITU Model and the measured path loss values, respectively).

Model for the same floor case is as [5]

$$PL(d) = 39.6 + 30 \cdot \log(d) \qquad (11)$$

where $PL(d)$ is the path loss in dB, and d is the distance in meters.

ITU Model estimations and the measurements are displayed together in Fig.26. It can easily be concluded from Fig.26 that the ITU Model performance is not satisfactory in the industrial area, where we collected our measurement data.

4.1 Empirical Channel Model Design

We have derived an empirical log distance path loss model based on our measurements and the generic log distance model, which is expressed as

$$L(d) = L(1) + \eta \cdot \log(d) \qquad (12)$$

By rewriting (12) as

$$L(d) - L(1) = \eta \cdot \log(d) \qquad (13)$$

and considering the distances varying between 1 meter and 54 meters (d_1 through d_{54} = 1m through 54m), we can represent (13) in matrix form:

$$\begin{bmatrix} \log(2) \\ \vdots \\ \log(54) \end{bmatrix} \cdot \eta = \begin{bmatrix} L(2) \\ \vdots \\ L(54) \end{bmatrix} - \begin{bmatrix} L(1) \\ \vdots \\ L(1) \end{bmatrix}$$

By letting

$$A = \begin{bmatrix} \log(2) \\ \vdots \\ \log(54) \end{bmatrix}, b = \begin{bmatrix} L(2) - L(1) \\ \vdots \\ L(54) - L(1) \end{bmatrix}$$

we obtain the system of

$$A \cdot \eta = b \qquad (14)$$

The least squares solution of the above system is given by

$$\eta = (A^T A)^{-1} \cdot A^T b = \frac{\sum_{i=2}^{54} \log(i) \cdot [L(i) - L(1)]}{\sum_{i=2}^{54} \log^2(i)} \qquad (15)$$

The numerical value of (15) for the data yields

$$\eta = 27.7753 \qquad (16)$$

Noting that the path loss at reference distance 1m is measured as $L(1)$ = 46.3118, our path loss model is thus finalized as:

$$L(d) = 46.3118 + 27.7753 \cdot \log(d) \qquad (17)$$

Fig.27 displays the performance of our path loss model when compared with the real path loss measurements.

4.2 Position Estimation Implementations Based on the Designed Model

After completing the design procedures, we tested our path loss model in position estimations by using path loss values corresponding to distances of all the possible positions to where the ZigBee receiver is placed. Since we could not obtain enough number of ZigBee modules, we tested our model on the simulator software we had developed. We made the simulations using both WCL and Trilateration methods for the beacon placement case 6, by setting the simulation field dimensions to 20 x 50.

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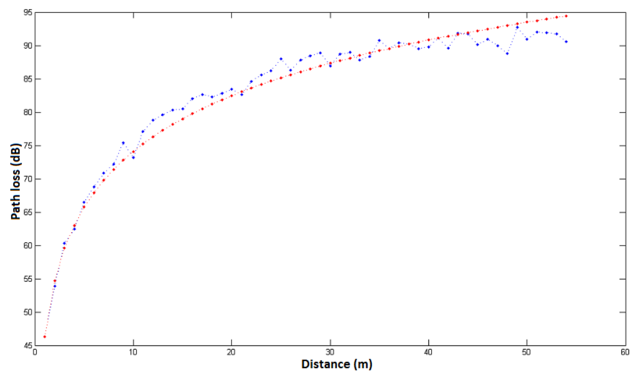

Fig. 27: Predictions of our path loss model vs measured path loss values (The red curve and the blue plot represent the theoretical path loss estimations of our model and the real path loss measurements, respectively).

At each step of the simulations, once the distance between the node and a beacon is calculated, then the corresponding path loss value obtained from our measurements to the calculated distance, is input to our model. Then the distances output from our model are used in position estimations, as explained in previous sections.

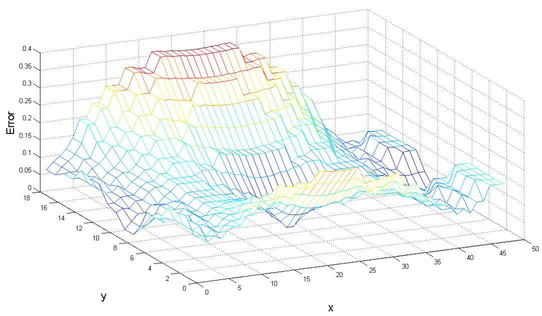

Fig. 28: Position estimations performed by our path loss model with the WCL method.

Considering the results shown in Fig.28 and Fig.29 we see that the overall performance of WCL has a minor difference when compared to running the algorithm with ideal distance values. But the case is worse for the Trilateration simulations, such that the error is about 16%, supporting our assertion that the Trilateration method is much more dependent on the errors in the channel model parameters.

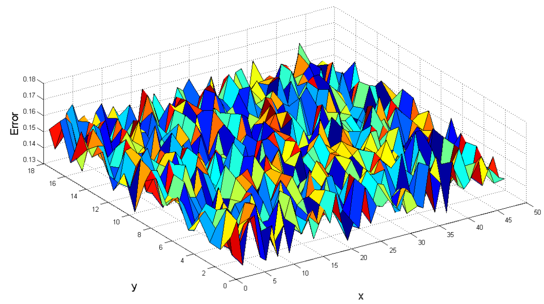

Fig. 29: Position estimations performed by our path loss model with the Trilateration method.

5 Conclusion

In this paper, a 2-D indoor position estimation system is designed and implemented following the design of a log-distance based empirical indoor channel path loss model for ZigBee sensor networks using the path loss data measured in an industrial area. The designed model is realized by applying curve fitting on the path loss measurements using the Least Squares Solution method. The performance of the designed model is compared with the ITU model for indoor attenuation. Based on the collected path loss data, our model gives obviously more successful distance estimates. We also compared the position estimation methods which are the WCL and the Trilateration, with simulations based on both the exact distances exposed to Gaussian noise, and the distance estimation results of our model. It is concluded that; under the same noise characteristics, Trilateration method gives more precise position estimates compared to the WCL, if the channel model perfectly matches with the real channel characteristics. In contrast, WCL is much more robust against errors in the channel model parameters, when compared to the Trilateration. Hence, WCL will be a better choice unless the path loss based distance estimating channel model perfectly represents the real channel characteristics of the indoor area in question. Future work will concentrate on designing a 3-D position estimation system for multi-floored buildings.

6 Acknowledgement

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