# A Received Signal Strength based Self-adaptive Algorithm Targeting Indoor Positioning

Xiaoyue Hou, Tughrul Arslan, Arief Juri
University of Edinburgh

*Abstract*—**This paper proposes a novel received signal strength indicator (RSSI)-based self-adaptive indoor positioning algorithm which can be utilized in non-line-of-sight (LOS) environments through the employment of a weighted feedback framework. This algorithm is composed of the following parts: optimized RSSI algorithm, offset-triangulation algorithm and weighted feedback framework. The developed self-adaptive algorithm has been tested in a variety of indoor environments. Results so far indicate that path loss errors are reduced significantly and the proposed self-adaptive algorithm results in high indoor positioning performance under complex non-LOS environments。**

***Keywords—Indoor positioning, RSSI, Non-Los environment, Weighted feedback framework***

## I. Introduction

In recent years, GPS and cellular signal-based outdoor positioning have become widely used throughout our daily lives in areas such as car navigation systems and digital map location [1][2]. Meanwhile, with the development of positioning technologies, operators and manufacturers have begun to pay increased attention to the design of indoor positioning systems.

Thus, Indoor Location Based Services (ILBS) play an increasingly important role in driving future applications, such as healthcare and smart living [3] because people spend a large amount of time in both private and public indoor areas. An indoor positioning and navigation system could, for example, help visitors to locate their destination within unfamiliar and complex environments.

Presently RSSI based positioning algorithms are widely used in indoor positing systems because of their low computation and hardware limitations [4]. However, most of the current researches on RSSI-based indoor position algorithms assume a LOS environment but ideal LOS is practically non-existent in a real environment [5]. The strength of the signal is reduced by obstacles in a physical environment such as walls or bookcases. In this situation, the accuracy will be decreased. Moreover, obstacles are difficult to predict. This unpredictable impact limits the accuracy of triangulation-based indoor positioning.

Furthermore, the impact caused by obstacles is not stationary. A manually updated database could not keep up with this frequent dynamic change. Repositioning furniture will destroy the validity of the whole database within the area. This is a limitation also faced by fingerprint algorithms.

In this situation, most RSSI-based indoor positioning algorithms could not give an accurate location in a non-LOS environment [5]. In this paper, an RSSI-based self-adapted indoor positioning algorithm that can be used in non-LOS environments is proposed. By applying a weighted feedback framework combined with optimized algorithm, some obstacles and negative effects can be detected and corrected to implement accurate indoor positioning under a non-LOS environment.

## II. Self-adaptive Algorithm

A novel indoor position algorithm has been proposed in this paper to solve the non-LOS environment problem. This algorithm consists of three major parts: an optimized RSSI algorithm, an offset-triangulation algorithm and a weighted feedback framework. The function of each sub-module is described below.

### *A. RSSI algorithm*

RSSI is a power value measured by the unit of $mW$, which can be used to direct the electromagnetic energy of the transmission medium. According to the Pass Loss Model, a known distance of $r$ and the received power at this distance $P(r)$ have the following relationship [6]:

$$\frac{P_{(r_0)}}{P_{(r)}} = \left(\frac{r}{r_0}\right)^n \qquad (1)$$

Where:

$r_0$ is the known reference distance. $P(r_0)$ is the received power at the reference distance $r_0$.

$n$ is the path loss coefficient with a range between 2 and 6.

For the receiving end, the formula for the received signal strength is shown below:

$$P(r_0) = Pt - Pl(r_0) \qquad (2)$$

Where,

$Pt$ is the signals transmit power. $Pl(r_0)$ is the received signal strength RSSI. $P(r_0)$ is the path loss when the distance is $r_0$.

This equation can be extended to Gaussian distribution with the unit $dBm$. The Equation 3 is shown below [7]:

$$P(r) = P(r_0) - 10n \times lg(r/r_0) + X\sigma \qquad (3)$$

Where,

$P(r)$ is the received signal power of the unknown node at the distance r.

$P\ (r_0)$ is the received signal power of the unknown node at the distance $r_0$.

$X\sigma$ is a zero mean Gaussian random variable.

According to the Equation 2 and 3, the RSSI equation is described as follows:

$$\text{RSSI}= Pt-Pl\ (r_0)\ -10n\times lg(r/\ r_0)+X\sigma \ (4)$$

The transmitted signal will pass through more than one transmission medium within the real environment. In this case, the path loss coefficients are dynamic in different transmission mediums. A newly proposed extended-RSSI equation, developed as part of the self-adaptive algorithm, extracts the multiple-path loss effect from the Gaussian random variable according to the basic equation and provides a modus with which to measure it.

$$P(r) = Pt - \sum_{i=1}^{m} Pl(r_{0i}) - 10\sum_{i=1}^{m} n_i\ lg\left(\frac{r_i}{r_{0i}}\right) + X\sigma \quad (5)$$

In a real environment, it is difficult to predict the value of pass loss coefficient $n_i$ and $r_i$ accurately in Equation 5. Prediction without specific targets cannot result in higher accuracy of the mentioned parameters but only increase the computation and workload. As a solution, a posterior calibration method is proposed in section B to provide a forecast range. Meanwhile, experimental results show that the signal strength is decreased dramatically when the signal goes through only one obstruction layer (plywood and brick). A multilayer obstruction can be ignored in most cases, and the size of the one layer obstacle such as a signal layer wall, can be estimated roughly (no more than 50cm). Equation 5 can thus be simplified to the following equation:

$$P(r) = P(r_{01}) - P(r_{02}) - 10\sum_{i=1}^{2} n_i\ lg\left(\frac{r_i}{r_{0i}}\right) + X\sigma \quad (6)$$

Where,

$r_{0i}$ is the reference distance for different Transmission media, normally $r_{01}$ is the LOS reference distance, $r_{02}$ is the obstruction reference distance.

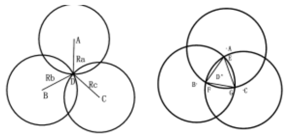
$n_i$ is the path loss coefficient, normally $n_1$ is the LOS coefficient, $n_2$ is the obstruction coefficient.

In Equation 6, multilayer (more than two) obstructions are ignored as the signal strength is weakness and difficult to detect.

According to the experiments result, signal strength is decreased by one layer obstruction dramatically. In this case, multilayer obstruction under real environment can be ignored because most of the handheld terminal could not receive the signal which pass through more than one layer obstruction.

*B. Centroid core triangulation algorithms*

Triangulation is a common technique used for RSSI-based indoor positioning on account of its low level of computation. The traditional triangulation algorithm is shown below in Figure 3.



a b

Figure. 3a. Triangulation algorithm under ideal LOS environment

3b. Centroid core based triangulation algorithm under real environment

A, B, C are the access points (AP) with location A($x_1$,$y_1$),B ($x_2$,$y_2$)and C($x_3$,$y_3$). If the unknown coordinate D is D(x,y), the position of node D can be calculated by using the position of the node A, B, C and the calculated distance Ra, Rb and Rc. The algorithm to calculate the distance between the unknown anchor node D and the known anchor nodes Ra, Rb and Rc has shown in the RSSI algorithm.

In a real environment, because of reflection and other impacts, the distance calculated by the RSSI algorithm is not accurate. The calculated result will be larger than the actual distance [8]. As a result, the three circles A, B and C will not cross on one point. Three common points E, F and G between each two circles will be instead of the unknown anchor node D, as shown in Figure 3b.

To solve this problem, the centroid core of the triangle composed of the three common points E, F and G is calculated as the position of the unknown anchor node D. Assuming that the location of the common points are E($x_4$,$y_4$), F($x_5$,$y_5$) and G($x_6$,$y_6$), the position of D(x,y) is shown as follows:

$$\begin{cases} x = \frac{x_4+x_5+x_6}{3} \\ y = \frac{y_4+y_5+y_6}{3} \end{cases} \quad (7)$$

This algorithm has certain limitations. The user's position will only be calculated once the three circles have cross points between each other. Two examples of an unexpected situation are shown in Figure 4.

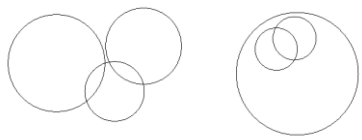


Figure. 4. Circles do not have cross points between each other

In Figure 4, some of the circles do not have cross points, which indicates that at least one root of the equation is an imaginary number. Consequently, the calculation process will be interrupted. In order to solve this problem, the use of algorithms such as least-square [9] algorithm has been proposed. Furthermore, apart from the occasion descried in Figure 4, there are a number of other unexpected cases, most of which are difficult to create the corresponding sub-algorithms. An excessive number of sub-algorithms could not only decrease the compatibility of the algorithms, but may also increase the computation and hardware workload dramatically.

As the issue mentioned above, this paper proposes the offset triangulation to solve the problem, which is different from traditional triangulation algorithms (the cross point based triangulation principle). Instead of calculating the centroid core coordinate of the triangle generated by the three cross points in Figure 3b, the centroid core of the triangle generated by the three APs which the user position belongs to is used as a datum point in Figure 5. The user's specific position is calculated by achieving the offset to the datum point and the offset margin according to the distance ratio between the user's position and each AP. As long as three AP signals have been received by the mobile device and the three APs are not deployed in one line, this algorithm can be employed no whatever the results are accurate or not. In this case, if the triangle consisting of APs where the user position belongs to can be determined accurately, the results generated by this proposed algorithm will be accurate.

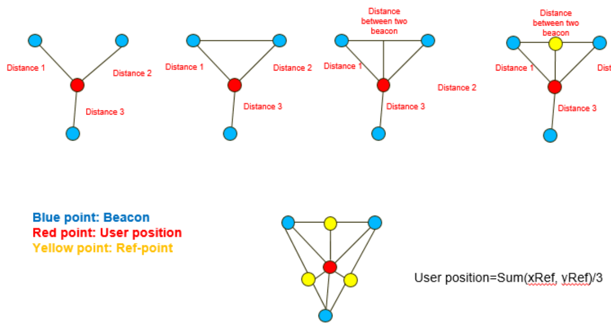



Figure. 5. Off-set triangulation algorithm

### C. *Weighted feedback algorithm*

The user's position can be determined by employing the offset triangulation algorithm. The results will be accurate if the received signals are provided by the correct APs. The function of the weighted framework is to verify the accuracy of the localization.

1. A Priori corrected weighted framework

As mentioned above, the influence of the path loss coefficient is unpredictable. However, it is able to use this weighted framework to detect obstacles with high probability under real environmental conditions.

When deploying the APs on the map, a relative area identity is given to each AP. As a result, those APs within the same area as the LOS transmission path will be given the same area identity. When terminals such as mobile devices begin to detect the AP, the AP with the greatest signal strength will be given the highest priority, and other APs with the same identity will have the same weight. Those APs with highest priority will utilize the LOS model. Meanwhile those APs with different identities will be given a lower competence, meaning that their RSSI equations will have more than one path loss coefficient and Equation 6 will apply instead of LOS equation.

2. A Posterior calibration feedback framework

The feedback framework is employed to correct the localization result dynamically when mobile device is moving. When user's position is stationary, the average value and standard division of the location will be balanced dynamically; if the user's position is moving, the mean and standard division will be different according to the changes in the environment. By comparing the standard deviation value, the weight of the pervious coordinates will be changed dynamically and the previous coordinates combining with their weight value will feedback to the system in order to correct the current user position.

## III. Experiments under Real Environment

A testing network with five APs driven by Bluetooth 4.0 [10] was utilized to test the performance of the Optimized RSSI algorithm. Meanwhile three experiments under different environment have been employed to examine the performance of the self-adaptive algorithm. The experimental results are shown below.

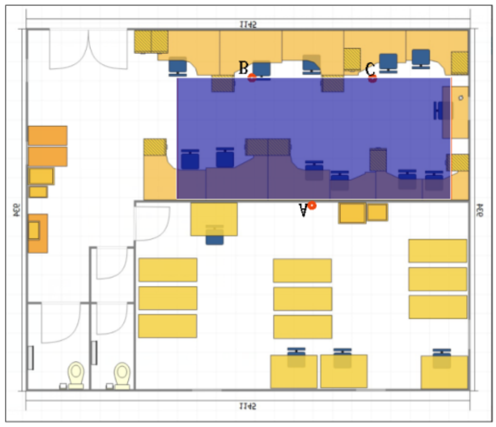



Figure. 6. Experiment and beacon layout (3 beacons)

### A. *RSSI algorithmms*

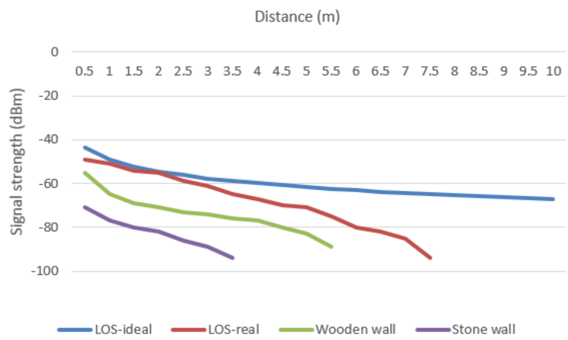



Figure .7. The RSSI value for different environment, the ideal LOS environment, test result under real LOS (approximately) environment, 30cm wooden (plywood) wall and 35cm stone (brick) wall

The test results in Figure 7 indicate that the RSSI values under real conditions are less than the ideal values due to the effect of $X\sigma$. The signal trend is not negatively affected by $X\sigma$ when the distance is less than five meters during testing. However, when the distance is larger than five meters, the relationship between the RSSI and distance is difficult to calculate due to the increasing complexity of the environment. Consequently, five meters range is determined to be the maximum length for the distance between beacons and mobile devices.

In a real environment, in order to reduce the unnecessary computation, signal attenuation caused by obstruction within a reasonable range can be assumed as constant, because the size of the obstacles will not change sharply. Under this model, by applying the priori corrected weighted framework which mentioned in II-C section and the Equation 6, signal attenuation caused by disorders can be found early and removed.

During the process of testing two obstacles, a 30 cm plywood wall and a 35 cm brick wall, were added as non-LOS elements to test the performance of the optimized RSSI algorithm. The results indicate that due to the strong negative effects stemming from the two different types of communication media were effectively removed (assuming the obstacles have been found), the precision of the calculated distance increased dramatically.

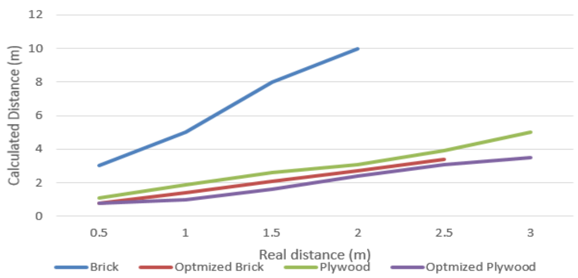



Figure. 8. Optimized result for obstacles: Brick and Plywood

## *B. Weight feedback framework*

Combined with weighted framework, the performance of this proposed algorithm has been examined in three different environments: the third floor of the Noreen and Kenneth Murray library in Kings Building located in Edinburgh (King's Buildings, Thomas Bayes Road, Edinburgh EH9 3FG); a small cabin behind the Scottish Microelectronics Centre (SMC) building (Scottish Microelectronics Centre, Kings Buildings, Edinburgh, EH9 3JF) and a Sainsbury's supermarket located in the Cameron Toll shopping mall (Cameron Toll Shopping Centre, 6 Lady Road, Edinburgh, EH16 5PB). The features of the three environments are different. The library has multiple small rooms and separated by reinforced walls, the small cabin is made of plywood and can be delimited as a LOS environment, and the supermarket is an open non-LOS environment with moving people.


Figure. 9. Layout for BLE beacons in the library (7 beacons)

Figure 9 shows that in the library, BLE beacons were deployed in two different areas: the blue areas can be define as indoor LOS and the red area is an indoor non-LOS environment. Distance between each beacon is 4 meters (inside room) and 6 meters (outside room). In the blue area, the average localization error was 1.5 meters meanwhile in the red area, the average value of localization error was 1.9 meters. The cases when mobile devices are located very close to one of the beacons (RSSI value less than -59dBm) have been ignored, as the user's position will be forcibly set to the coordinate of the nearest beacon. Results indicate that under LOS and sample non-LOS environments, the localization error was less than three meters (based on more than 50000 RSSI sample).

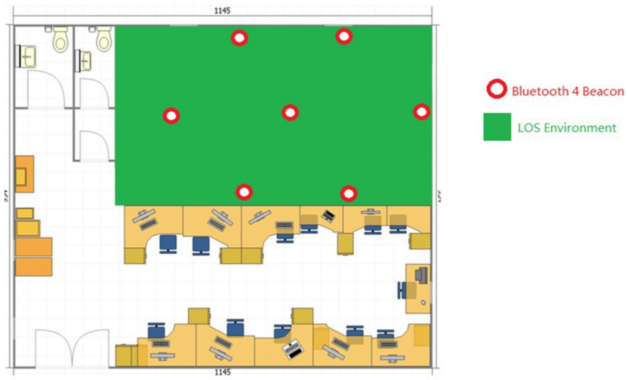



Figure. 10. Layout for BLE beacons in the small cabin (7 beacons)

In the small cabin in Figure 10, the experiment outcome of the localization error was 1.2 meter on average. Result shows that it is difficult to decrease the localization error to less than 1 meter at this stage by applying the proposed algorithm, which consistently matches the simulation result. Localization errors are not expected to decrease dramatically under the LOS environment with a very high signal cover density. The cases when mobile devices are located very close to one of the beacons (RSSI value less than -59dBm) have also been ignored.

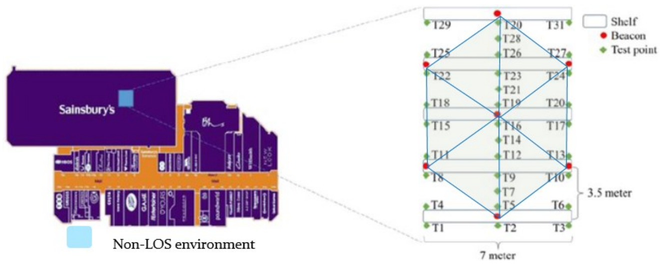



Figure. 11. Layout for BLE beacons in the shopping mall (7 beacons)

The shopping mall in Figure 11 is an open area which integrating dynamic non-LOS propagation channels. During the test, many unexpected RSSI values were detected. The complexity of the testing environment was significantly underestimated because of the negative effects produced by stacked goods. However, the accuracy of the localization was higher than expected. The average error was less than two meters in general when mobile devices were deployed in the effective area. The results therefore appear to show that the proposed algorithm demonstrated its strong adaptability in a complex environment with a medium-level deployment density.

## IV. CONCLUSION

In this paper, an RSSI based self-adaptive algorithm targeting indoor positioning system is proposed with the aim of removing the path loss effect. The RSSI algorithm is optimized to process fixed obstacles in non-LOS environments. The offset triangulation algorithm is used to verify the accuracy of the calculated result. The results are then integrated into a weight feedback framework to remove multiple path loss effects. Meanwhile a reference result is fedback to the RSSI algorithm in order to modify key parameters. Multiple experiments with Bluetooth 4 beacons are set up to examine the performance of the proposed algorithm. The results show that the negative effects caused by obstacles can mostly be removed and the accuracy of indoor positioning is increased dramatically. However, the proposed-algorithm has certain limitations. $X\sigma$ remains negative influence on the accuracy of indoor positioning. Further researches should therefore include the integration of a filter to limit the effects of moving objects. A Bayes [11] filter for RSSI algorithm is also needed to reduce the noise caused by signal reflection. Meanwhile optimizations of the weight feedback framework are needed to increase the adaptability of this algorithm under complex environmental conditions and decrease the minimum value of the localization error mentioned above. Furthermore, a multi-floor network with 50 APs will be established to verify the performance of the adaption of this algorithm.

## V. REFERENCES


[1] F. Seco, C. Plagemann, A. R. Jiménez, and W. Burgard, "Improving RFID-based indoor positioning accuracy using Gaussian processes," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, 2010, pp. 1-8.

[2] I. Sharp and K. Yu, "Enhanced least-squares positioning algorithm for indoor positioning," *Mobile Computing, IEEE Transactions on,* vol. 12, pp. 1640-1650, 2013.

[3] A. Hatami and K. Pahlavan, "A comparative performance evaluation of RSS-based positioning algorithms used in WLAN networks," in *Wireless Communications and Networking Conference, 2005 IEEE*, 2005, pp. 2331-2337.

[4] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *Mobile Computing, IEEE Transactions on,* vol. 11, pp. 1983-1993, 2012.

[5] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* vol. 37, pp. 1067-1080, 2007.

[6] B. Kim, W. Bong, and Y. C. Kim, "Indoor localization for Wi-Fi devices by cross-monitoring AP and weighted triangulation," in *Consumer Communications and Networking Conference (CCNC), 2011 IEEE*, 2011, pp. 933-936.

[7] F. Yang, H. Shi, L. Zhu, and H. Zhao, "An intelligent localization system based on RSSI ranging technique for WSN," *Chinese Journal of Sensors and Actuators,* vol. 21, pp. 135-140, 2008.

[8] H. Shi, "A new weighted centroid localization algorithm based on RSSI," in *Information and Automation (ICIA), 2012 International Conference on*, 2012, pp. 137-141.

[9] Y. Yang, Y.B. Zhao, and M. Kyas. "A statistics-based least-squares (sls) method for non-line-of-sight error of indoor localization." *in Proc. IEEE WCNC on*, 2013, pp. 1–6.

[10] B. K. Maharjan, U. Witkowski, and R. Zandian, "Tree network based on Bluetooth 4.0 for wireless sensor network applications," in *Education and Research Conference (EDERC), 2014 6th European Embedded Design in*, 2014, pp. 172-176.

[11] A. Galov and A. Moschevikin, "Bayesian filters for ToF and RSS measurements for indoor positioning of a mobile object," in *Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on*, 2013, pp. 1-8.