8-31-2018

Indoor Positioning Algorithms with Offline Positioning Capabilities for Local Positioning Systems

Farhan Zaki
University of Windsor

Indoor Positioning Algorithms with Offline Positioning Capabilities for Local Positioning Systems.

By

Farhan Zaki

A Thesis
Submitted to the Faculty of Graduate Studies
through the Department of Electrical and Computer Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science
at the University of Windsor

Windsor, Ontario, Canada

Indoor Positioning Algorithms with Offline Positioning Capabilities for Local Positioning Systems.

by

Farhan Zaki

APPROVED BY:

____

A. Edrisy
Department of Mechanical, Automotive and Materials Engineering

____

B. Shahrrava
Department of Electrical and Computer Engineering

____

R. Muscedere, Co-Advisor
Department of Electrical and Computer Engineering

____

R. Rashidzadeh, Co-Advisor
Department of Electrical and Computer Engineering

DECLARATION OF CO-AUTHORSHIP AND PREVIOUS PUBLICATIONS

I. Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research as follows:

The works showed in chapters 3, 4 and 5 were co-authored by me and my supervisor Dr. Rashid Rashidzadeh. In all cases, the key ideas, experimental designs, data analysis, interpretation were conducted by both the author and the co-author, and the writings were carried out by the author.

I am aware of the University of Windsor Senate Policy on Authorship and I certify that I have properly acknowledged the contribution of other researchers to my thesis and have obtained written permission from the co-author to include the materials in my thesis.

I certify that, with the above qualification, this thesis, and the research to which it refers, is the product of my own work.

II. Previous Publications

This thesis includes 3 original articles that have been previously published/submitted for publication in peer reviewed journals, as follows:

Chapter	Publication Title	Publication Status
Chapter -3	F. Zaki and R. Rashidzadeh, "An indoor location positioning algorithm for portable devices and autonomous machines," 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Alcala de Henares, 2016, pp. 1-6.	Published
Chapter -4	A Light Weight Indoor Positioning Method using Bluetooth Low Energy Beacons	Submitted for review

Chapter -5	Indoor Positioning via RSS Loss Analysis	Prepared

I certify that I have obtained a written permission from the copyright owner(s) to include the above published material(s) in my thesis. I certify that the above material describes work completed during my registration as a graduate student at the University of Windsor.

III. General

I declare that, to the best of my knowledge, my thesis does not infringe upon anyone's copyright nor violate any proprietary rights and that any ideas, techniques, quotations, or any other material from the work of other people included in my thesis, published or otherwise, are fully acknowledged in accordance with the standard referencing practices. Furthermore, to the extent that I have included copyrighted material that surpasses the bounds of fair dealing within the meaning of the Canada Copyright Act, I certify that I have obtained a written permission from the copyright owners to include such materials in my thesis.

I declare that this is a true copy of my thesis, including any final revisions, as approved by my thesis committee and the Graduate Studies office, and that this thesis has not been submitted for a higher degree to any other University or Institution.

ABSTRACT

Location based applications such as indoor navigation is on the rise. A high resolution indoor positioning algorithm generally requires a server grade computer for implementation. Such a requirement, in turn makes access to a network connection a necessity. This has a potential to become an obstacle for indoor navigation and location-based applications. Performing positioning computations at the user end reduces network dependency for location based applications. However, the positioning algorithms have to be optimized to reduce the computational costs. This work introduces new algorithms for indoor positioning using Bluetooth Low Energy Beacons (BLE) tags with offline capabilities. These algorithms run on smartphones and can achieve accuracies of less than 2-meter error distance.

DEDICATION

I dedicate this work to my parents, and my brother, for their unconditional support.

ACKNOWLEDGEMENTS

I would like to sincerely thank my supervisor, Dr. Rashid Rashidzadeh, for the patience he had and the support he provided. I am grateful for the opportunity he provided that let me extend my knowledge and skills.

I am grateful to my co-supervisor Dr. Roberto Muscedere for providing all the resources and support.

I would also like to thank Dr. Behnam Sharrava, for his guidance during the early stages of my research. His insights have led me to discover some of the core functionalities of the algorithms presented in this thesis.

I would also like to thank my committee members for their encouragement, constructive comments and positive criticism which helped me identify flaws and rectify them.

I would like to extend my gratitude to my colleagues at the Research Centre for Integrated Microsystems (RCIM). I appreciate their friendship, support, encouragement, their constant involvement and valuable feedback.

Finally, I would like to thank the research and financial support received from Natural Sciences and Engineering Research Council (NSERC) of Canada and the support provided by the CMC Microsystems.

TABLE OF CONTENTS

DECLARATION OF CO-AUTHORSHIP AND PREVIOUS PUBLICATIONS iii

ABSTRACT v

DEDICATION vi

ACKNOWLEDGEMENTS vii

LIST OF TABLES xi

LIST OF FIGURES xii

LIST OF ABBREVIATIONS xiii

Chapter -1 1

Introduction 1

1.1 Indoor Positioning Wireless Technology (Wi-Fi vs BLE) 1

1.2 Location Based Applications and Accuracies 2

1.3 Scalability and Robustness: 2

1.4 Problem Statement: Lack of Local Indoor Positioning Systems (LIPS). 2

1.5 Research Goals 3

1.6 Thesis Overview 4

1.7 References 4

Chapter -2 5

Related work 5

2.1 Range-based methods: 5

2.2 Range-free methods: 5

2.3 Wireless technology: 6

2.4 Current Implementations: 6

2.5 References 6

Chapter -3 8

An indoor location positioning algorithm for portable devices and autonomous machines. 8

3.1 Introduction 8

3.2 Proposed Solution 9

3.2.1 Concept 9

3.2.2 The Algorithm 11

3.2.2.1 Mapping Phase:..11

3.2.2.2 Computation Phase:..12

3.2.3 Algorithm Explained 14

3.3 Experimental Results...20

3.4 Conclusion 22

3.5 References..22

Chapter-4 23

A Light Weight Indoor Positioning Method using Bluetooth Low Energy Beacons 23

4.1 Introduction: 23

4.2 Proposed algorithm..23

4.2.1 Concept 23

4.2.2 Proposed solution:...23

4.2.3 Algorithm Explained 31

4.3 Experimental Results: 31

4.4 Conclusion: 31

Chapter-5 33

Indoor Positioning via RSS Loss Analysis. 33

5.1 Introduction: 33

5.2 Proposed Algorithm...33

5.2.1 Concept 33

5.2.2 Proposed Solution:..34

5.2.3 Algorithm Explained 42

5.3 Experiment Results:...51

5.4 Conclusion: 53

Chapter -6 55

Conclusions and future work 55

6.1 Conclusions..55

6.2 Future Works 55

APPENDIX :COPY RIGHT PERMISSION..56

VITA AUCTORIS 57

LIST OF TABLES

Table #	**Caption**	**Page #**
1	Received Power at Different Distances from Transmitter	10
2	Total Percentage Loss at Different Distances	11
3	Effect on Accuracy Due to N-LOS	17
4	Accuracy Comparison	21
5	Computation Parameters	26
6	Input Variables	35
7	List of Variables	36
8	Reference Coordinates	37
9	Sum of a Sample Set	38
10	Generated coordinates from all iterations of all sample set	40
11	Computing Final set from all sample sets	42
12	Sample data	43
13	Sample sets and Beacon coordinates	52
14	Accuracy Performance	52
15	Comparison	54

LIST OF FIGURES

Figure #	**Caption**	**Page #**
1	Placement of anchor nodes for an area of 700 m^2	12
2	Shifted beacon coordinates	16
3	Relation between Error and Distance from the center	18
4	Range of Accuracy at Different Locations	19
5	Variation of Error Due to Effect of No Line-of-Sight	19
6	Experiment Results in a 1600 m^2 area	20
7	Set-up	24
8	POI and Zone Assignment	25
9	Check Process	29
10	Update Process	30
11	Coordinate Manipulation	41
12	Percentage change of generated coordinates	45
13	Generated X and Y coordinates	47
14	Updated coordinates after rescaling	49
15	Final Output of the measured location (24.5,7)	51

LIST OF ABBREVIATIONS

RSS	Received Signal Strength
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
BLE	Bluetooth Low Energy
WLAN	Wireless Local Area Network
POI	Points of Interest
IoT	Internet of Things
LBA	Location Based Applications
IPS	Indoor Positioning System
LIPS	Local Indoor Positioning Systems
IPN	Indoor Positioning Network
GIPN	Global Indoor Positioning Network
LOS	Line-of-sight
N-LOS	No Line-of-sight

Chapter -1

Introduction

Location awareness in general, is essential in everyday lives of people. With the rise in the internet of things (IoT) and rapid growth in cellphone technologies, location awareness for mobile devices is also growing in significance. Global Positioning Systems (GPS) have enabled outdoor positioning with remarkable success. However, GPS does not perform well in indoor environments due to loss of GPS signal. For this reason, indoor positioning methods began to emerge. Most indoor positioning techniques require a network connection, which makes indoor positioning less accessible to the public compared to outdoor GPS. In outdoor environments, GPS can function with or without a network connection. Navigation can be performed if off-line maps are downloaded. This is not the case for indoor positioning systems. There are several methods of performing indoor positioning currently [1]. Due to the indoor infrastructure, indoor positioning systems must deal with various error factors [2]. Moreover, the computations required to handle this error are generally complex and can only be performed using server-grade computers which in turn increases the need for a network requirement for portable devices, and the loop continues. Thus, unlike GPS, most indoor positioning systems are dependent on the availability of a network connection.

1.1 Indoor Positioning Wireless Technology (Wi-Fi vs BLE)

For outdoor positioning, global navigation satellite systems (GNSS) provides the global wireless network platform for performing various positioning applications. Similarly, wireless local area networks (WLAN) are required for indoor positioning. Wi-Fi technology is most commonly available for indoor spaces, which makes this technology suitable for indoor positioning as it is cost effective for implementation. On the other hand, indoor environments that don’t have existing Wi-Fi, implementing an indoor positioning system may not be cost efficient. A cost-effective alternative to Wi-Fi networks is the use of Bluetooth low energy (BLE) beacons to form a WLAN dedicated to local indoor positioning systems (LIPS). Using a dedicated WLAN for indoor positioning can be termed as an indoor positioning network (IPN) and they have certain advantages. For instance, having a standard IPN enables the development of a global indoor positioning network (GIPN) consisting of local indoor positioning systems, like GNSS and GPS.

1.2 Location Based Applications and Accuracies

The accuracy compared to outdoor positioning needs to have a higher precision for indoor environments. Outdoor positioning algorithms can allow a relatively high tolerance of error distance because of the immense scale of the outdoor environment. Indoor environments have small and large spaces with varying sizes. Large rooms are divided by walls, which in turn puts burden on the accuracy requirements.

Another factor that weighs in for determining the accuracy requirements of the positioning algorithm is the application tolerance to error. For outdoor positioning, applications such as navigation of people have low tolerance of up to 10 meters. Whereas, navigation for autonomous drones would require a tolerance of a few meters.

Achieving higher accuracies requires the use of complex computations, which in turn requires the use of large processing power, when it comes to indoor positioning algorithms. For indoor environments, people navigation can have a tolerance of up to 2 to 3 meters. This tolerance can also vary based on the requirements of the application. A lower tolerance will enable the use of less complex computations reducing the processing demands for computations.

1.3 Scalability and Robustness:

Scalability and robustness are very crucial for the case of local indoor positioning systems. Indoor environments differ in size and layout for every building. The positioning algorithm is required to be scalable for all sizes of indoor spaces. Also, the positioning algorithm should be robust enough to function in any type of indoor layout.

1.4 Problem Statement: Lack of Local Indoor Positioning Systems (LIPS).

Indoor positioning systems are commonly dependent on a network connection. For this reason, positioning systems for indoor environments are taking longer to be implemented on a large scale. The availability of a Local Indoor Positioning System (LIPS) will not only enhance the performance for GPS, but also enable the growth of location-based applications in the long run. LIPS can be described as a local positioning system, enabling location awareness for portable devices in indoor environments with higher precision.

1.5 Research Goals

The goal for this research was to design and test lightweight algorithms that can perform indoor positioning, for implementing Local Indoor Positioning Systems. To implement a LIPS, there are certain requirements that are needed to be met, which are as follows:

Local transmitters: GPS uses satellites for signal transmission. These signals are received by portable devices for communication. This feature makes global positioning independent of any network connection. Similarly, a local network of BLE beacons is required for LIPS. This network is a one-way information flow where local information is advertised for any device with a Bluetooth chip that can receive it.

Computation performed at the user end: GPS are run on heavy processors, so computational complexities is not a major issue. In the case of BLE beacons, all processing must be done at the user end at a software level. This restricts the design with a computational load tolerance. That is, the algorithm must be lightweight enough not to drain the battery of portable devices.

Acceptable accuracy tolerance: The maximum acceptable accuracy tolerance for LIPS is considered to be under 3-meter error margin.

Identifying points of interests (POIs): GPS has a database of POIs which are known locations such as gas stations, restaurants, etc. These POIs provide additional assistance to users during navigation as users can identify the physical locations. Identifying POIs in indoor environments will provide similar assistance to users allowing them to compare POI locations to their physical environments.

1.6 Thesis Overview

This thesis is organized as follows:

Chapter -1 introduces the research topic and provides an overview of parameters and goals regarding the thesis paper.

Chapter -2 discusses known methods related to indoor positioning and also highlights the drawbacks and restrictions these methods have when it comes to implementing an independent LIPS.

Chapter-3 presents an overview of the first solution proposed for indoor positioning. This algorithm was designed with the goal of achieving meter range accuracies with simple computations that can be run on cellphone processors. The findings of this paper were published in the 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN).

Chapter-4 details the second solution which introduces a method of identifying points of interests (POIs) in the indoor environment as seen in the case of GPS. The algorithm is intended for indoor navigation via identification of POIs.

Chapter-5 explains the third method of generating a sequence of estimated location coordinates, enabling real-time navigation capabilities.

Chapter-6 summarizes the thesis with conclusion and future work.

1.7 References

[1] Zahid Farid, Rosdiadee Nordin, and Mahamod Ismail, "Recent Advances in Wireless Indoor Localization Techniques and System," *Journal of Computer Networks and Communications*, vol. 2013, Article ID 185138, 12 pages, 2013. doi:10.1155/2013/185138

[2] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "*Survey of Wireless Indoor Positioning Techniques and Systems*", IEEE Transaction on Systems, Man, and Cybernetics, vol. 37, no. 6, pp. 1067-1080, Nov. 2007.

Chapter -2

Related work

Research in the field of indoor positioning has been going on for decades. There are several methods and algorithms which can be classified into two main groups.

i. Range-based methods.
ii. Range-free methods.

2.1 Range-based methods:

Range-based methods use electromagnetic wave propagation characteristics to determine the distance between a transmitter and a receiver. Popular methods include time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), etc.

The advantage of such methods is obtaining high precision accuracies. However, range-based methods require additional resources, which increases the cost of implementing such methods for local indoor positioning systems (LIPS).

2.2 Range-free methods:

These methods perform location estimations via statistical analysis. In this method, a database of RSS is created, generally known as a radio map. Location estimation is performed by obtaininglive samples of data and comparing them with the previously recorded data. This method is commonly known as fingerprinting method, and there are many fingerprinting algorithms that exist [1].

Fingerprinting methods are popular because they utilize existing resources which lowers implementation costs. Fingerprinting schemes are now being applied to BLE technology [2] as they are cost effective to set up.

2.3 Wireless technology:

The indoor environment requires a suitable wireless technology for indoor positioning. Wi-Fi technology is most commonly used because of availability. The disadvantage in using Wi-Fi access ports is the reliability of RSS data. The variation of RSS for Wi-Fi technology depends on multiple factors apart from those of indoor propagation loss. For example, access ports tend to regulate signal strength depending on the traffic of users connected to them.

BLE technology, especially in the case of BLE beacons, does not have any varying RSS regulation making it a more stable choice of technology for indoor positioning. Moreover, BLE beacons are cost effective and have the potential to perform offline indoor positioning with the right algorithm.

2.4 Current Implementations:

Currently, indoor positioning systems are being implemented in shopping malls and airports for people navigation. However, these implementations are being done at a slow rate. This is because there is no standard method available that is scalable and robust enough to be applied to every indoor environment. Fingerprinting algorithms in particular, require an offline database [3-11]. The offline database needs to be updated routinely to maintain steady performance.

2.5 References

[1] Zahid Farid, Rosdiadee Nordin, and Mahamod Ismail, “Recent Advances in Wireless Indoor Localization Techniques and System,” *Journal of Computer Networks and Communications*, vol. 2013, Article ID 185138, 12 pages, 2013. doi:10.1155/2013/185138

[2] R. Faragher and R. Harle, “Location Fingerprinting With Bluetooth Low Energy Beacons”, *IEEE Journal on Selected Areas in Communications*, vol. 33, Issue 11, pp. 2418-2428, 2015.

[3] H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef, and R. R. Choudhury, “No need to war-drive: unsupervised indoor localization,” *International Conference on Mobile systems, applications, and services (MobiSys '12)*, Low Wood Bay, Lake District, United Kingdom, 2012, pp. 197-210.

[4] M. Youssef and A. Agrawala, "Small-scale compensation for wlan location determination systems," *IEEE Conference on Wireless Communications and Networking*, New Orleans, LA, USA, 2003, vol. 3, pp. 1974-1978.

[5] N. Chang, R. Rashidzadeh, M. Ahmadi, "Robust indoor positioning using differential Wi-Fi access points," *IEEE Transactions on Consumer Electronics,* vol. 56, no. 3, pp. 105-113, Aug. 2010.

[6] T. He, C. Huang, B.M. Blum, J.A. Stankovic, T. Abdelzaher, "Range-free Localization Schemes for Large Scale Sensor Networks", *International Conference on Mobile systems, applications, and services (MobiSys '03),* an Francisco, California, USA, 2003, pp. 81-95.

[7] E. Jedari, Z. Wu, R. Rashidzadeh, M. Saif, "Wi-Fi Based Indoor Location Positioning Employing Random Forest Classifier," *International Conference on In Indoor Positioning and Indoor Navigation (IPIN),* Alberta, Canada, Sept. 2015, pp. 1-5.

[8] Z. Wu, K. Fu, E. Jedari, S. Shuvra, R. Rashidzadeh and M. Saif, "A Fast and Resource Efficient Method for Indoor Positioning Using Received Signal Strength," *IEEE Transactions on Vehicular Technology* ,vol. PP, no. 99, pp.1-12, Feb. 2016.

Chapter -3

An indoor location positioning algorithm for portable devices and autonomous machines.

3.1 Introduction

In recent times, various positioning techniques [1], [2], [3], [4], have shown promising results in achieving location positioning with accuracies of < 1 m. For high indoor positioning accuracies, advanced algorithms are developed that, in most cases, require dedicated servers for computations. With the introduction of Bluetooth Low Energy (BLE) beacons, the cost of setting up a wireless sensor network has gone down significantly. However, the cost of having access to dedicated servers, and the laborious process of performing calibrations required by fingerprinting schemes deter the implementation of location based applications [5], [6], [7], The reason behind this cost and complexity is achieving the best accuracy possible. But what determines “best accuracy” is the application for which the algorithm will be applied. Applications that require high accuracy and precision such as robots and drones would require complex algorithms and the cost factor involving such algorithms will not be significant for such cases. But applications such as navigating in an indoor mall, does not require very high accuracy. For instance, if a person is walking in a mall, and is looking for a specific store, accuracies of < 4 m is acceptable. Once the person is within the 4-m radius of the desired location, he/she can easily locate the location as it will be within sight. A standard algorithm for indoor positioning may not be an efficient algorithm as the accuracy requirement is dependent on the application. To determine the position of a person or a location in an indoor environment, a lightweight algorithm can be developed at the cost of positioning accuracy reduction. The goal is to reduce the complexity of the algorithm and use low cost resources for indoor positioning systems while maintaining an acceptable accuracy and precision.

The method introduced in this chapter is lightweight in terms of computational complexity, and low cost in terms of set up and resources. It does not require any surveying of the indoor environment while supporting an acceptable accuracy for positioning of locations in indoor environments. The proposed algorithm is ideal for applications where the hardware resources and processing power are limited such as cellphones and small intelligent machines.

3.2 Proposed Solution

The proposed solution was illustrated in the published manuscript as follows:

3.2.1 Concept

Fingerprinting algorithms require a database of unique signatures. These signatures are basically a set of RSS values from anchor nodes that are recorded. Since at every location the RSS values are unique, the combination of RSSs from different anchor nodes must also be unique at each location for a given time. In order to use this information, a range-free algorithm has to be developed.

At first, the input resources are identified; which in this case are the RSSs that can be received from the anchor nodes and the location of the anchor nodes. The output variable will be the unknown location of the mobile device.

In the proposed positioning method, the goal is to avoid both surveying and the use of an offline database. Performing a weighted average of the coordinates of the anchor nodes, with the weight being the RSS in mW, enables us to estimate the location of the unknown nodes in real time.

Since the weight of each anchor coordinate corresponds to the anchor's RSS, the most common issue that arises is that RSS in an indoor environment does not always correspond to the actual distance. This is mainly due to the effect of line-of-sight. This will introduce errors in estimating location positioning. Although this error may not be acceptable in applications that require positioning robots or drones where a high accuracy and precision is required, the accuracy will be acceptable for the applications mentioned previously.

Then again, RSS when measured beyond a certain distance away from the transmitter will have losses in power that will nullify the effect of line-of-sight. The example below will help clarify.

Example: Line-of-Sight(LOS) vs No Line-of-Sight(N-LOS).

The effect of LOS will certainly have an impact when compared to N-LOS. But how significant will the impact be?

Let us assume that a beacon placed at distance d = 0 m transmits a signal of 1 W. Also assume that all other losses are negligible. If a LOS exists, ideally the power of the received signal should obey the inverse square law as shown in the second column of Table 1.

Table 1: Received Power at Different Distances from Transmitter

	No Obstruction	Obstruction at 1m	Obstruction at 3m	Obstruction at 5m
Distance	Power(W)	Power(W)	Power(W)	Power(W)
0	N/A	N/A	N/A	N/A
1	1.000000	0.936904	1.000000	1.000000
2	0.250000	0.234226	0.250000	0.250000
3	0.111111	0.104100	0.234151	0.111111
4	0.062500	0.058557	0.058538	0.062500
5	0.040000	0.037476	0.026017	0.046651
6	0.027778	0.026025	0.014634	0.011663
7	0.020408	0.019120	0.009366	0.005183
8	0.015625	0.014639	0.006504	0.002916
9	0.012346	0.011567	0.004779	0.001866

Now let us assume that there is an obstruction such as a wall at distance d = 1 m. Let us assume that the loss in power due to the wall is 12 dB. Then the received power at d = 1 will be 0.94 W, which is 94% of the transmitted value. The received power at farther distances will correspond to the inverse square law as shown in the third column of Table 1. Table 1 also shows the scenario of having the obstructions at different distances from the transmitter. Table 2 shows a comparison of overall loss in power between LOS and N-LOS at different distances from the transmitter.

Table 2: Total Percentage Loss at Different Distances

Distance	No Obstruction	Obstruction at 1m	Obstruction at 3m	Obstruction at 5m
	Loss %	Loss %	Loss %	Loss %
0	N/A	N/A	N/A	N/A
1	0.000	6.310	0.000	0.000
2	75.000	76.577	75.000	75.000
3	88.889	89.590	76.585	88.889
4	93.750	94.144	94.146	93.750
5	96.000	96.252	97.398	95.335
6	97.222	97.397	98.537	98.834
7	97.959	98.088	99.063	99.482
8	98.438	98.536	99.350	99.708
9	98.765	98.843	99.522	99.813

It can be seen that when RSS is measured at distances beyond 3 m, the loss in signal strength is >93%, regardless of the existence of LOS or not.

3.2.2 The Algorithm

Proposed algorithm consists of two phases.

3.2.2.1 Mapping Phase:

This is a crucial phase because the reliability and accuracy of the algorithm relies heavily on how the anchor nodes are set up. The anchor nodes must be set up according to the following scheme:

The anchor nodes must be set up in such a way that they form the outer boundary of the region. For example, in an area of 900 m^2it is required to place the anchor nodes in a circular pattern from the center of the region, see Fig. 1.

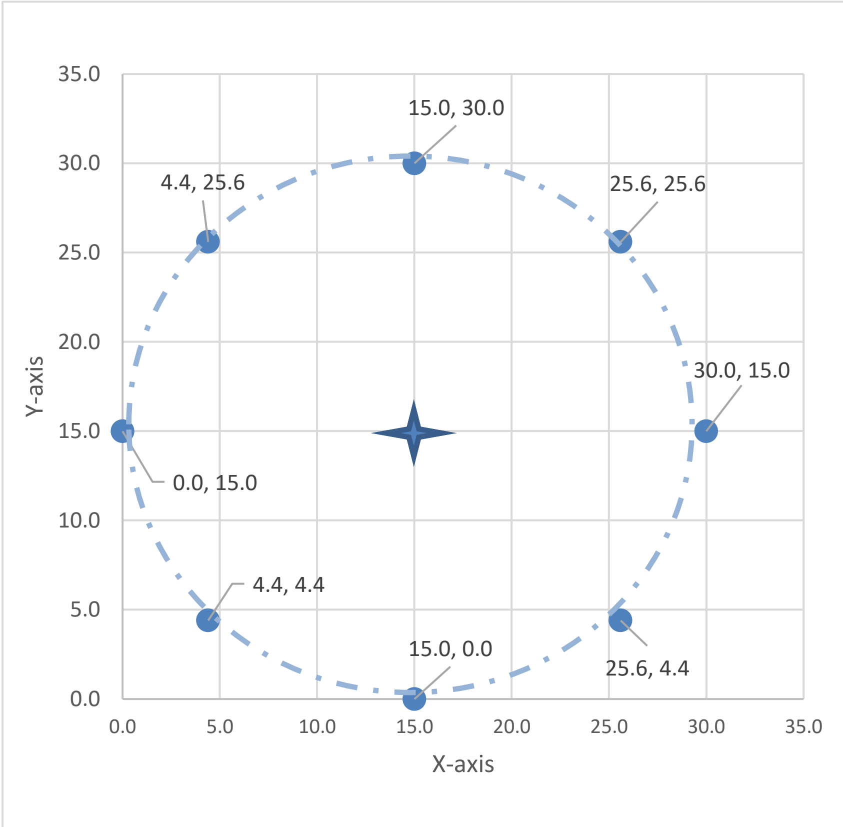


Figure -1 Placement of anchor nodes for an area of 700 m^2.

The radius or distance of the anchor nodes from the center will depend on the range of the beacons. For most BLE beacons, a 15-m radius would be suitable.

The node placement also has to be symmetrical with respect to the center of the region for the most accurate result.

If the range of the beacons do not cover the desired area, additional anchor nodes should be placed forming an inner or outer circular area from the same center point as shown in Fig. 2. This sub region would also need to be symmetrical for better performance.

3.2.2.2 Computation Phase:

This phase is carried out after the mapping phase is complete. The following parameters are defined for computational purposes.

X_{est} : Estimated x-coordinate;

Y_{est} : Estimated y-coordinate;

X_i : Estimated x-coordinate for each instant;

Y_i : Estimated x-coordinate for each instant;

W_j : Weight for a given anchor node;

P_j : Received power from anchor node (in mW);

x_j : X-coordinate for each anchor node;

y_j : Y-coordinate for each anchor node;

$\bar{x}_j$: Translated x-coordinate for each anchor node (translated by shifting the center location to the origin);

$\bar{y}_j$: Translated y-coordinate for each anchor node (translated by shifting the center location to the origin);

N : Total number of anchor nodes;

K : Total number of measurements;

Computations are performed in the following steps.

a. Shifting anchor node coordinates:

During computations, the coordinates of the anchor nodes must be shifted by moving the center of the region to the origin as shown in Fig. 3. The anchor coordinates are calculated by shifting all the coordinates by an offset of the coordinates of the center of the region, which is also the mean of the anchor node coordinates as shown below.

$$(\bar{x}_j, \bar{y}_j) = \left((x_j - [\sum_{j=1}^{N} x_j]/N) \ , (y_j - [\sum_{j=1}^{N} y_j]/N) \right) \qquad (1)$$

b. Calculating the Weight:

Weight of each anchor node is calculated by normalizing the power of the received signal with respect to the total power of the received signal from all anchor nodes; as shown in (2).

$$W_j = \frac{P_j}{\sum_{j=1}^{N} P_j} \tag{2}$$

c. Estimating location at every instant:

Using (1) and (2), location for the mobile node is calculated using the formula shown in (3).

$$(X_i, Y_i) = (\{W_1\bar{x}_1 + \cdots + W_N\bar{x}_N\}, \{W_1\bar{y}_1 + \cdots + W_N\bar{y}_N\}) \tag{3}$$

Estimating final location: The estimated location is calculated by taking the mean of K number of samples, and then translating it by the offset value, as shown in (4).

$$(X_{est}, Y_{est}) = (\frac{\sum_{i=1}^{K} X_i}{K} + \{[\sum_{j=1}^{N} x_j]/N\}, \frac{\sum_{i=1}^{K} Y_i}{K} + \{[\sum_{j=1}^{N} y_j]/N\}) \tag{4}$$

3.2.3 Algorithm Explained

Weighted average is often performed to estimate an expected output in cases where the "weight" of the input variables has significance. The proposed algorithm applies the concept of weighted average, where the coordinates of the anchor nodes are assigned weights which are determined by the RSS of each respective anchor node. The signal strength becomes weaker as the distance between the transmitter and the receiver increases. For this reason, the anchor nodes were assigned weights based on the RSS from the respective nodes. Stronger RSS from an anchor node will mean that the unknown mobile node is closer to that node relative to other anchor nodes.

Indoor environments have many factors that reduce the strength of RSS in addition to wave propagation loss. For this reason, RSS does not provide an accurate estimation of distance. In the proposed algorithm, weight of the anchor node is a normalized value with respect to the sum of RSSs from all available anchor nodes. This process simplifies the computations by considering sources of errors as a common factor and reducing their overall effect. This is because factors affecting wave propagation such as multipath and reflection affect all transmitters present in the environment.

A significant source of error is the effect of no-line-of-sight. As mentioned previously, the proposed algorithm reduces the effect of obstructions such as walls significantly. In order to verify the robustness of the algorithm, two cases have been studied. In Case-1, it is assumed that there is line of sight between the anchors and the mobile node. In Case-2 barriers are added to block the line of sight.

1) Case-1 (Without Obstruction): This case will show the functionality of the proposed algorithm theoretically. For the purpose of simplicity, the following assumptions were made.

- The indoor environment was set up according to Figure-1(a).
- Line-of-sight exists.
- All forms of indoor wave propagation losses are negligible except for the inverse square law relating signal strength to distance travelled.
- All transmitters transmit with the same transmitting power (1 W).

According to the first step of the computation, all the anchor node coordinates are shifted by a negative offset by the mean value of the coordinates. This will shift the whole region on both the positive and negative axes (see Fig. 2). Given the symmetry of the setup, the shifting creates both positive and negative anchor coordinates. This enables the utilization of direction in the computation.

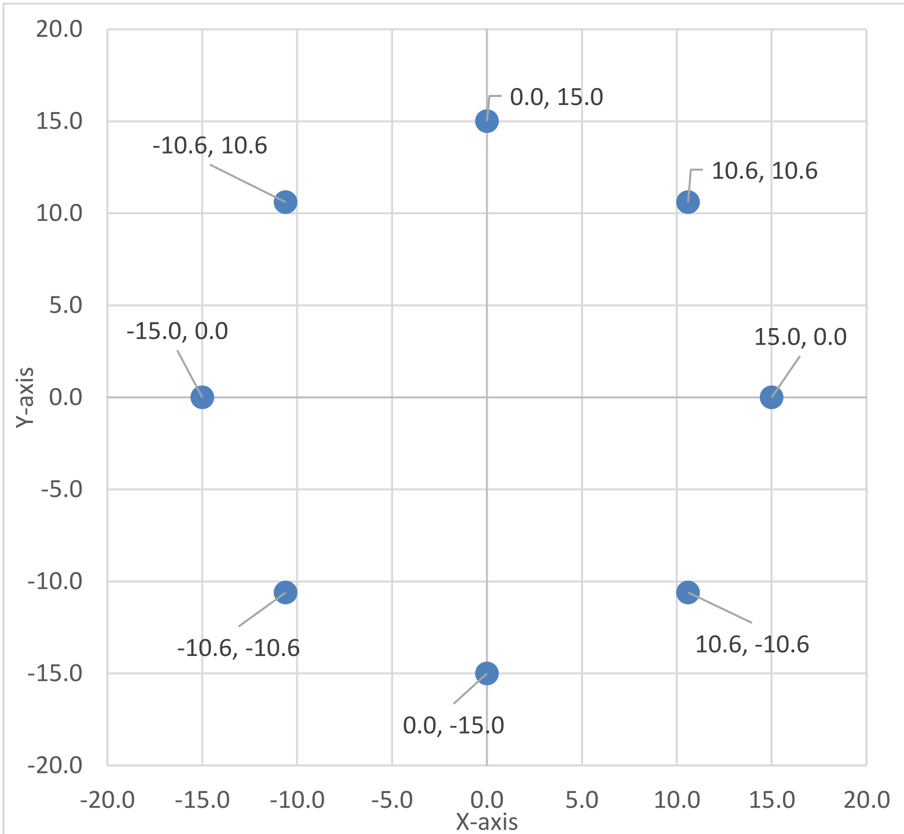


Figure -2 Shifted beacon coordinates.

For case-1, assuming all conditions are ideal, and the reading is taken at the center, the algorithm will provide the exact location because the center point is at equal distance from each beacon.

2) Case-2 (With Obstruction): Under the same condition as case-1, a theoretical analysis will be carried out for the following scenario:

- Effect of beacons with no line-of-sight:

Case-1 established that in an ideal case, if the measurement was taken at the center, the location computed by the algorithm will be the same. The computations are carried out again, with the assumption that beacons do not have line-of-sight in single as well as multiple cases due to the presence of a wall. It is also assumed that there is a 12 dB drop in power due to wall absorption. Table 3 shows the variation of error due to the effect of no line-of-sight. It can be seen that the maximum error distance is <0.08 m in an ideal case, thus showing that the effect due to the presence of walls does not produce a significant error.

Table 3: Effect on Accuracy Due to N-LOS

Number of beacons without line-of-sight	Error		
	Actual coordinates	Computed coordinates	Error Distance (m)
0	(15,15)	(15,15)	0.0000
1	(15,15)	(15.02,14.98)	0.0282
2	(15,15)	(15.05,15.02)	0.0521
3	(15,15)	(15.07,15)	0.0682
4	(15,15)	(15.07,14.97)	0.0740
5	(15,15)	(15.05,14.95)	0.0685
6	(15,15)	(15.02,14.95)	0.0525
7	(15,15)	(15,14.97)	0.0285
8	(15,15)	(15,15)	0.0000

Weighted average on principle is a measure of estimation. This means that in real life scenarios, it is almost impossible to achieve a 100% accuracy. The accuracy of the locations that are further away from the center of the region will be lower than the locations that are closer to the center region. Figure 3 shows how the range or errors vary depending on how far the location is from the center region.

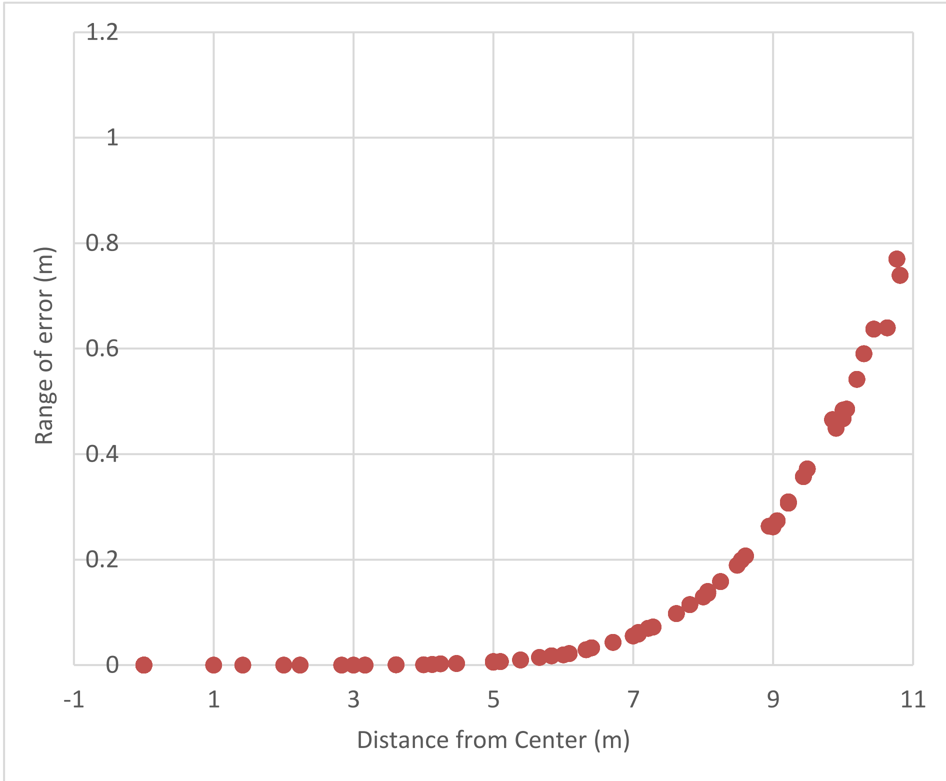


Figure -3 Relation between Error and Distance from the center.

This data was obtained by calculating location estimations at every possible location with integer coordinates within the sample region. The histogram shown in Fig. 4 details the range of accuracies that were obtained.

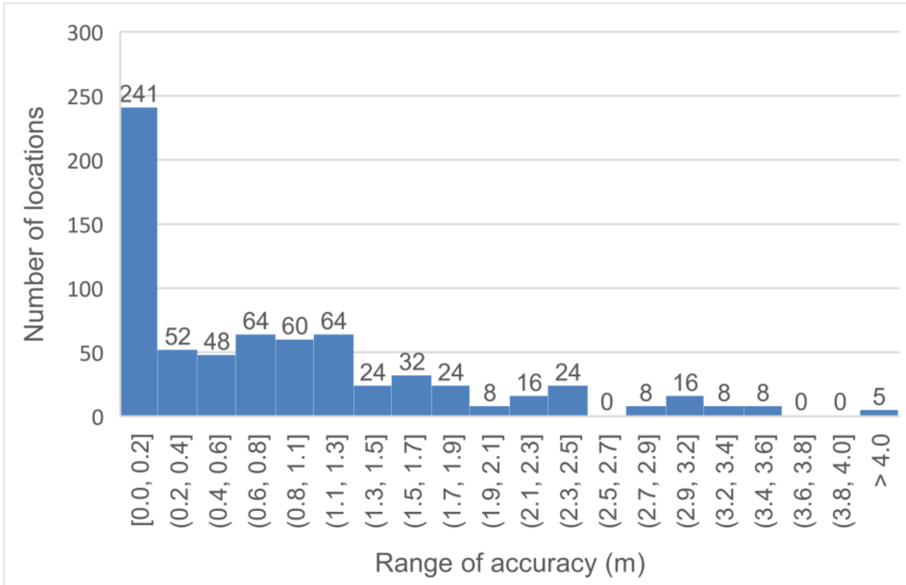


Figure -4 Range of Accuracy at Different Locations.

It can be seen that the majority of the locations have good accuracies. Fig. 5 shows the variation of error at a few other locations and compares them with that of the variation at the center coordinate.

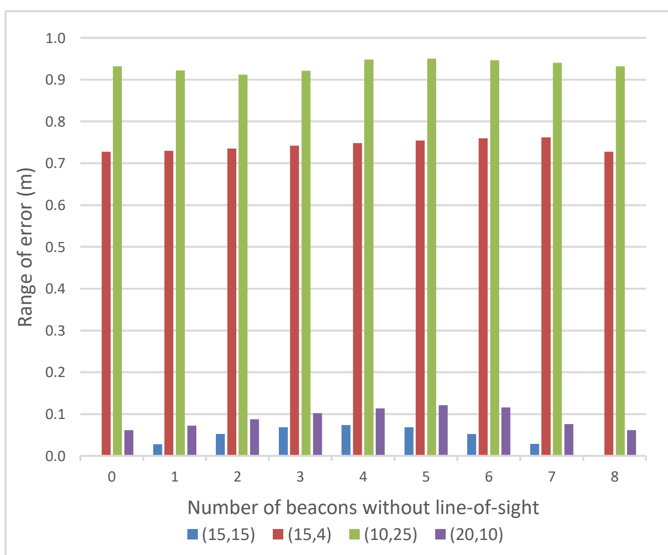


Figure -5 Variation of Error Due to Effect of No Line-of-Sight

The location (15, 15) was the coordinate of the center location. Locations with coordinates (15, 4), (10, 25), and (20, 10) are all away from the center. It can be observed that every location is within its own accuracy range depending on how far the location is from the center location. However, the variation of error due to lack of line-of-sight access is small.

3.3 Experimental Results.

The experimental results were reported in the manuscript as follows:

Several experiments were carried out in different sections of the "Centre for Engineering Innovation" building shown in Fig. 6.

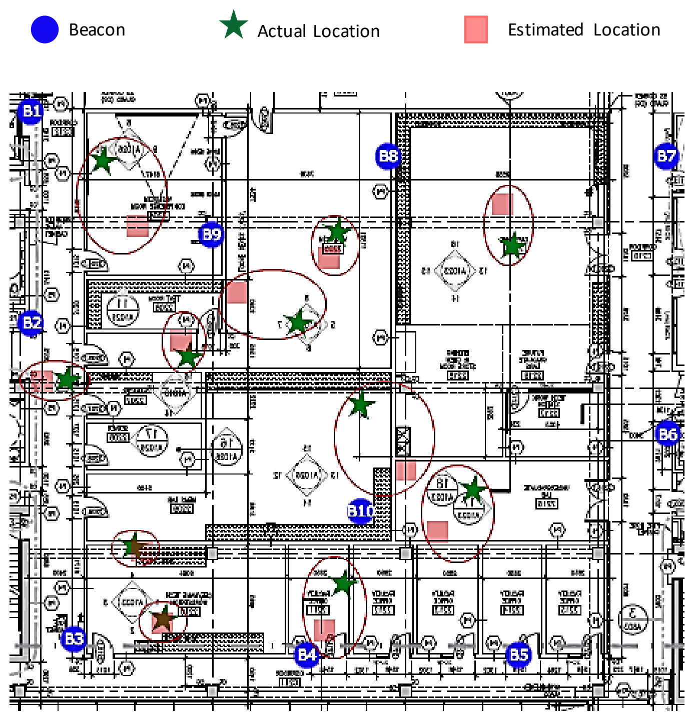


Figure -6 Experiment Results in a 1600 m^2 area

BLE beacons were used as anchor nodes and Android smart phones were used as receivers. All location computations were performed in JavaScript, and the results were organized using Microsoft Excel. Fig. 6 shows the overview of the experiment results. Thirty samples were recorded at each of the eleven test locations. The experiment results obtained an average accuracy of <2.1 m with a median of <1.9 m with a highest error distance of 4.3 m, and lowest error distance of 0.2 m. In this experiment, the beacons were positioned symmetrically on one section and asymmetrically on another section. The estimations in the symmetric region had higher accuracies than that of the other region. Table 4 compares the performance of the proposed scheme with existing schemes [15].

Table 4: Accuracy Comparison

System / Solution	Wireless technologies	Positioning Algorithm	Accuracy (m)	Precision
Horus [1]	WLAN, RSS	kNN, Viterbi-like algorithm	2	90% within 2.1m
BLE fingerprinting [10]	BLE, RSS	Bayesian Approach	2.6	95% within 2.6m
Proposed Algorithm	BLE, RSS	Weighted Average	2.1	81% within <3m (out of 30 samples)

In fingerprinting based algorithms, a radio map is required where locations are estimated by comparing live data with the radio map. The process to perform such tasks includes many iterations that require a high computational processing. The proposed algorithm does not require a radio map. It utilizes only two input parameters (RSS and location of anchor nodes), and computes live data to provide an estimated location. Eliminating the use of a radio map lowers the computational load significantly.

3.4 Conclusion

This work presents a positioning algorithm that is feasible and lightweight for implementation on portable devices, which does not require external servers. There are various indoor positioning techniques with good performance for indoor location-based applications, however either the cost of implementing or the required processing power limits their applications and make them less feasible for implementation. A range-free algorithm using weighted averages of received signals from anchor nodes is proposed in this work. It supports an acceptable performance in terms of accuracy and it does not require radio mapping of the area of interest. Experimental measurements indicate positioning accuracies of less than 2.6m can be achieved using low-cost portable devices.

3.5 References

[1] M. Youssef and A. Agrawala, "The horus wlan location determination system," *International Conference on Mobile systems, applications, and services (MobiSys '05)*, Seattle, WA, USA, 2005, pp. 205-218.

[2] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka, "You are facing the mona lisa: Spot localization using phy layer information," *International Conference on Mobile systems, applications, and services (MobiSys '12)*, Low Wood Bay, Lake District, United Kingdom, 2012, pp. 183-196.

[3] R. Nandakumar, K. K. Chintalapudi, and V. N. Padmanabhan, "Centaur: locating devices in an office environment," *Annual International Conference on Mobile Computing and Networking (MobiCom '12),* Istanbul, Turkey, 2012, pp. 281-292.

[4] M. Azizyan, I. Constandache, and R. Roy Choudhury, "Surroundsense: mobile phone localization via ambience fingerprinting," *Annual International Conference on Mobile Computing and Networking (MobiCom '09),* Beijing, China, 2009, pp. 261-272.

[5] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-effort crowdsourcing for indoor localization," *Annual International Conference on Mobile Computing and Networking (MobiCom '12),* Istanbul, Turkey, 2012, pp. 293-304.

[6] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: Wireless indoor localization with little human intervention," *Annual International Conference on Mobile Computing and Networking (MobiCom '12),* Istanbul, Turkey, 2012, pp. 269-280.

[7] H. Liu, Y. Gan, J. Yang, S. Sidhom, Y. Wang, Y. Chen, and F. Ye, "Push the limit of wifi based localization for smartphones," *Annual International Conference on Mobile Computing and Networking (MobiCom '12),* Istanbul, Turkey, 2012, pp. 305-316.

Chapter-4

A Light Weight Indoor Positioning Method using Bluetooth Low Energy Beacons

4.1 Introduction:

The positioning algorithm in this chapter involves identifying points of interests in the environment. The algorithm is designed for people navigation for large indoor environments. The output of the algorithm identifies the location based on the location of known sites such as washrooms, fire exits, etc.

4.2 Proposed algorithm

4.2.1 Concept

Navigation is a two-step process of (a) locating a POI on the map; and (b) identifying the POI in the physical surrounding. The idea is to incorporate a similar two-step verification process in an algorithm. The algorithm would generate many location coordinates using a small sample of input data. These coordinates are then iteratively converged to a small unit area and then compared to a database of POIs obtained from the physical environment.

The goal for this algorithm is to identify POIs accurately in an indoor environment. To carry this out, it is required to create a library of POIs which consists of a set of x and y coordinates assigned to POIs; and a range of x and y coordinates assigned to each zone. This library is created only once and does not require any updating.

4.2.2 Proposed solution:

There are two phases.

1) Mapping Phase:

This phase is an offline phase and consists of two tasks.

a) Beacon Positioning:

Beacon placements are carried out according to the following conditions.

- The indoor environment must be enclosed forming a mesh of BLE beacons.

- The distance between consecutives beacons will depend on the range of BLE beacons used. For example, if a beacon advertising range is 30 meters, it would be ideal to place beacons within 30 meters of each other which will ensure adequate coverage range. Additional beacons may also be required depending on the layout of the indoor environment. Fig-7 illustrates an example for setting up beacons for a section of an indoor environment.
- Each beacon will be assigned coordinates (x and y) relative to their actual location in the indoor environment.

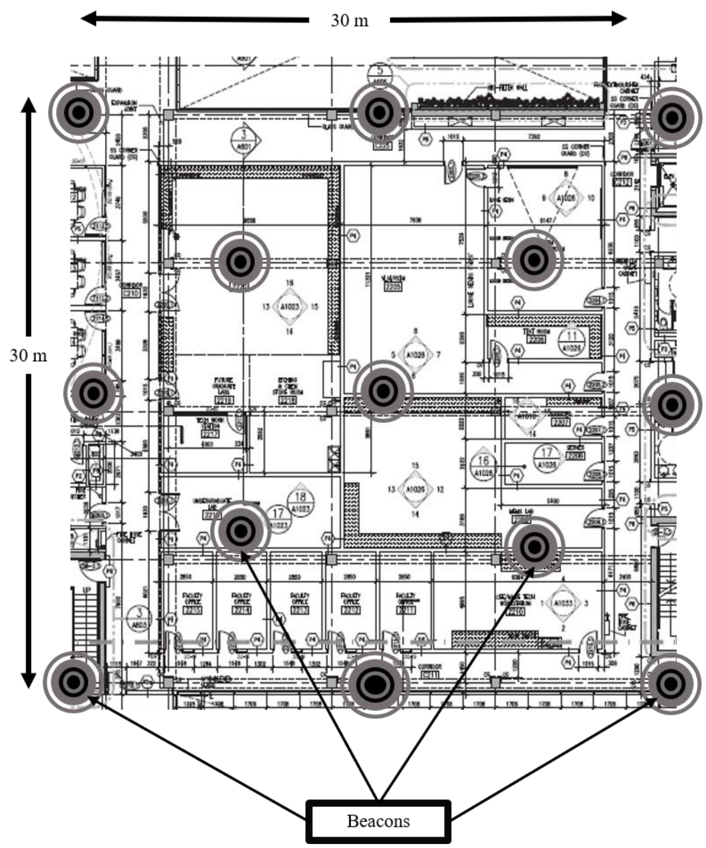


Figure -7 Set-up

b) Creating a library of Points of Interest (POIs):

POIs are described as locations in the indoor environment that are known (such as stores in a mall, washrooms, emergency exits, etc.). Each POI will consist of a set of zones as shown in Fig. 8. A zone is defined as a virtual grid which divides the indoor environment into blocks of $2m^2$ as indicated in Fig. 8

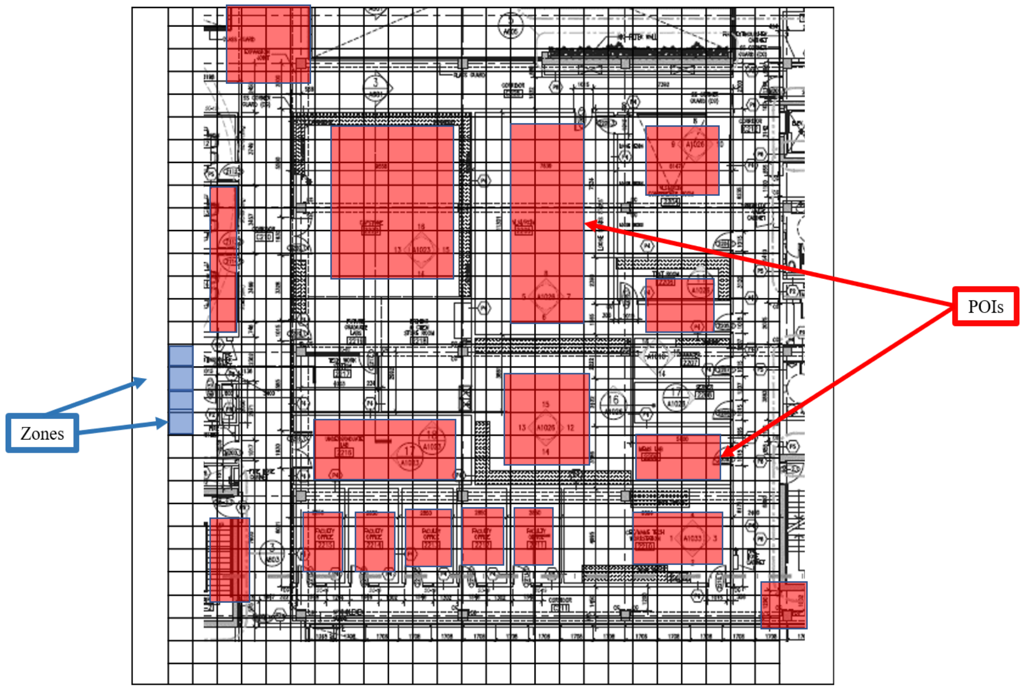


Figure 8: POI and Zone Assignment

Each zone consists of a set of x and y coordinates. Each POI is assigned an x and y coordinate based on the POI's true location in the environment. The zones are assigned to the POIs based on a minimum distance from the POI coordinates to the zone coordinates. The minimum distance is set based on the average error-distance produced from computations. For example, if the average error distance is < 2 m, each POI in the database would be assigned zones with the coordinates that are within 2m radius of the respective POIs.

2) Computation phase:

This phase performs three tasks.

a) Scanning:

First, perform a scan and record the RSS of every beacon that is in the required range. The scan duration will be set based on the user requirements.

b) Computations:

Table-5 provides a list of parameters defined for computational purposes.

Table 5: Computation Parameters

VARIABLE	DESCRIPTION
N	Number of beacons
W_i	Weight
$P_{received\_i}$	Received Power from beacon
X_b	Beacon X-coordinate
Y_b	Beacon X-coordinate
K	Number of generated coordinates
X_K	Beacon X-coordinate
Y_K	Beacon X-coordinate
P_{dBm_max}	RSS in dBm at 0m from beacon
P_{dBm_min}	Minimum RSS allowed for computation.
P_{dBm_i}	Measured RSS for computation
X_{MAX}	Generated X-coordinate (Max)
X_{MIN}	Generated X-coordinate (Min)
Y_{MAX}	Generated Y-coordinate (Max)
Y_{MIN}	Generated Y-coordinate (Min)
X_{AVG}	Average of generated X-coordinates
Y_{AVG}	Average of generated Y-coordinates
X_{UL}	Upper Limit of X
X_{LL}	Lower Limit of X
Y_{UL}	Upper Limit of Y
Y_{LL}	Lower Limit of Y
X_{SD}	Standard Deviation of X
Y_{SD}	Standard Deviation of Y

Converting RSS: In the scanning phase, RSS from each beacon is measured in the dBm scale. The first step is to form a linear model of the RSS and this can be done by using linear interpolation as shown in (1).

$$P_{received\_i} = \frac{P_{dBm\_\max\_i} - P_{dBm\_i}}{P_{dBm\_\max\_i} - P_{dBm\_min}} \qquad (1)$$

In equation (1), $P_{dBm\_\max\_i}$ is the RSS value for each beacon recorded at 0.1m distance. P_{dBm_i} represents the measured RSS during scanning phase. P_{dBm_min} is a constant which represents the minimum acceptable RSS. This value is determined based on the transmission range of the beacons, and the beacon placement. For example, if the beacon has a transmission range of 15m, ideally P_{dBm_min} would be determined by measuring the RSS of the beacon from 15m. However, if the minimum distance between each beacon is less than 15m, P_{dBm_min} will be measured from that distance instead. P_{dBm_min} is used to calibrate the sensitivity of the algorithm based on the desired application. The above step reduces the signal noise of RSS significantly and can be considered as a calibration procedure.

Calculating the weight: Each beacon is assigned a weight based on the RSS measured from it. This weight represents a ratio of the signal strength measured from a single beacon with respect to the sum of all signal strengths from all beacons obtained during the scanning phase.

The RSS values were converted from dBm scale to a linear scale and a linear representation is used to calculate the weight, as shown in (2) for weight calculation.

$$W_i = \frac{P_{received\_i}}{\sum_1^N P_{received\_i}} \qquad (2)$$

Generating location coordinates: In this process, a set of x and y coordinates are generated using beacon coordinates and calculated weights. This is done iteratively in the following way:

Iteration-1: If N number of beacons are discovered in the scanning phase, and K number of samples are taken, we first compute the location coordinates for each sample using (3a) and (3b).

$$X_K = \sum_1^N W_i * X_{b\_i} \tag{3a}$$

$$Y_K = \sum_1^N W_i * Y_{b\_i} \tag{3b}$$

This provides K number of x and y coordinates.

Iteration-2: Secondary x and y coordinates are generated using combinations of (N-1) number of beacons. Weight of each beacon is updated based on the combination of beacons used as shown in (4).

$$W_{C_i} = \frac{P_{received_i}}{\sum_1^{(N-1)c} P_{received_i}} \quad ; C = 1, 2, 3, \dots \frac{N!}{(N-1)!} \tag{4}$$

Here, W_{C_i} is the weight of the beacon calculated by obtaining a ratio between $P_{received\_i}$ and the total received power for that combination. This will result in N*K sets of secondary x and y coordinates.

Final location: The generated coordinates are then iteratively processed by performing an optimized averaging scheme that has been modelled via experimentation. The scheme consists of a check process and an update process. The X and Y data points of the generated coordinates first go through the check process. In this process, the scheme checks whether the range of X and Y data points are less than the standard deviation of each data set as shown in Fig.9.

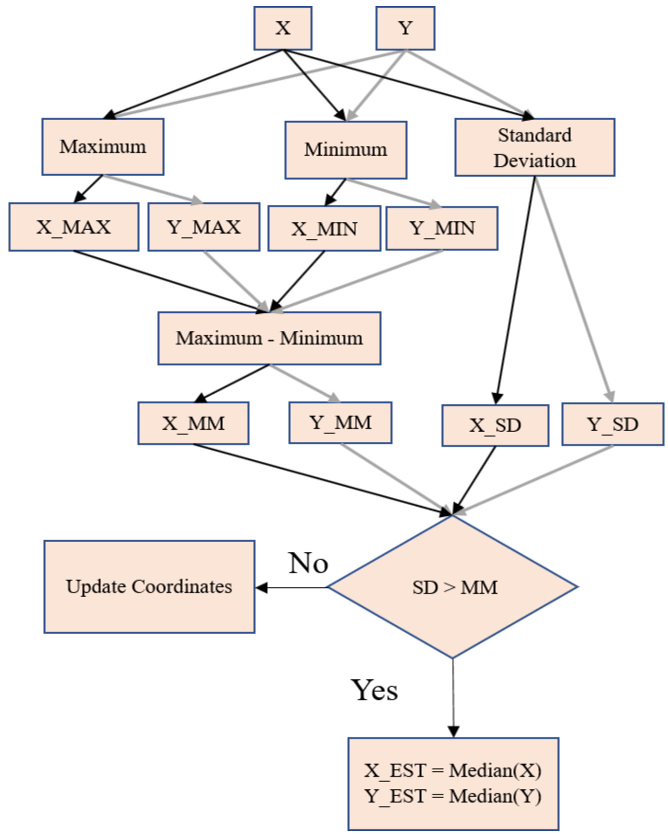


Figure 9: Check Process.

If the range of data points are less than the standard deviation of the data sets, the estimated X and Y coordinates are obtained by taking the median value of each data set. Otherwise, the generated coordinates are updated via the updating process as shown in Fig.10.

In this process, an upper limit and a lower limit of each data set is calculated using (5a), (5b), (5c), (5d) respectively. All the data points that are outside this upper and lower limit are updated as shown in Fig.10, while the data points within the upper and lower limit are kept the same. The updated data sets are then processed through the check process again. These processes are repeated iteratively until the condition in the check process is met.

$$X_{UL} = X_{AVG} - \frac{X_{AVG}+X_{MAX}}{i*X_{SD}} \; ; \; i = 1, 2, 3 \ldots \tag{5a}$$

$$Y_{UL} = Y_{AVG} - \frac{Y_{AVG}+Y_{MAX}}{i*Y_{SD}} \; ; \; i = 1, 2, 3 \ldots \tag{5b}$$

$$X_{LL} = X_{AVG} - \frac{X_{AVG}+X_{MIN}}{i*X_{SD}} \; ; \; i = 1, 2, 3 \ldots \tag{5c}$$

$$Y_{LL} = X_{AVG} - \frac{Y_{AVG}+Y_{MIN}}{i*Y_{SD}} \; ; \; i = 1, 2, 3 \ldots \tag{5d}$$

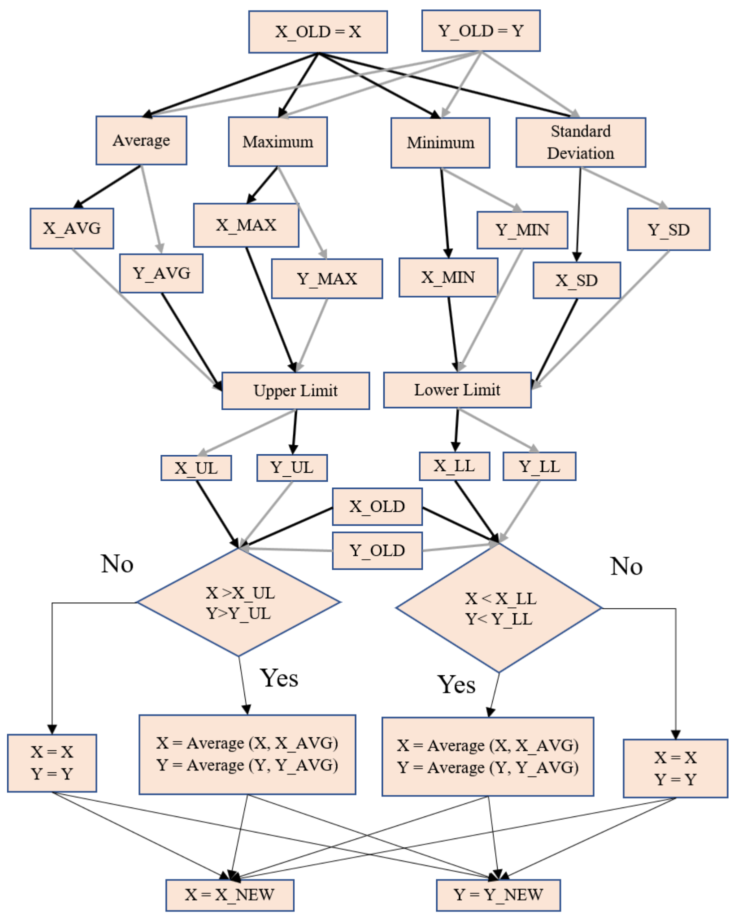


Figure 10. Update Process.

4.2.3 Algorithm Explained

In the proposed algorithm, the issues of accuracy and precision are addressed individually.

1. *Addressing Accuracy:*

Navigation requires the ability to detect POIs as well as the ability to estimate a relative position with respect to the POIs. Thus, implementing the ability to detect POIs for an algorithm would require a library of POIs as an input source. This library enables the algorithm to translate the estimated location to the nearest POI. Since POIs consist of a set of coordinates instead of just one, the algorithm will provide outputs with much higher accuracy given that the POI range is within the error-distance margin. The POI library provides a higher tolerance for error-distance.

2. *Addressing precision:*

Improving accuracy requires tackling the uncertainty of RSSI. The generated coordinates are obtained based on the RSSI of the beacons. Therefore, the generated coordinates are also expected to show fluctuations like that of RSSI fluctuations. The effect of RSSI fluctuations are usually reduced with the aid of some sort of reference data. The proposed solution applies an optimized averaging scheme that was designed based on experimental data. The optimizing scheme iteratively reduces the fluctuations of the output until the fluctuations fall below the standard deviation of each data set. At that point the algorithm stops, and the output is computed by taking a median of each data set.

4.3 Experimental Results:

The algorithm was tested experimentally. The experiment's results showed that the algorithm was able to identify known POIs, all the time, with a 2m error distance.

4.4 Conclusion:

A light weight off-line positioning algorithm is developed for people's indoor location detection and navigation without an external server or cloud connectivity. The proposed solution increases the user's privacy significantly as the location information is not revealed to any source other than the user. The positioning algorithm includes a two-step verification process. The first step is to estimate a set of x and y coordinates for a given location in the computation phase. The second step assigns the calculated coordinates to their respective zones which in turn is used to identify the points of interest. The presented algorithm identifies points of interests in an indoor environment and supports less than two-meter positioning accuracy. However, further tests are required to establish the consistency of the algorithm.

Chapter-5

Indoor Positioning via RSS Loss Analysis.

5.1 Introduction:

The world is entering an era where technology is being integrated to everyday tasks. A rapid growth in Internet of Things (IoTs) has resulted in smartphones becoming a necessary tool rather than essential. Smartphones enable users to interact with IoT smart devices. As the concept of Smart City emerges, smartphones will be required to process many tasks, of which location awareness will play a significant role. Positioning algorithms, particularly for indoor environments require heavy computational power. These computations are performed on server grade processors where local information is sent to the servers via network connection, and location information is sent back to the smartphone after being computed. This process makes indoor localization completely dependent on the availability of a network connection, which in turn hinders the growth of location-based applications (LBAs). This work introduces a novel method of RSS-based indoor positioning. A small sample of RSS is iteratively manipulated to address the problem of electromagnetic wave propagation loss in indoor environments. The loss characteristics are then used to compute an estimated location.

5.2 Proposed Algorithm

5.2.1 Concept

The algorithm is modelled using basic mathematic principles and electromagnetic wave properties and is verified with experiment results. The algorithm is based on three key principles.

1. The Inverse-Square law properties.
2. Effects of Weighted Averaging.
3. Mathematical properties of factors and multiples.

According to the inverse-square law, the strength of the received signal is inversely proportional to the square of the distance from the source. This property is not suitable for indoor environments because of line-of-sight errors, reflection, refraction and multipath fading, which cause fluctuations for RSS. The proposed algorithm is modelled based on the following assumptions:

Assumptions:

- Propagating electromagnetic waves incur loss in energy according to the inverse-square law.
- Electromagnetic waves in indoor environments incur energy loss from additional factors and the amount of loss between multiple transmitters varies. In other words, the loss for one transmitter will be different from other transmitters based on the indoor environment and the location of transmitters.
- Propagation loss due to distance travelled is the common factor for a set of RSSs recorded from multiple transmitters at any given time.
- Samples of RSS taken over time from a location exhibit a Gaussian model.

Based on these assumptions, the approach behind this algorithm was to estimate the location of a mobile device using the relative loss of signal strength from a set of RSS samples. The RSS samples are transmitted via Bluetooth Low Energy beacons with known locations, and the estimated position calculated, is relative to the beacons' actual positions.

5.2.2 Proposed Solution:

The proposed algorithm consists of two phases:

1) Mapping Phase:

This phase consists of setting up the BLE beacons in the indoor environment and recording their location by assigning an X and a Y coordinate for each beacon. The placements of beacons will vary based on the indoor environment. Therefore, beacon placement is carried out according to the following guidelines:

- The indoor area must be enclosed with beacons forming the outermost boundary first, and then forming a mesh inward to cover the area.

- Distance between beacons is determined by the transmitting range of the beacons and the indoor infrastructure. If the beacons have a 15m range, then beacons can be placed 15 meters apart from other beacons.

2) Computation Phase:

The live phase is carried out in two modes:

a) Scanning mode

In the scanning mode, a BLE scan is performed and data from nearby beacons are recorded. Multiple samples are recorded from each beacon during the scanning mode. The number of samples collected is determined by the number of beacons in range. If the number of in-range beacons is six, then six sets of RSS samples will be recorded. Table -6 illustrates the Input variables from scanning phase.

Table 6: Input Variables

	Beacon 1	**Beacon 2**	**Beacon 3**	**…**	**Beacon N**
Coordinate X	X_{B1}	X_{B2}	X_{B3}	…	X_{BN}
Coordinate Y	Y_{B1}	Y_{B2}	Y_{B3}	…	Y_{BN}
Sample Set-1	RSS_{11}	RSS_{21}	RSS_{31}	…	RSS_{N1}
Sample Set-2	RSS_{12}	RSS_{22}	RSS_{32}	…	RSS_{N2}
Sample Set-3	RSS_{13}	RSS_{23}	RSS_{33}	…	RSS_{N3}
….	…	…	…	…	…
Sample Set-S	RSS_{1S}	RSS_{2S}	RSS_{3S}	…	RSS_{NS}

b) Computing mode:

The computations are carried out iteratively. Table-7 contains the list of variables defined for the computation process.

Table 7: List of Variables

Variable	Definition
X_{BN}	X-coordinates of beacons
Y_{BN}	Y-coordinates of beacons
RSS_N	Received signal strength of beacon
RSS_{NS}	Received signal strength of beacon from a sample set
X_F	Initial X-vector quantity of beacon
Y_F	Initial Y-vector quantity of beacon
RSS_{SUM_S}	Sum of all RSS of a sample set
X_{REF}	X-coordinate of a reference point
Y_{REF}	Y-coordinate of a reference point
W_N	Computed weight of beacon
W_{NS}	Computed weight of beacon for a sample set
X_{WF}	Weighted X component of a beacon
Y_{WF}	Weighted Y component of a beacon
X_{UF}	Updated X-vector quantity
Y_{UF}	Updated Y-vector quantity
X_{SK}	Generated X-coordinate of a sample set
Y_{SK}	Generate Y coordinate of a sample set
X_{Fnew}	Starting X-vector quantity for next iteration
Y_{Fnew}	Starting Y-vector quantity for next iteration
XR_{SK}	Scaling ratio of X between iterative terms for a sample set
YR_{SK}	Scaling ratio of Y between iterative terms for a sample set
XR_{avgS}	Averaged scaling ratio of X for a sample set
YR_{avgS}	Averaged scaling ratio of Y for a sample set
X_{AvgL}	Averaged X-coordinate of all sample sets
Y_{AvgL}	Averaged Y-coordinate of all sample sets

The computation mode is carried out in the following steps.

Step-1: Compute arbitrary reference coordinates which are the average, minimum and the maximum values of the beacon coordinates that were recorded during the scanning phase as shown in Table-8. These coordinates will be used as the starting point for computations.

Table 8: Reference Coordinates

Coordinate	Average	Minimum	Maximum
X	X_{AVG} $(\frac{\sum_1^N X_{Bn}}{N})$	X_{MIN} $(MIN[X_{BN}])$	X_{MAX} $(MAX[X_{BN}])$
Y	Y_{AVG} $(\frac{\sum_1^N X_{Bn}}{N})$	Y_{MIN} $(MIN[X_{BN}])$	Y_{MAX} $(MAX[X_{BN}])$

Each beacon is assigned an X and Y value that is determined by the distances between a reference point and the respective beacon - the reference point being the values computed in the previous step. These X and Y values will be known as vector components of the beacons. In other words, the X and Y vector quantities of each beacon, is a representation of the distance to a reference coordinate with respect to all the scanned beacon coordinates. This method forms an un-weighted measure of the beacon location relative to other beacon positions.

Step-2: Computing vector quantities of the beacons from a reference point is done according to (1a) and (1b). These vector quantities represent the un-weighted magnitudes of each beacon in the X and Y direction. Therefore, the average of these magnitudes is the same as the magnitude of the reference point itself.

$$X_F = (X_N - X_{REF})^2 \qquad (1a)$$

$$Y_F = (Y_N - Y_{REF})^2 \qquad (1b)$$

Step-3: Similarly, the vector quantities of the distance between the minimum coordinate values as well as the maximum coordinate values are computed.

Step-4: Computing the weight.

Each beacon is assigned a weight based on the relative loss of signal strength of the received signal. This is done by first forming a sample set of RSSs for each beacon. This set will be composed by taking an average of a few samples for each beacon from the scanned data. A minimum N number of sample sets is considered for computations. The relationship between the RSS of each beacon of a sample set is then used to form a weight model. Note that all RSS must first be converted to milliwatt scale from dB scale after the sample sets are computed. For each sample set, a sum of the RSSs is computed and illustrated in Table-9.

Table 9: Sum of a Sample Set

	RSS_SUM	
Sample-1	RSS_{SUM_1}	
Sample-2	RSS_{SUM_2}	
Sample-3	RSS_{SUM_3}	
….	…	
Sample-S	RSS_{SUM_S}	

A primary weight is then calculated for each beacon using (2).

$$W_N = \frac{RSS_N}{RSS_{SUM\_S}} \qquad (2)$$

This weight gives a relative measure of the strength of RSS for each beacon with respect to the RSSs of all the beacons in the sample set. Since W_N is a measure of relative signal strength, $(1 - W_N)$ would be the measure of relative loss in signal strength for that sample set.

Step-5: Generate X and Y coordinates:

Starting from the first sample set, weighted X and Y components of the beacon vector quantities are computed using (3a) and (3b).

$$X_{WF} = X_{FN} * (1 - W_N) \qquad (3a)$$

$$Y_{WF} = Y_{FN} * (1 - W_N) \qquad (3b)$$

The beacon vector quantities for each beacon are then updated using the weighted components and beacon coordinates according to (4a) and (4b).

$$X_{UF} = \left(\sqrt{X_{WF}} - X_N\right)^2 \qquad (4a)$$

$$Y_{UF} = \left(\sqrt{Y_{WF}} - Y_N\right)^2 \qquad (4b)$$

New reference points are then computed using (5a) and (5b). This reference point is also the first generated coordinate of the estimated location due to the weight relation of the sample set.

$$X_{SK} = \sqrt{\frac{\sum_1^N X_{UF_n}}{N}} \qquad (5a)$$

$$Y_{SK} = \sqrt{\frac{\sum_1^N Y_{UF_n}}{N}} \qquad (5b)$$

Step -6 Repeat step 5 using computed weights for different sample sets. This will obtain sets of X and Y coordinates that are generated from all samples.

Step-7: Repeat the process using the new reference for K iterations for other sample sets as illustrated in Table-10.

Table 10: Generated coordinates from all iterations of all sample set

Sample Set (S)	**Iteration(K)**	**Generated X**	**Generated Y**
1	**1**	X_{11}	Y_{11}
1	**2**	X_{12}	Y_{12}
1	**…**	…	…
1	**K**	X_{1K}	Y_{1K}
2	**1**	X_{21}	Y_{21}
2	**2**	X_{22}	Y_{22}
2	**…**	…	…
2	**K**	X_{2K}	Y_{2K}
…	**…**	…	…
S	**1**	X_{S1}	Y_{S1}
S	**2**	X_{S2}	Y_{S2}
S	**…**	…	…
S	**K**	X_{SK}	Y_{SK}

Manipulating coordinates:

The obtained coordinates are then iteratively manipulated according to the flow chart in Fig-11. The manipulation is performed based on the assumptions made previously.

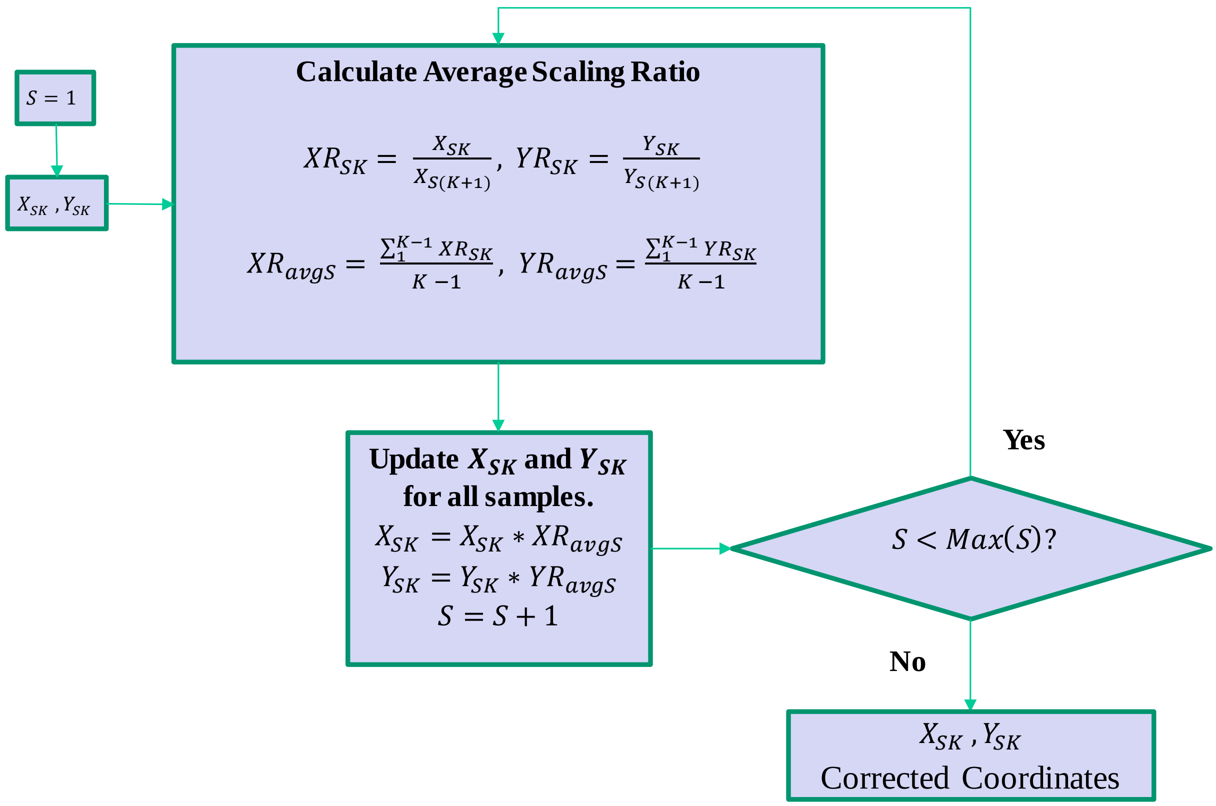


Figure 11. Coordinate Manipulation.

The new set of X and Y coordinates are further manipulated to form a set which is the resultant set from all sample sets for each iteration. This set of coordinates can be used to form a sequence of coordinates iteratively by taking the average of the coordinates of consecutive iterations. If the iterations are extended by averaging the output of the last term with the first term, the output results in a series of coordinates which tends to be bounded by a minimum and a maximum value with increasing iterations. The estimated location lies within this boundary. The values in the final set are computed as shown in Table-11.

Table 11: Computing Final set from all sample sets

Iteration (L)	**Final Set X**	**Final Set Y**
1	$X_{Avg1} = Average(X_{11}, X_{21}, .., X_{2S})$	$Y_{Avg1} = Average(Y_{11}, Y_{21}, .., Y_{2S})$
2	$X_{Avg2} = Average(X_{Avg1}, X_{31}, .., X_{3S})$	$Y_{Avg2} = Average(Y_{Avg1}, Y_{31}, .., Y_{3S})$
…	…	…
L	$X_{AvgL} = Average(X_{Avg(L-1)}, X_{(L-L+1)})$	$Y_{AvgL} = Average(Y_{Avg1}, Y_{(L-L+1)})$

Similar sets of coordinates are computed using other the initial reference points shown in previously (Table -I).

Final output:

The three series of coordinates are then used to form a window bound by two sets of coordinates. The estimated location lies with the maximum and minimum values of the series. The window limits consist of the mid series values and an average of the minimum and maximum series values.

5.2.3 Algorithm Explained

This algorithm estimates the location by generating coordinates that approaches the desired location starting from an arbitrary reference coordinate. The idea is to compute the location by generating a set of coordinates that move away from the reference point. The reference points are not chosen at random but are calculated after the scanning phase. In other words, the algorithm is designed to generate coordinates that moves away from its starting reference points. The average of these coordinates can be used to form a cumulative averaging sequence which the result of which converges to the estimated location. This is achieved by iteratively obtaining location coordinates determined by the relative position of the beacons and their respective RSSs from a set of small samples.

The algorithm is explained with numeric values obtained using few of the sample sets from experiments. Table-12 contains the input data from scanning phase.

Table 12: Sample Data

	Beacon 1	Beacon 2	Beacon 3	Beacon 4
Coordinate X (m)	0.2	30.2	0.1	30.2
Coordinate Y (m)	9.8	9.8	0.1	0.7
Sample Set-1(dB)	-90	-74	-93	-88
Sample Set-2(dB)	-90	-77	-94	-88
Sample Set-3(dB)	-90	-73	-94	-91
Sample Set-4(dB)	-96	-76	-93	-87

Explanation for Step-1:

The algorithm requires input from multiple beacons. The location information for each beacon is determined by an X and a Y coordinate. X and Y coordinates of each beacon carries individual weights due to their numeric value. For instance, coordinates with larger values will have more weight and this will hinder the performance of the algorithm. For this reason, the location information for each beacon are calculated with respect to a reference point, which is un-weighted.

Explanation for Step-2:

According to the distance formula, the square of a distance between two points is equal to the sum of the square of the difference between the X coordinates and the Y coordinates of the two points. These values can also be called the vectors of the distances from the reference point. There are two advantages of computing with vectors.

- The location value of each beacon is now subject to an initial reference point which is common for all beacons. In other words, the location information for all beacons are relative to a reference point.

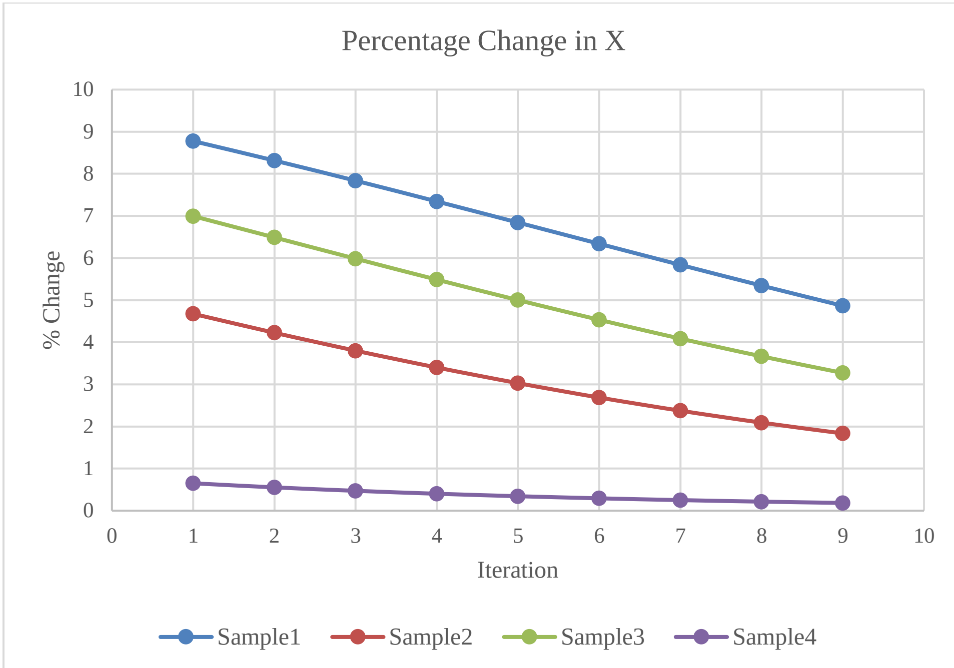
- Square of the difference of two values in mathematics can also be defined as the multiple of its individual factors. This means that the vector components can be scaled to any value but will always be a multiple of its original vector quantity. Therefore, the estimated location vectors can be determined by taking an average of the new vector quantities obtained from the weighted scaled vectors.

Explanation for Step-4:

Weight for each beacon is determined based on the RSS obtained from each beacon from a sample set with respect to the summation of all the RSS from the same sample set. This provides a relative measure of the RSS of each beacon with respect to all the beacons for a given sample. This also enables the formulation of a weight model, based on loss in signal strength. The RSS obtained at a location is a depleted value of the RSS at the source. If the RSS of every beacon consisted of the same transmitting energy, a measure of the relative loss in signal strength can be determined by subtracting each weighted ratio from the sum for each sample. This provides a weighted relation of RSS based on signal strength loss. In other words, the weight of each beacon is a measure of the loss in signal strength relative to a given sample set.

Explanation for Step-5:

This process iteratively generates a set of X and Y coordinates based on the relative RSS loss from a sample set. During each iteration, the vector quantities of every beacon are recalculated by reducing a weighted portion from every beacon's vector quantity. An average of the said vector quantities is used to generate an X and a Y coordinate. In practice, each iteration generates coordinates of a location that is away from the arbitrary reference location. Increasing the number of iterations, generates coordinates, that are further away from the reference coordinate but, the percentage change of the coordinates between each iteration, reduces as shown in Fig-12.



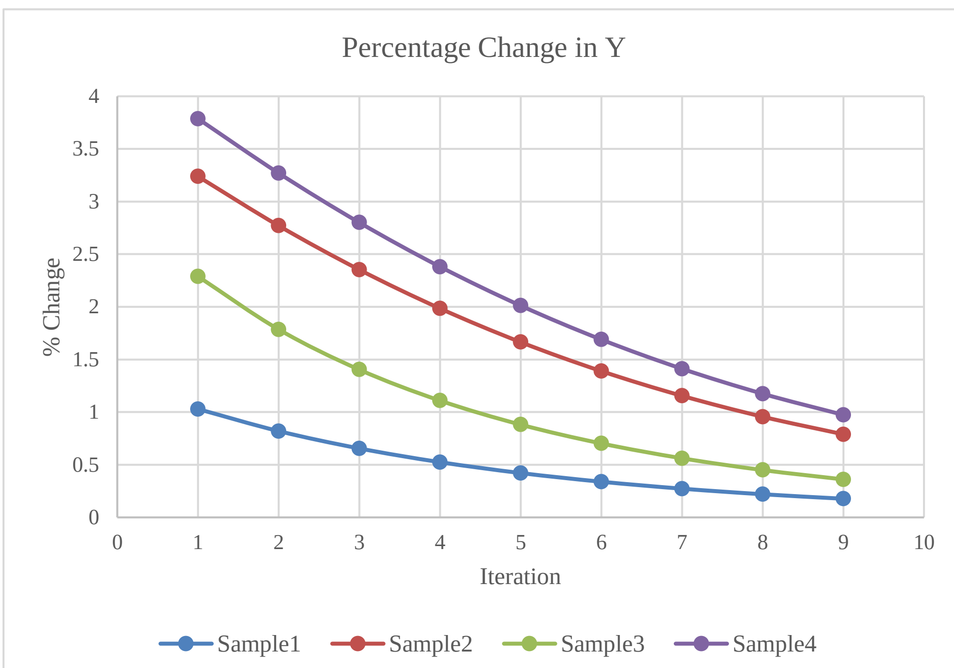
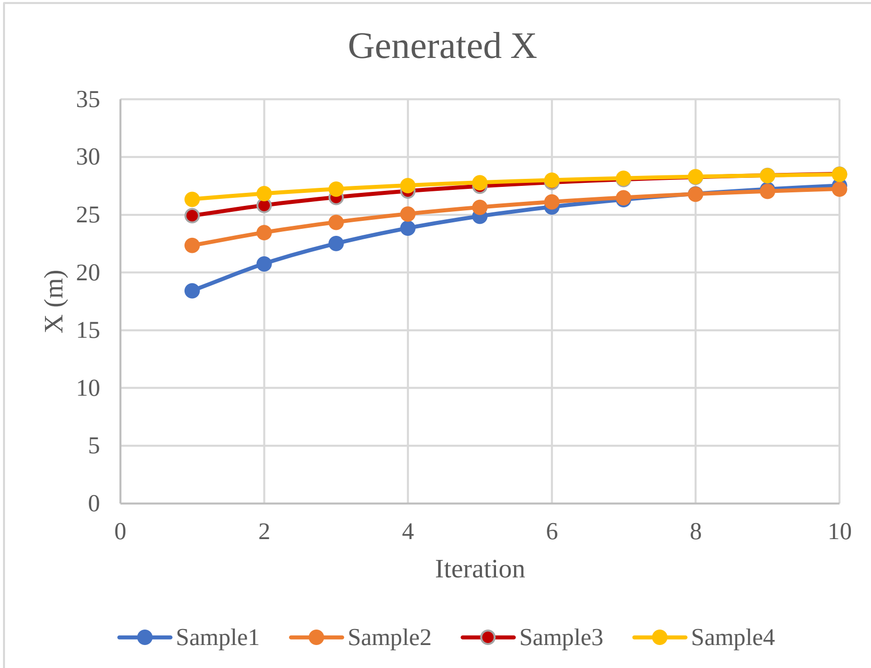


Figure. 12: Percentage change of generated coordinates.

The generated coordinates obtained from each iteration can also considered as a set of weighted moving averages. This is because each generated coordinate is obtained using the coordinates generated in the previous iteration. Thus, it can be said that every iteration produces coordinates that is approaching a location where the sample was recorded from. Therefore, increasing the number of iterations will eventually saturate the output after a certain value. Experiments showed that the saturated coordinate values did not correspond to the actual location. The coordinates that corresponded to the actual location were generated during early iterations. This was due to the RSS variations. Since the same weighted relation is applied for each iteration, the effects of electromagnetic wave properties are amplified after each iteration. The loss in signal strength due to electromagnetic wave propagation is common for all beacons. Therefore, every iteration result in strengthening the propagation effects, and in turn, reduces the effects of other error factors as those factors are not common to all beacons. In other words, the iteration process amplifies the characteristics that are common for all the beacons which in turn reduces the effects of the varying factors.

Mathematically, X and Y coordinates are generated by scaling the vector components for each beacon based on their respective weights. This is done by first, applying the weight to the vector quantities, and then, calculating new vector quantities using original beacon coordinates. Fig-13 shows the generated coordinates for each sample.



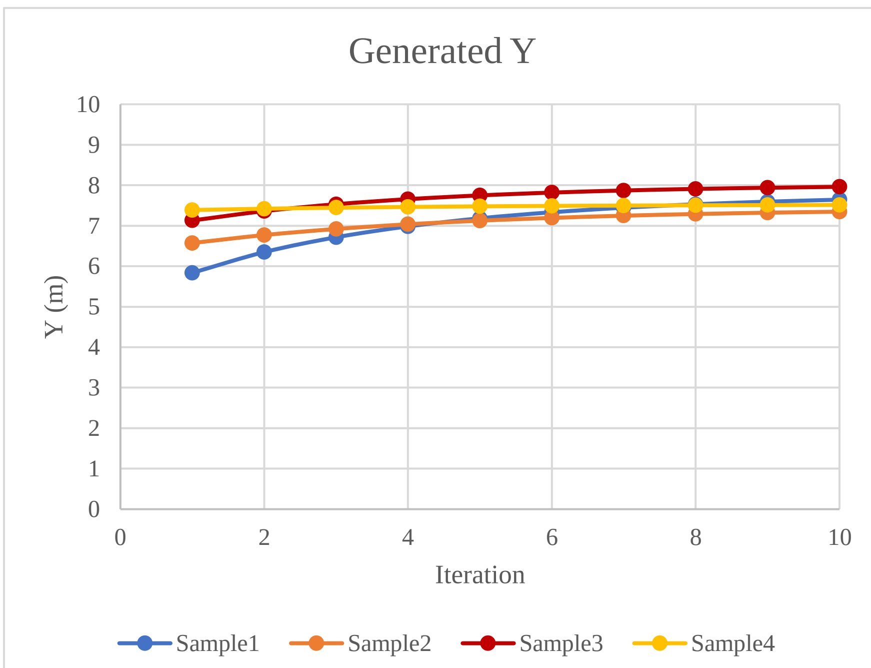


Figure 13: Generated X and Y coordinates

Explanation for Manipulating the Coordinates:

The set of generated coordinates, for a given sample, reveals a general trend by which the generated coordinates scale from one iteration to another. This trend varies during initial iterations but saturates towards the same location coordinates with increasing iterations. These variations between different sample sets correspond to the error factors that vary between beacons, such as multipath fading, line-of-sight effects, etc. The effects of these varying factors are minimized by applying averaged scaling factors from each sample set, to all the generated coordinates from all sample sets sequentially in coordinate manipulation.

The coordinate manipulation process scales every generated coordinate with an average scale factor from each sample iteratively. At first, an average scaling factor is obtained from the generated coordinates of the first sample. This scaling factor is applied to update all the generated coordinates. Then, the average scaling factor for the updated second sample is computed and the generated coordinates are again updated. This process is repeated for each sample set. The final output of this process is a set of coordinates that have been rescaled with averaged scaling factors from each sample set. In fact, this process scales every coordinate with an averaged scaling factor obtained from each sample. This process amplifies the propagation loss characteristics of the electromagnetic waves as the propagation loss is the common error factor for each signal. However, loss characteristics from other sources such as multipath fading and line-of-sight vary from beacon to beacon. Therefore, the error due to their effects become minimal and the inverse-squared law becomes the dominant factor. Fig-14 shows the output of the corrected coordinates. Comparing Fig-13 and Fig-14 shows that there is a shift in the coordinates for each iteration, from before and after updating the coordinates.

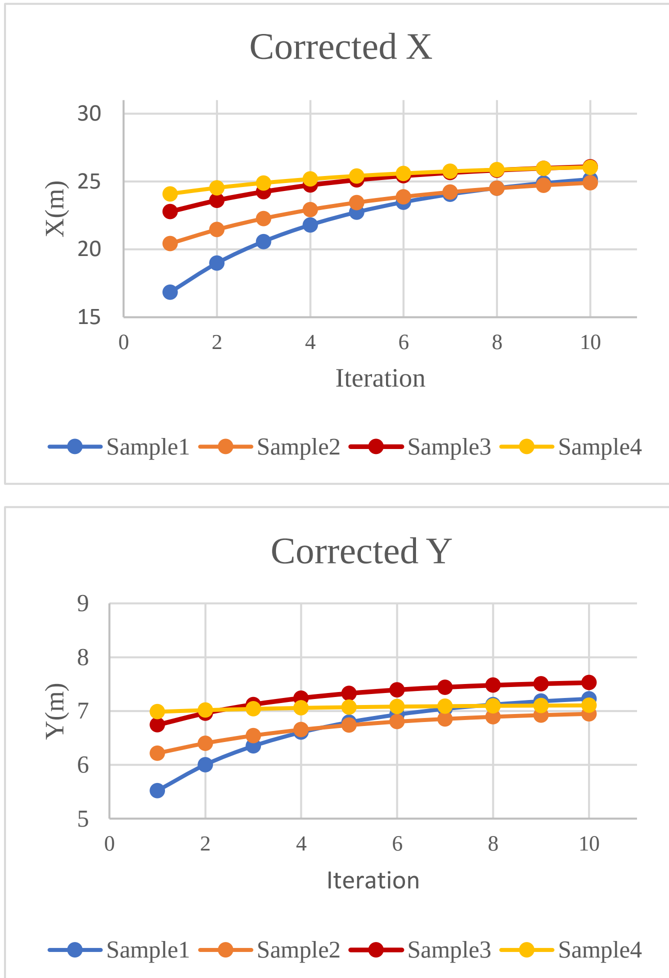


Figure 14: Updated coordinates after rescaling.

Explanation of Final output:

The computation processes are carried out in parallel using three separate reference points. Each parallel process provides a range of values of coordinates bound by a minimum and a maximum value. The overall function of the algorithm is to start computing the location from an unweighted state and iteratively reach a weighted state which saturates towards the estimated location. Using the averaged beacon coordinates as a reference position, the iterative process saturates towards the estimated location. There is a degree of uncertainty to the accuracy of the output as there is no verification process. For this reason, a verification set was constructed which was formed by the averaged output of the minimum and maximum reference coordinates. These two sets form the boundary of the region. The estimated location lies within, or very close to these boundary regions. Fig-15 shows the output of the example data. The final location is computed by taking the geometric mean of the coordinates of the two sets.

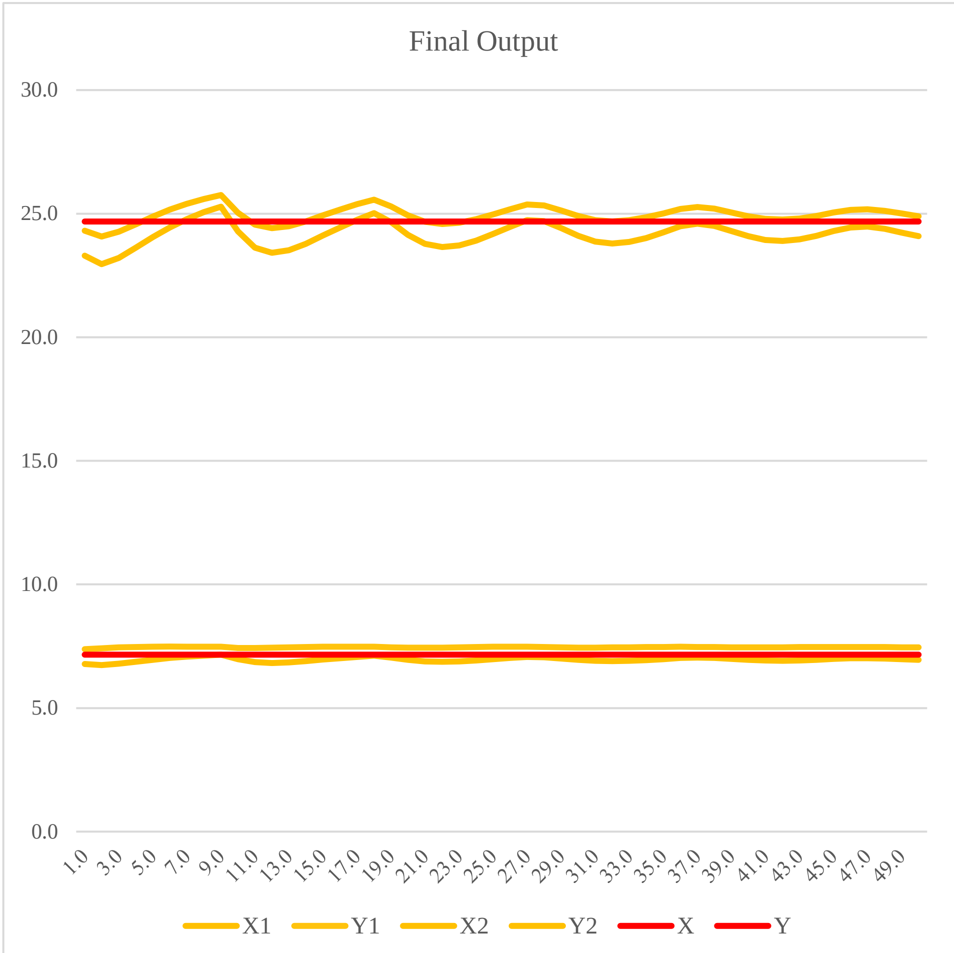


Figure 15: Final Output of the measured location (24.5,7)

5.3 Experiment Results:

Experiment:

Arbitrary locations were chosen at random in a 300 m^2 room, and their locations recorded. Four BLE beacons were placed on four corners of the room at floor level. At each location, BLE scan was performed and multiple samples of RSS were recorded at separate times. Table-13 illustrates some of the results of the experiments.

Table 13: Sample sets and Beacon coordinates

Location	Trial	Calculated X	Calculated Y	Measured X	Measured Y	Error(m)
1.00	1.00	24.70	7.20	24.50	7.20	0.20
	2.00	24.40	7.10	24.50	7.20	0.14
	3.00	24.50	7.10	24.50	7.20	0.10
2.00	1.00	22.00	5.70	21.20	6.00	0.85
	2.00	21.10	5.70	21.20	6.00	0.32
	3.00	21.10	5.80	21.20	6.00	0.22
3.00	1.00	10.70	4.40	10.50	3.20	1.22
	2.00	9.80	4.00	10.50	3.20	1.06
	3.00	10.30	4.00	10.50	3.20	0.82
4.00	1.00	9.10	5.50	9.50	5.70	0.45
	2.00	10.00	4.50	9.50	5.70	1.30
	3.00	9.90	4.70	9.50	5.70	1.08

Results:

Multiple trials were conducted to test the accuracy and precision of the algorithm. Table-14 summarizes the performance of the algorithm.

Table 14: Accuracy Performance

Minimum Error Distance	Precision (out of 40 trials)
< 0.50 meters	45% Confidence
< 1.0 meters	75% Confidence
< 1.5 meters	100% Confidence

5.4 Conclusion:

This chapter introduces a novel RSS-based indoor positioning algorithm. It is designed to work on a software level performing a series of iterative calculations. It utilizes the loss characteristics of radio waves to determine the estimated location in the form of a range of coordinates. Experimental results indicate that the algorithm can achieve accuracies of < 1.5 meters always.

Compared to known methods of indoor positioning, the algorithm provides a crude range of accuracy. However, the proposed solution uses less resources and also has offline capabilities, as shown in Table-15

Table 15: Comparison Table

System / Solution	Wireless technologies	Positioning Algorithm	Accuracy (m)	Precision	Off-Line Positioning	POI Identification	Required Computation Platform
Horus	**WLAN, RSS**	**kNN, Viterbi-like algorithm**	**2**	**90% within 2.1m**	**N/A**	**N/A**	**Server Grade Processing**
BLE fingerprinting	**BLE, RSS**	**Bayesian Approach**	**2.6**	**95% within 2.6m**	**N/A**	**N/A**	**Server Grade Processing**
Proposed Algorithm Method-1	**BLE, RSS**	**BLE Advertisement Approach**	**2.1**	**81% within <3m (out of 30 trials)**	**Yes**	**N/A**	**Software Level Processing for Portable Devices**
Proposed Algorithm Method-2	**BLE, RSS**	**BLE Advertisement Approach**	**1.6**	**90% within <2m (out of 48 trials)**	**Yes**	**Yes**	**Software Level Processing for Portable Devices**
Proposed Algorithm Method-3	**BLE, RSS**	**BLE Advertisement Approach**	**1.0**	**95% within <1.5m (out of 50 trials)**	**Yes**	**Yes**	**Software Level Processing for Portable Devices**

Chapter -6

Conclusions and future work

6.1 Conclusions

In this work a new method of indoor positioning that is robust, scalable, and feasible to be implemented in indoor environments is presented. The algorithms illustrated in chapters 3, 4, and 5 can be implemented on a software level and are independent of network connection. The algorithms enable offline indoor positioning and support location-based applications. The performance parameters of the methods are within acceptable margins compared to the known methods. The performance of the proposed solutions have been verified through experimental measurement results.

6.2 Future Works

The indoor positioning algorithms in this work are designed in such a way that they are flexible and easily integrable with existing technology. Moreover, each of the algorithms consists of processes that can be changed or tweaked to the application's needs. For instance, the three methods can be combined to form a software-based, local indoor positioning system. Attention should be put towards dynamic, self-learning algorithms, where the system takes in a small sample of data to obtain basic parameters, forms a model and then runs the computation with new scanned data, using the self generated model.

APPENDIX :COPY RIGHT PERMISSION

Copyright Clearance Center RightsLink®

Home | Create Account | Help

IEEE Requesting permission to reuse content from an IEEE publication

Title:	An indoor location positioning algorithm for portable devices and autonomous machines
Conference Proceedings:	Indoor Positioning and Indoor Navigation (IPIN), 2016 International Conference on
Author:	Farhan Zaki
Publisher:	IEEE
Date:	Oct. 2016

LOGIN

If you're a copyright.com user, you can login to RightsLink using your copyright.com credentials.

Already **a RightsLink user** or want to learn more?

Thesis / Dissertation Reuse

The IEEE does not require individuals working on a thesis to obtain a formal reuse license, however, you may print out this statement to be used as a permission grant:

Requirements to be followed when using any portion (e.g., figure, graph, table, or textual material) of an IEEE copyrighted paper in a thesis:

1) In the case of textual material (e.g., using short quotes or referring to the work within these papers) users must give full credit to the original source (author, paper, publication) followed by the IEEE copyright line © 2011 IEEE.
2) In the case of illustrations or tabular material, we require that the copyright line © [Year of original publication] IEEE appear prominently with each reprinted figure and/or table.
3) If a substantial portion of the original paper is to be used, and if you are not the senior author, also obtain the senior author's approval.

Requirements to be followed when using an entire IEEE copyrighted paper in a thesis:

1) The following IEEE copyright/ credit notice should be placed prominently in the references: © [year of original publication] IEEE. Reprinted, with permission, from [author names, paper title, IEEE publication title, and month/year of publication]
2) Only the accepted version of an IEEE copyrighted paper can be used when posting the paper or your thesis on-line.
3) In placing the thesis on the author's university website, please display the following message in a prominent place on the website: In reference to IEEE copyrighted material which is used with permission in this thesis, the IEEE does not endorse any of [university/educational entity's name goes here]'s products or services. Internal or personal use of this material is permitted. If interested in reprinting/republishing IEEE copyrighted material for advertising or promotional purposes or for creating new collective works for resale or redistribution, please go to http://www.ieee.org/publications_standards/publications/rights/rights_link.html to learn how to obtain a License from RightsLink.

VITA AUCTORIS

NAME: Farhan Zaki

PLACE OF BIRTH: Dhaka, Bangladesh

YEAR OF BIRTH: 1990

Education:

Master of Applied Science (Electrical and Computer)	August, 2018
University of Windsor	Windsor, ON
Bachelor of Applied Science (Electrical and Computer)	Sept, 2015
University of Windsor	Windsor, ON