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Hybrid Indoor Position Estimation using K-NN and MinMax

Fazli Subhan[1*], Shakeel Ahmed[1], Sajjad Haider[1], Sajid Saleem[1], Asfandyar Khan[3], Salman Ahmed[2], Muhammad Numan[1]

[1]Department of Computer Science, National University of Modern Languages
NUML, Islamabad, Pakistan.
fsubhan@numl.edu.pk, ahmedshakeelktk@gmail.com, shaider@numl.edu.pk, sjsaleem@numl.edu.pk, numannaseeb@gmail.com,
[2]Department of Computer and System Engineering, University of Engineering and Technology, Peshawar, Pakistan
sahmed@uetpeshawar.edu.pk
[3]Institute of Business and Management Sciences, University of Agriculture
Peshawar, Pakistan
asfand43@yahoo.com
*Corresponding author: Fazli Subhan

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Abstract

Due to the rapid advancement in smart phones, numerous new specifications are developed for variety of applications ranging from health monitoring to navigations and tracking. The word indoor navigation means location identification, however, where GPS signals are not available, accurate indoor localization is a challenging task due to variation in the received signals which directly affect distance estimation process. This paper proposes a hybrid approach which integrates fingerprinting based K-Nearest Neighbors (K-NN) and lateration based MinMax position estimation technique. The novel idea behind this hybrid approach is to use Euclidian distance formulation for distance estimates instead of indoor radio channel modeling which is used to convert the received signal to distance estimates. Due to unpredictable behavior of the received signal, modeling indoor environment for distance estimates is a challenging task which ultimately results in distance estimation error and hence affects position estimation process. Our proposed idea is indoor position estimation technique using Bluetooth enabled smart phones which is independent of the radio channels. Experimental results conclude that, our proposed hybrid approach performs better in terms of mean error compared to Trilateration, MinMax, K-NN, and existing Hybrid approach.

Keywords: Indoor Positioning, Fingerprinting, K-NN, MinMax, Trilateration, GPS

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1. Introduction

Position estimation refers to finding the actual coordinates of an object with reference to some coordinate systems. These systems can be categorized as two and three coordinate systems. Most of the research work performed in position estimation is of two coordinate systems [1]. The term position estimation used in literature varies according to different domains, i.e. sometimes it is referred as location identification, localization, object tracking, indoor navigation, indoor guidance systems etc. For localization or object tracking, they are further classified as outdoor and indoor localization or position estimation. For outdoor localization, Global Positioning Systems (GPS) is the most popular navigation and tracking system developed by the Department of Defense, United States for military purpose. GPS works for outdoor navigation, which is satellite based solution. The problem in GPS is mainly being a line of sight based technology working in outdoor environment only. GPS signals are not available in indoor scenarios so for this purpose indoor localization or object tracking technologies are used [2, 3].

Position estimation plays an important role in our daily lives, tracking objects, human beings, devices, surveillance of homes, offices and nearby surroundings are few of the demanding applications in smart phones. To categorize the environment, applications can be classified into two categories, i.e indoor and outdoor monitoring. For outdoor monitoring or navigation, GPS is the available technology but for indoor environment none of the technology so far considered a standard solution. The reason for this is the accuracy, which is one of the most important performance metric in building an accurate solution for indoor environment. The word accuracy in the domain of object tracking is defined as the difference between actual and estimated location of the object. Accuracy also depends on the environment and application domain. For outdoor environment when tracking or navigation of vehicles are involved, five to ten meters accuracy or position estimation error is acceptable or even in some cases 15 to 20 meters accuracy for finding the target location i.e. landmark, is acceptable but for indoor environment even lesser than five meters accuracy is not acceptable. Other than this, in case of industrial application or automation finding, the location of an object needs accurate solutions. The reason for this difference in accuracy depends on indoor environment such as physical objects, presence of humans, radio signals, temperature which creates interference in the received signals and hence variations in the received signals occurs [3, 4].

There are many position estimation techniques proposed for indoor environment. These techniques can be categorized as range , time and pattern matching based or fingerprinting based position estimation techniques. Range based positon estimation techniques depend on the radio propagation model, which converts the received signals to distance estimates. Trilateration, Multilateration, MinMax are range based position estimation techniques [7, 8]. These techniques depend on the received signals, and modeling of the radio channels specific to the indoor environment which is a challenging task. If there is any change in the environment, radio channel used for position estimates would not result in an accurate distance estimates and hence effecting position estimation accuracy as well. Similarly in Angular based approaches, such as Angle of Arrival requires expensive hardware to measure the reception of signals accordingly, which itself is a difficult task. The same situation with time based position estimation techniques such as Time of Arrival (TOA), Time Difference of Arrival (TDOA) requires time synchronization with respect to received signals [4, 5]. In Fingerprinting based approaches there are two main phases which are offline and online. In offline phase, first of all fingerprints of the environment are required which is a difficult task. Again if there is any kind of change in the indoor setup, this process needs to be updated [7, 8]. In second phase of fingerprinting, which is a positon estimation process, the received signals are matched with the offline fingerprints, which result in an estimated positon. In fingerprinting based position estimation, K-NN is one of the most popular indoor position estimation technique [9]. Moreover, hybrid approaches are also developed for position estimation which integrates the good features of lateration and fingerprinting based approaches [9]. One of the recent developed hybrid approach combines the good features of lateration based approach that is Trilateration with K-NN and use Euclidian distance formula together with Kalman filter for dynamic based position estimation. Our proposed hybrid approach is motivated from this recent hybrid approach [27]. The difference between existing and our proposed hybrid approach is the use of MinMax, which is also a lateration based position estimation technique and is independent of the radio channels. Moreover, main contributions of this paper are summarized as follows.

a. We have performed real time experiments using Bluetooth enabled smart phones which act as access points and for data collection.
b. For considering environmental effects and variations in Received Signal Strength Indicator (RSSI), we took 10 RSSI readings for each access point on each grid point and calculated its average value considering the dense indoor environment.
c. RSSI offline map was generated using real time experimental values.
d. Design of Hybrid position estimation technique by integrating K-NN with MinMax without radio propagation model.
e. For comparative analysis with existing radio propagation model-based position estimation techniques i.e. Trilateration, and MinMax, we have simulated radio propagation model for selecting ideal environmental radio propagation constants in order to validate our proposed hybrid position estimate technique and its accuracy.
f. For comparative analysis we have implemented K-NN, Trilateration, MinMax and its predecessor hybrid position estimation technique using our own experimental data to validate the accuracy of our proposed position estimation technique.
g. Based on our experimental analysis, we have concluded that, our proposed hybrid position estimation technique performs better in terms of mean error as compared to K-NN, Trilateration, MinMax and existing hybrid approach, which used filtered RSSI values and used Kalman Filter for accurate position estimation.

The paper is organized as follows. Section 2 discusses existing position estimation techniques followed by related work specific to lateration and fingerprinting based position estimation techniques. Section 3 discusses design of our proposed hybrid position estimation technique. Section 4 discusses comparative analysis with existing techniques and finally section 5 presents summary and future research directions.

2. Existing Position Estimation Techniques

Indoor positioning estimation techniques use sensing technology to estimate the object location. Among all sensing technologies, Radio Frequency is the most popular technology due to its easy accessibility [7, 8, 9]. Examples of such technologies are Wireless Local Area Network (WLAN), Bluetooth and Zigbee [10]. In this paper we have selected Bluetooth, which is available in almost every smartphone and also in other handheld devices. The range of Bluetooth devices ranges from one meter to hundred meters according to Bluetooth specifications. The Indoor positioning systems which use radio frequency can be classified into two major categories i.e. Fingerprinting and Lateration based position estimation techniques. In Fingerprinting, object position is estimated based on pattern matching approach. There are two phases in fingerprinting, offline and online phase. In offline phase, fingerprints of the desired locality are stored in a database while in online phase when the object enters the desired locality, the sensors collect the readings and searches for its matching. If it matches the fingerprints in already stored offline database, then the position is estimated. The problem in these technique is the very tough phase of offline fingerprints. Offline database reflects the selected or desired indoor environment. Any sort of change in the selected environment reflects on the final position estimation. This approach is a kind of static estimation. The most popular fingerprinting based position estimation techniques are K-Nearest Neighbors (K-NN) and K-Weight Nearest Neighbors (K-WNN). K, means nearest neighbors, the value of K, is random, we can fix it to three, four, five and so on. It depends on the environment [11, 12]. **Fig. 1** elaborates concept of fingerprinting based position estimation technique.

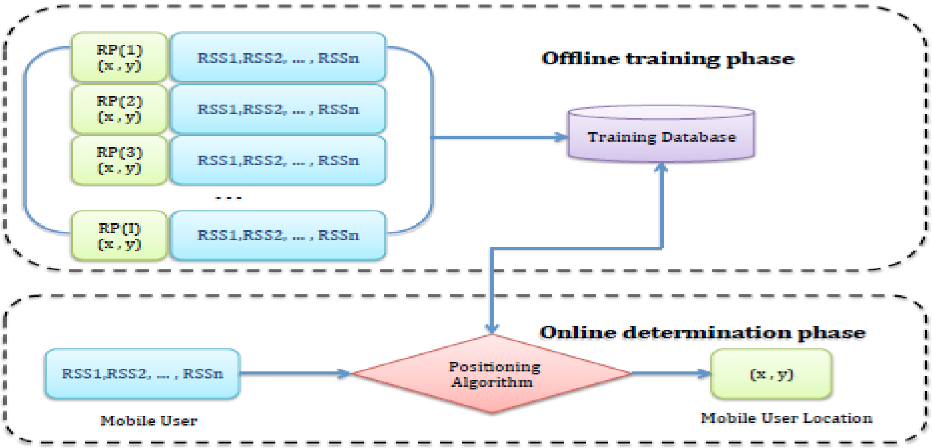

Fig. 1. Fingerprinting based position estimation technique [28]

In Lateration approach, the position estimation depends on distance estimates and radio propagation model. To estimate distance, channel modeling is required to extract distance from RSSI measurements [13]. There are mainly two most common traditional approaches i.e.

Trilateration, and MinMax approaches [14-19]. **Fig. 2** represents the idea of Trilateration with three and four access points. If three access points are used it is called Trilateration and in case of four access points it is called Multilateration which is depicted in the following figure.

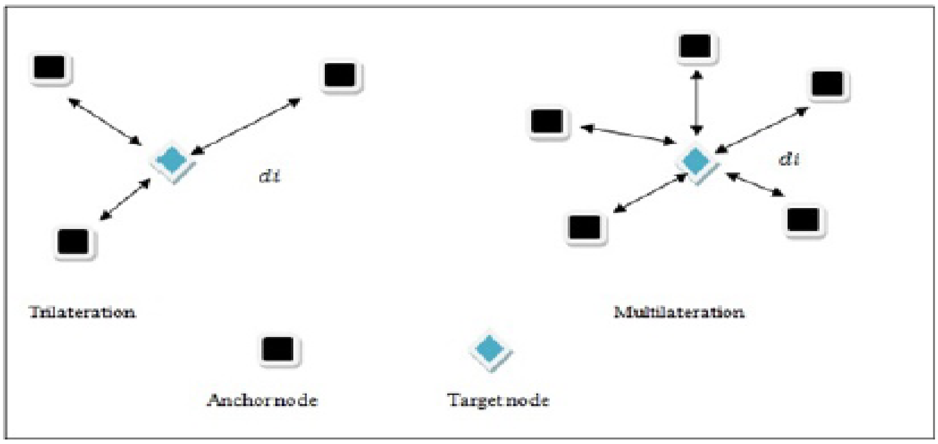

Fig. 2. Trilateration and Multilateration

Another most popular lateration based approach is the Maximum Likelihood Estimation (MLE). MLE is lateration based position estimation approach. The problem of ambiguity in dimension is addressed by MLE and is considered as iterative triletration approach. The functioning rules of MLE depends upon statically consideration that, a noise is produced in RSSI due to anchor nodes. It is a recursive method and the focal point of this approach is to decrease the Mean Square Error (MSE). Using RSSI, distance estimation result from each of anchor nodes. The error e_i among predictable and real distance is defined by predictable target nodes and is given by following equation,

$$e_i(x_0 - y_0) = d_i - \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2} \quad (1)$$

$$i = 1,2,3,\ldots n\text{-}1.$$

Where b =(x_0, y_0) signifies the location of a target node which is not known and (x_i, y_0) is the location of i_{th} node.

The major aim of MLE is to decrease the mean square error. For huge indoor system, this approach is used but for small indoor system this process is restricted. Consequently for three access nodes the result of this approach is not sufficient.

All these techniques require distance estimates that need optimal radio propagation constants. If the distance estimation results are accurate, then position estimation error would also result in high accuracy [14, 15]. The main issue in these techniques are the variations in RSSI and conversion of RSSI to distance estimates [16, 17]. If the input parameters are within the acceptable range then, position estimation error will also be in acceptable range. The word acceptable means, for a blind person to locate the desired landmark, accuracy must be lesser than 1 meter but for normal positioning, less than 3 meters error is also acceptable.

Other than, position estimation techniques, accuray also depends on wireless technology, In [20], the authors developed an indoor positioning system using Bluetooth Low Energy

(BLE) beacons for position estimation with improved accuracy compared to the existing approaches used in the experimental validations.

Similary, In [21] the authors developed an indoor positioning system using fingeprinting and Baysian estimation with the help of smartphones. The smart phones were connected with WIFI for user gudinace in case of disasters. They used two step procedure for user estimation i.e section and zone with improved recognition and calculation time.

In [22], the authors combined two well kown position estimation techniques i.e. fingerprinting and dead recking approach. The Root Mean Square Error (RMSE) obtained in indoor environment in a room size of (11 x 5) meters were 2.35 and 0.80 meters using Support Vector Machine (SVM) and Random Forest (RF). In [23], the authors developed a Long Short Term Memory (LSTM) approach using smart phone accelerometer which provides optimal based position estimation accuracy in indoor environments. Other than conventional approaches, time based position estimation techniques have also been used for indoor position estimation. In [24], the authors developed an indoor positioning system using ultra wide band signals with the help of Time of Arrival. The distance between fixed sensor and mobile object is computed using time of flight.

Moreorver, researchers also developed hybrid approaches which combines fingerprinting, means the good features of fingerprinting and lateration approaches for better accuracy.

The Hybrid Indoor Position Estimation means to combine the properties of fingerprinting and lateration base position estimation approaches for improving the accuracy of position estimation.

In [25], another hybrid approach was proposed which uses three steps to estimate an object position. In first step an offline database is used to correlate distance with RSSI readings. In step 2, a searching algorithm is used which is a binary search approach for distance between object and access point and finally in step 3, the most popular Trilateration approach is used for position estimation. Numerical results suggest that their proposed hybrid approach performs better than trilateration and almost similar to K-NN. The drawback of this approach is the lengthy three step process instead of two steps as compared to fingerprinting based position estimation technique.

In [26], the author proposed the hybrid indoor position estimation approach based on WLAN. The hybrid indoor position estimation finds the actual location of an entity in two phases. In the first step, it uses fingerprinting approach to compute the NNs, while in the second step it uses trilateration approach to find the actual location of the target node. Though lateration base position estimation approaches and pragmatic radio propagation model is used for exchanging of RSSI to distance estimate. This is nearly same as the radio propagation model. The author used the radio propagation model for the exchanging of RSSI to distance estimate in various situations and compared the accuracy of position estimation with fingerprinting and trilateration based K-NNs techniques. The numerical result shows that the accuracy of position estimation is enhanced than trilateration approach, because nodes deceit nearby to the NNs. Afterwards the distance between NNs and target nodes are computed through radio propagation model. The numerical result shows that the proposed approach is efficient from trilateration technique and less efficient than KNN.

The recent hybrid approach developed used Gradient filter for smoothing RSSI measurements and then integrated fingerprinting with Trilateration approach for position estimation. For accuracy improvement Kalman Filter is also used once the position is estimated [27]. This paper explores the idea of the most recent hybrid approach [27] further without the use of Gradient and Kalman filters. The next section presents the design of our proposed hybrid position estimation technique.

3. Proposed Hybrid Position Estimation Technique K-NN and MINMAX

As discussed in section 2, position estimation can generally be categorized as fingerprinting and lateration based position estimation techniques. In fingerprinting based approach, normally a radio map is created from experimental data set and then the object position is determined based on pattern matching approach. Other than this, another category is lateration approach which depends on distance estimates. The most popular lateration based position estimation techniques are Trilateration and MinMax approaches. Trilateration and MinMax both are based on trigonometric principles. In case of trilateration, each access point is considered as the center of circle and the point of intersection of these circles, if so, is the estimated position. If there is a unique point of intersection, it means the position estimation error is zero. If the circles do not intersect at single point, it means there is a position estimation error. Similarly, in MinMax approach, instead of circles, rectangles are drawn for each access point and the point of intersection is considered as the estimated position. If the point of intersection is unique then it means there is no position estimation error or in other words it is almost zero. The proposed hybrid indoor position estimation technique consists of two stages. In first stage, our proposed hybrid approach uses Fingerprinting approach and in second stage it uses MinMax Approach. In first phase, we have used K-NN which calculates Nearest Neighbors, once the nearest neighbors are calculated then the distance between the nearest neighbors are calculated using Euclidian distance formula. Once the distances are calculated, then the target position is estimated using MinMax approach. Moreover, we have also implemented one of the recently developed hybrid approach, which is a combination of K-NN and Trilateration approach.

3.1 Mathematical Model of the Proposed Hybrid Approach

As discussed in previous section, the proposed hybrid approach consists of two steps. In step 1, we have used Fingerprinting approach, which is one the most popular pattern matching position estimation technique. In step 1, we calculated the nearest neighbors of the target position which is going to be estimated. For this purpose, K-NN algorithm is used to calculate the nearest neighbors. The mathematical formula for calculating the nearest neighbors using Euclidian distance formula is as under.

$$d = \sqrt{\sum_{i=1}^{n} \left(si - si'\right)^2} \qquad (2)$$

Where *d* shows Euclidian distance, s_i represents RSSI and s_i shows the corresponding RSS in the database, while *n* is the number of anchor nodes for which the Euclidian distance is calculated.

In step 2, we have used MinMax approach, which is a lateration based position estimation technique. Unlike Trilateration approach, MinMax algorithm works differently, i.e. instead of drawing circles, MinMax draws bounding boxes/rectangles for every access point which is fixed already. The radii of each bounding box i.e. rectangles is the distance calculated from NNs. Here the difference between conventional MinMax and other lateration based position estimation techniques is the use of Euclidian distance formula for finding the distance for radii of the bounding boxes. In conventional approaches, the radio propagation model is used to convert RSSI measurements into distances, but in hybrid approach, once the NNs are calculated, then the distance between NNs are calculated using Euclidian distance formula, which acts as a radii for MinMax and there is no need to use radio propagation model. This will enhance position estimation accuracy and will also minimize the effect of noise over position estimation. The main reason behind using the hybrid approach is to minimize the effect of noise, which can effect the position estimation accuracy. The mathematical formulation of MinMax approach is as under.

$$\left(\max_{(x_i-d_i)}, \max_{(y_i-y_i)}\right) * \left(\min_{(x_i+d_i)}, \min_{(y_i+y_i)}\right), \qquad (3)$$

Where (x_i, y_i) represent the fixed position of access point and d_i, represents distance between estimated target position and access point.

4. Comparative Analysis with Existing Position Estimation Techniques

Experiments were performed in an indoor environment of size 10 *10 meters square. Four samsung android mobile phones were used with latest version of Bluetooth support. These mobile phones were fixed on the corner of the 10 *10 acted as access points. The region 100 squares meter were partitioned into 1 meter square grid size. Total grids were 100. RSSI readings were collected for each grid point and the mean value of 10 RSSI measurements were calculated for each grid position. Another mobile phone having the same features was used for RSSI measurements. In another experiment, we measured RSSI values with two devices. One device acted as access point and another as mobile client. The measurements were taken from 0 to 13 meters distance from each other. This process is performed to validate the offline database development for fingerprinting approach. Initally RSSI measurement was taken when both devices were kept at the same place i.e. when the distance is zero. And then the distance was increased with 1 meter step size. RSSI readings were measured for 1, 2, 3 till 13 meters. The RSSI value observed at zero meter separation was -15 dBm and when the distance is 10 meter RSSI was -90 dBm.

4.1 Position estimation at Point (1, 1)

Table 1 shows the mean error of estimated position at point (1, 1) using K-NN, Trilateration, Hybrid Trilateration, MinMax and our proposed hybrid approach. As shown in the following table, the position estimation error of K-NN is 0.5 m which is almost similar to our proposed hybrid position estimation technique. The reason behind this is that as our proposed technique is a hybrid approach combination of K-NN and MinMax. So similarity may happen out of 100 grid points. Other than this, the position estimation error of MinMax is 3.80 meters and Trilateration is 4.5 meters. **Fig. 3** represents graphical representation of real position in two dimensional coordinate system (x, y) and estimated position using Trilateration, K-NN and Hybrid based on trilateration. Similarly, **Fig. 4** represents real position, and estimated position using MinMax, K-NN and our proposed hybrid approach. As discussed in previous chapter, Trilateration is a trigonometric based position estimation technique which estimates target position by drawing circles, on the other side, MinMax approach draws rectangles. If the point of intersection in both cases are unique, it means there is no position estimation error or the estimated position is the same as real position.

Table 1. Comparative Analysis of Position Estimation Techniques at Point (1, 1)

S. No	Position Estimation Techniques	Mean Error (m)
1	K-NN	0.50
2	Trilateration	4.5
3	Hybrid Trilateration	0.84
4	MinMax	3.80
5	**Proposed Hybrid MinMax**	**0.56**

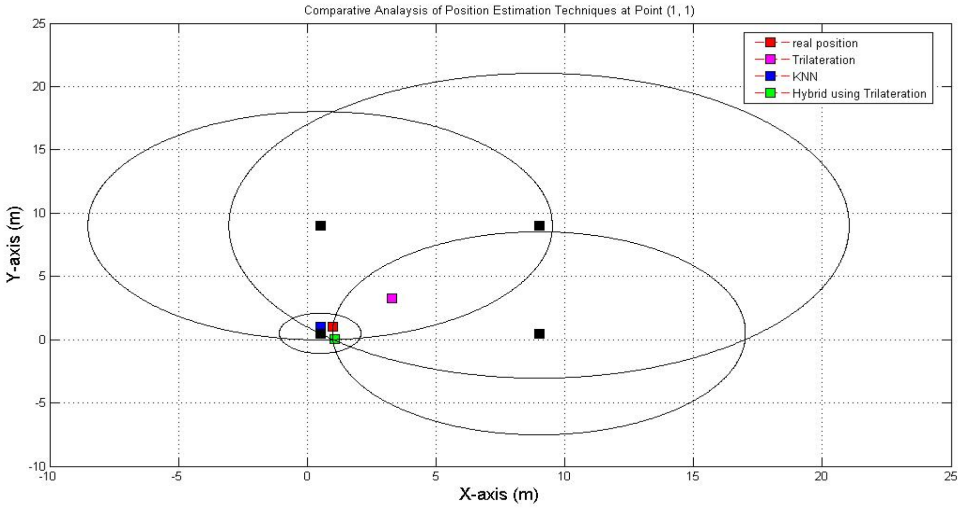

Fig. 3. Estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

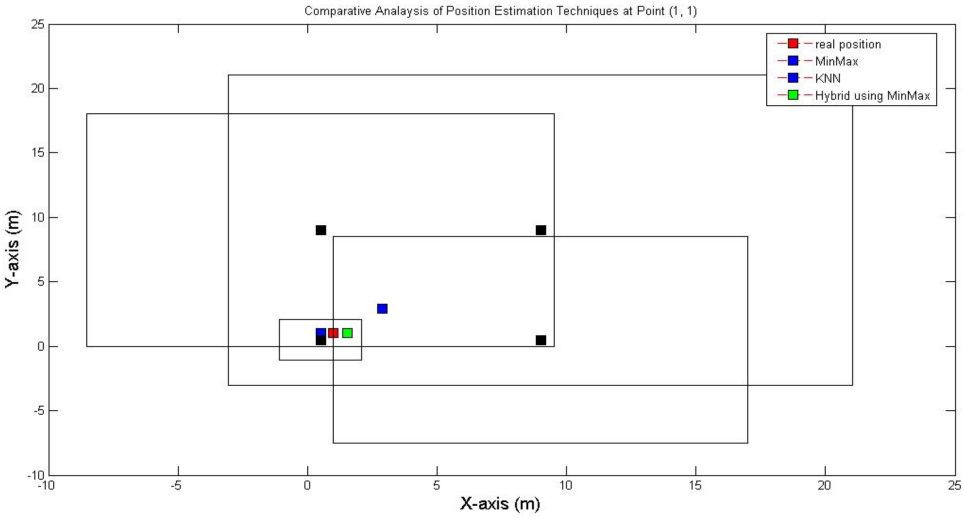

Fig. 4. Estimated position at (1, 1) using MinMax, K-NN and Proposed hybrid technique

4.2 Position estimation at Point (7, 5)

Table 2 shows numerical results when the object is placed at (7, 5). Here it is important to mention again that the estimated position error using K-NN and our proposed position estimation is similar, but position estimation error of other techniques are different from each other. The reason behind this is the effect of environmental conditions and noise. Similarly **Fig. 5** shows estimated position using Trilateration, K-NN, and existing hybrid position estimation technique based on Trilateration. The figure clearly indicates that, the point of intersection is not unique. Same situation in **Fig. 6** shows estimated position using MinMax, and our proposed hybrid MinMax.

Table 2. Comparative Analysis of Position Estimation Techniques at Point (7, 5)

S. No	Position Estimation Techniques	Mean Error (m)
1	K-NN	0.5
2	Trilateration	1.8
3	Hybrid Trilateration	0.9
4	MinMax	1.1
5	**Proposed Hybrid MinMax**	**0.5**

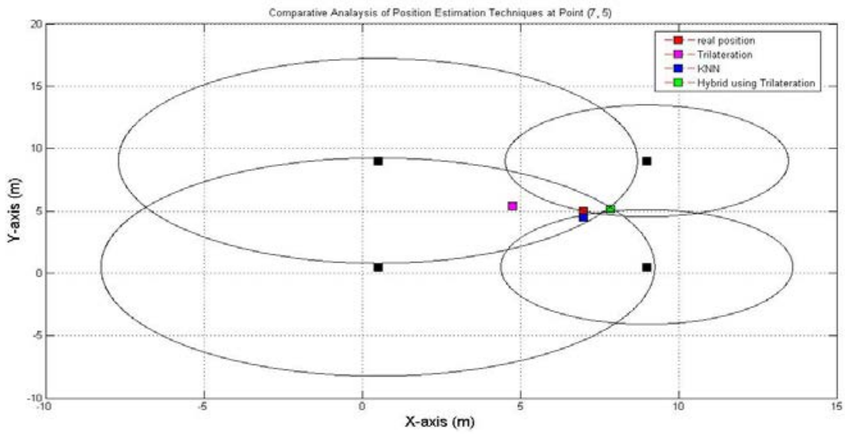

Fig. 5. Estimated position at (7, 5) using Trilateration, K-NN and Hybrid Trilateration

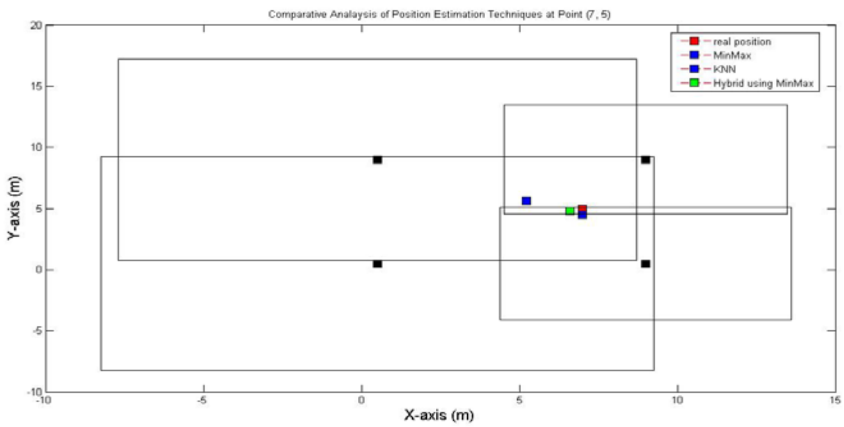

Fig. 6. Estimated position at (7, 5) using MinMax, K-NN and Proposed hybrid technique

4.3 Position estimation at Point (5, 7)

Table 3 shows numerical results at grid point (5, 7), which means, when the real target position is placed when the x-axis is 5 and the y-axis is 7. The mean error analysis shows that, K-NN performs better than all position estimation techniques. The position estimation error of K-NN is 0.2 meters which is the lowest one, while the position estimation error of our proposed hybrid based on MinMax is 0.5 m. On the other hand again position estimation error of existing hybrid position estimation technique is poor than our proposed approach.

Table 3. Comparative Analysis of Position Estimation Techniques at Point (5, 7)

S. No	Position Estimation Techniques	Mean Error (m)
1	K-NN	0.2
2	Trilateration	1.5
3	Hybrid Trilateration	2.0
4	MinMax	0.9
5	**Proposed Hybrid MinMax**	**0.5**

Fig. 7 and **8** depicts graphical representation of existing and our proposed hybrid techniques. In both figures, the circles and rectangles have different size. Due to position estimation error, none of the circles and rectangles intersect at one point.

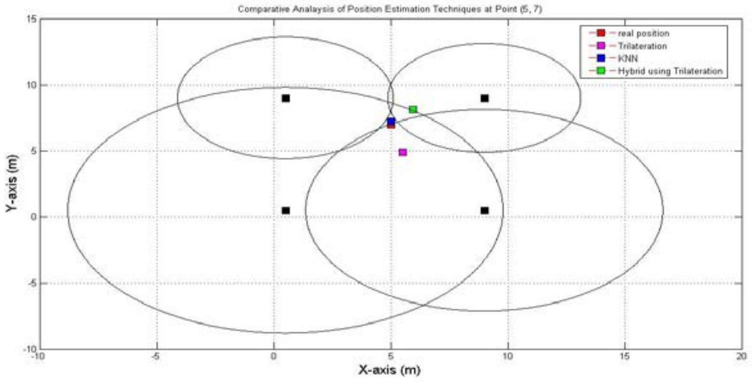

Fig. 7. Estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

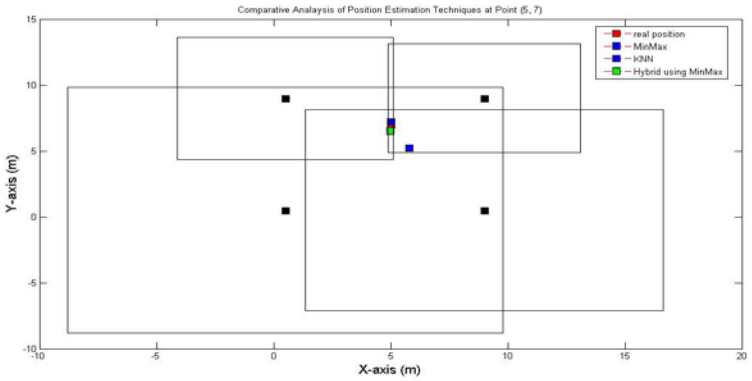

Fig. 8. Estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

4.4 Position estimation at Point (9, 9)

Similarly **Table 4** shows mean error analysis existing and our proposed hybrid position estimation technique. Here position estimation error of K-NN is poor than our proposed hybrid approach which is 1.7m while position estimation error of K-NN is 2.2 m. In our experiments, we have used Bluetooth modules embedded in our smart phones. As per Bluetooth Specification, the range of Bluetooth is from 1 meter to 100 meters for class A devices. As mention in chapter 3, our experiments were conducted in a computer lab and the RSSI readings were collected when the maximum distance between two devices was 10 meters. So point (9, 9) is the corner location, that's why, the position estimation error is 1.7 meters. **Fig. 9**and **10** graphically represents the real position and estimation position using existing and our proposed hybrid approach.

Table 4. Comparative Analysis of Position Estimation Techniques at Point (9, 9)

S.No	Position Estimation Techniques	Mean Error (m)
1	K-NN	2.2
2	Trilateration	6.3
3	Hybrid Trilateration	4.3
4	MinMax	2.6
5	**Proposed Hybrid MinMax**	**1.7**

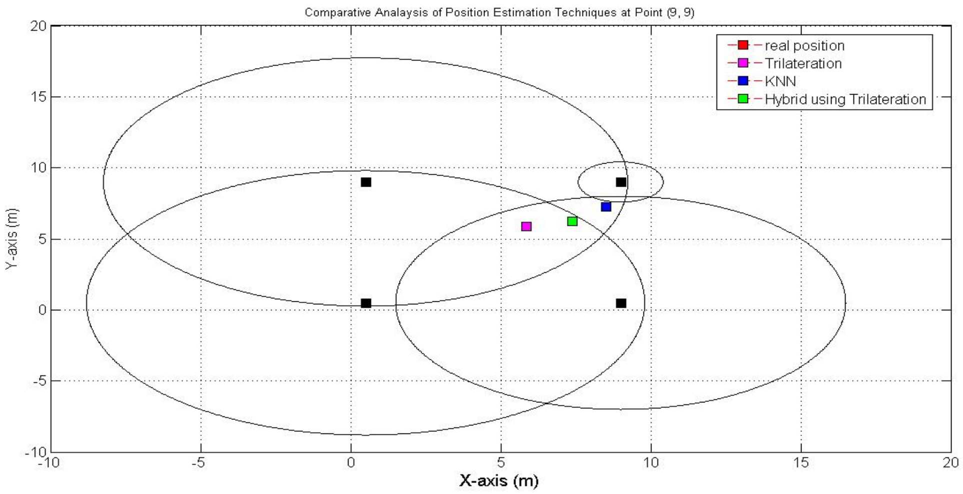

Fig. 9. Estimated position at (9, 9) using Trilateration, K-NN and Hybrid Trilateration

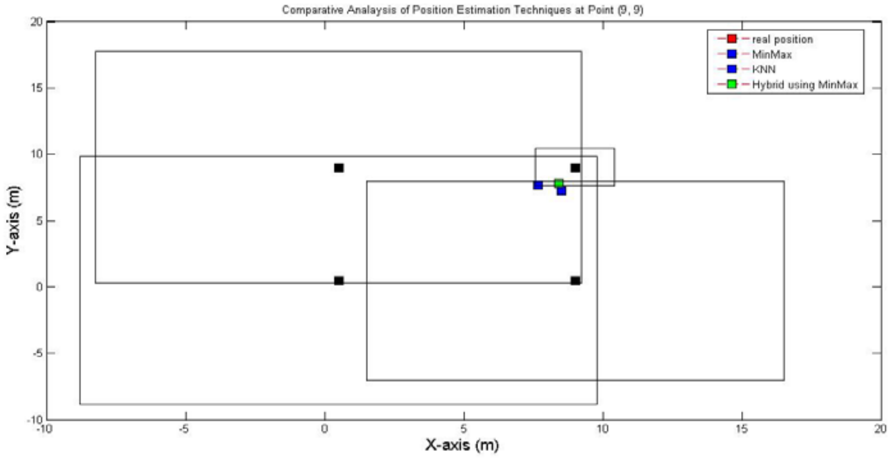

Fig. 10 Estimated position at (9, 9) using Trilateration, K-NN and Hybrid Trilateration

4.5 Position estimation at Point (8, 3)

This section further elaborates mean error analysis of existing and our proposed hybrid approach. As shown in **Table 5**, the mean error of K-NN is 0.5 while the mean error of existing hybrid approach is 2.2 meters. The mean error of our proposed hybrid approach is better than all existing position estimation techniques i.e. 0.3 meters. Here it is important to mention that we did extensive analysis of K-NN and we found that, when the nearest neighbours that is if the value of K= 4, then the results are much better, if we fix the value of K, 2, 3 or 5 the results are not satisfactory. For our proposed hybrid approach, we have fixed the value of K= 2, because we need four access points to locate the object. The radii of each circles and rectangles are calculated using Euclidian distance formula instead of radio propagation models. **Fig. 11** and **12** visualize the estimated and real positions. Again the figures clearly indicate that, the point of intersection is not unique due to position estimation error in existing and our proposed hybrid position estimation technique.

Table 5. Comparative Analysis of Position Estimation Techniques at Point (8, 3)

S.No	Position Estimation Techniques	Mean Error (m)
1	K-NN	0.5
2	Trilateration	0.7
3	Hybrid Trilateration	2.2
4	MinMax	0.5
5	**Proposed Hybrid MinMax**	**0.3**

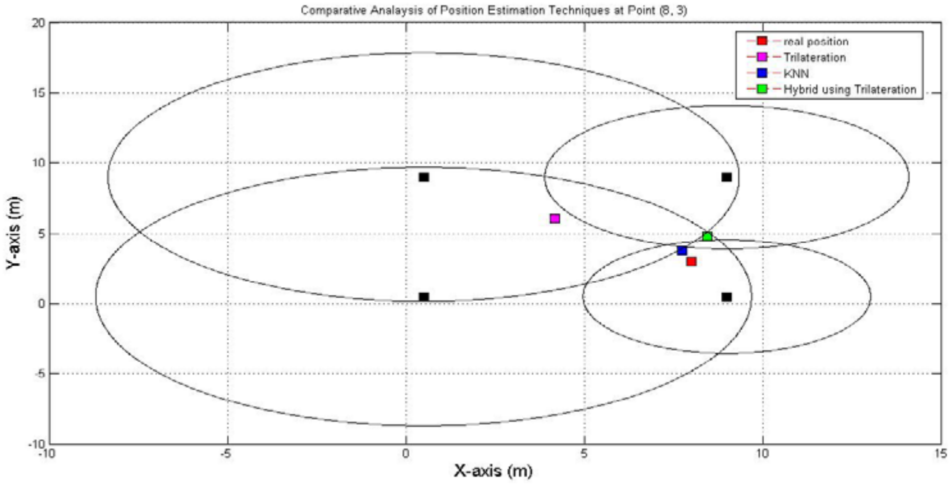

Fig. 11. estimated position at (8, 3) using Trilateration, K-NN and Hybrid Trilateration

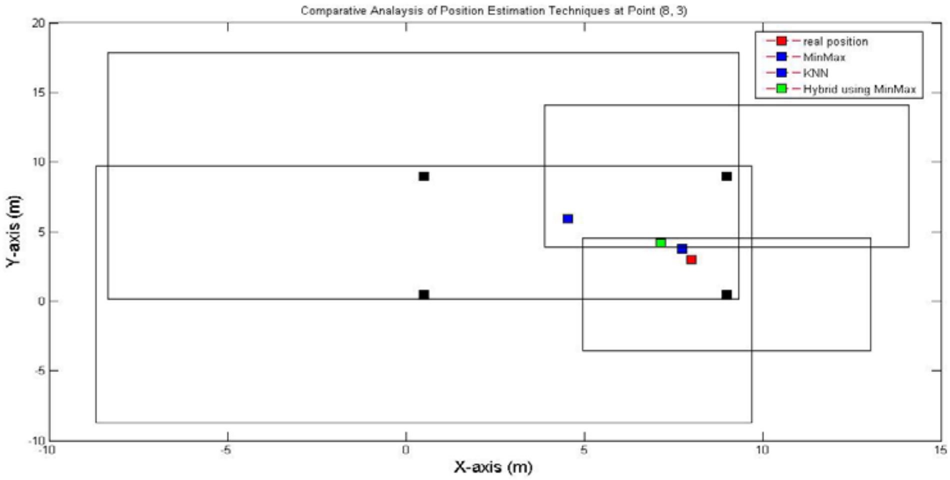

Fig. 12. Estimated position at (8, 3) using Trilateration, K-NN and Hybrid Trilateration

4.6 Position estimation at Point (2, 8)

Table 6 is the ideal situation for K-NN, and existing hybrid technique based on trilateration. As shown in **Fig. 13** the point of intersection is unique as the position estimation error is zero while in **Fig. 14** the position estimation error is also near to zero. So the point of intersection is not unique. Numerical results here shows that, our proposed hybrid technique is better than MinMax and Trilateration but comparatively a bit lower than K-NN and existing Trilateration approach.

Table 6. Comparative Analysis of Position Estimation Techniques at Point (2, 8)

S. No	Position Estimation Techniques	Mean Error (m)
1	K-NN	0
2	Trilateration	0.4
3	Hybrid Trilateration	0.0
4	MinMax	0.7
5	**Proposed Hybrid MinMax**	**0.1**

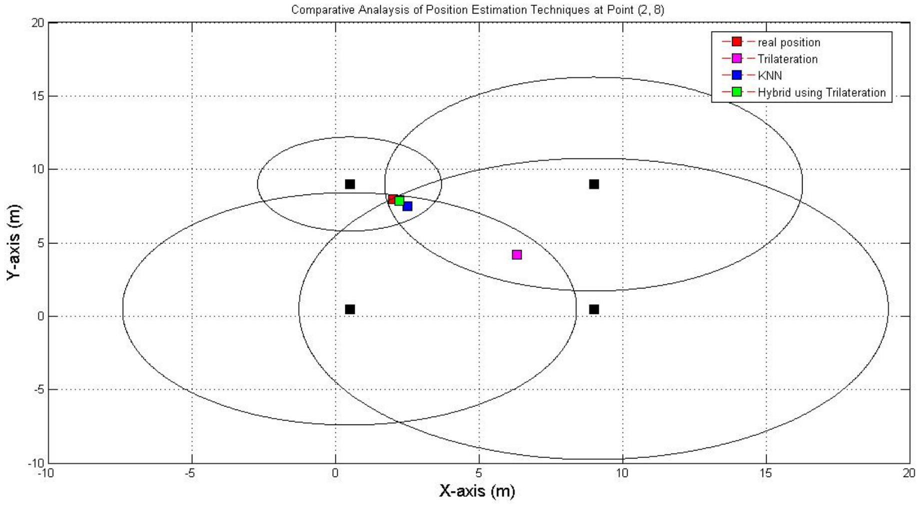

Fig. 13. Estimated position at (2, 8) using Trilateration, K-NN and Hybrid Trilateration

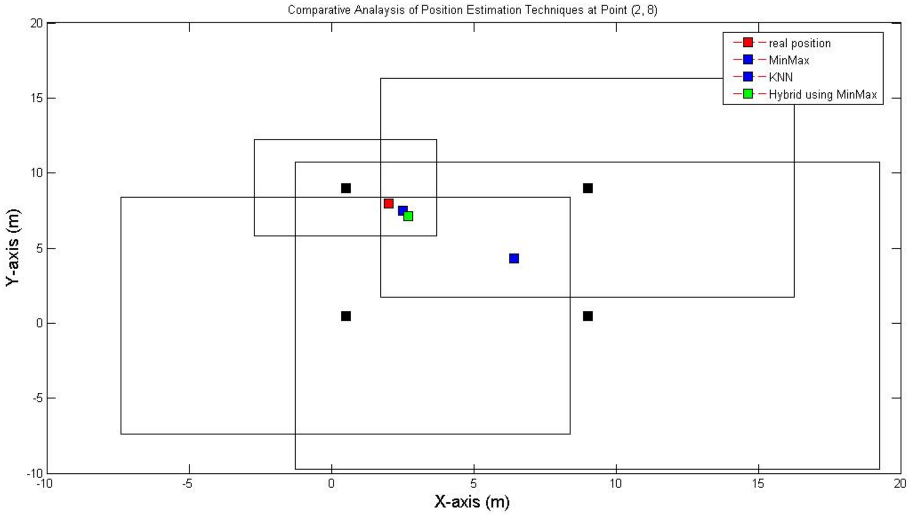

Fig. 14. Estimated position at (2, 8) using Trilateration, K-NN and Hybrid Trilateration

4.7 Position estimation at Point (5, 5)

Table 7 shows numerical results obtained at the center of the (10x10) grid, i.e. when the real position or target position is fixed at the center of the grid. Here, our proposed hybrid approach performs better than K-NN, Trilateration, existing hybrid approach, and MinMax. Still we believe that, the position estimation error exist and we can only minimize it. Moreover, the previous hybrid approach used Gradient filter to clean the RSSI measurements prior to position estimation. Also the existing hybrid approach used the most popular Kalman Filter which further enhances position estimation error. In our case, we used RSSI average measurements, and implemented all position estimation techniques with the same data and parameters. Fig. 15 and 16 depicts the graphical representation of real position and estimated position.

Table 7. Comparative Analysis of Position Estimation Techniques at Point (5, 5)

S. No	Position Estimation Techniques	Mean Error (m)
1	K-NN	1.2
2	Trilateration	0.7
3	Hybrid Trilateration	0.8
4	MinMax	1.0
5	**Proposed Hybrid MinMax**	**0.7**

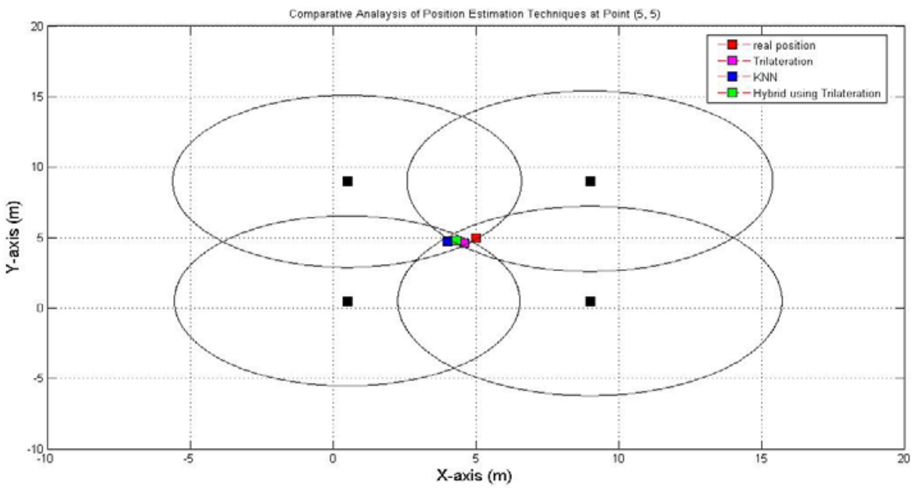

Fig. 15. Estimated position at (5, 5) using Trilateration, K-NN and Hybrid Trilateration

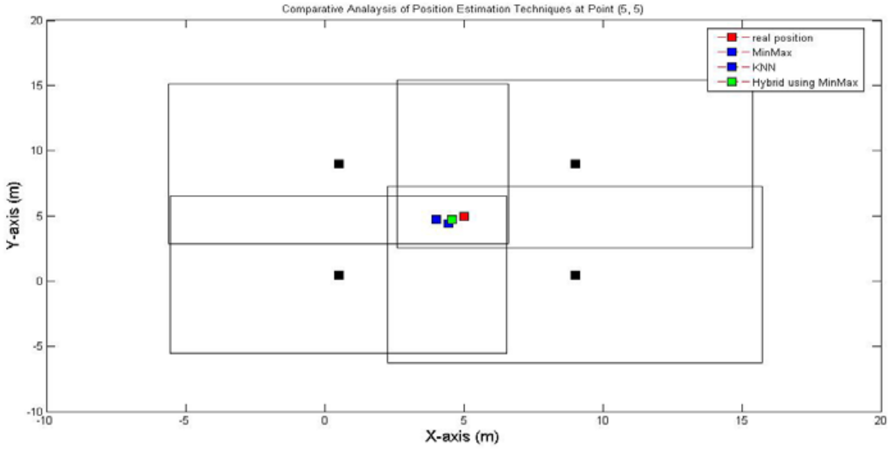

Fig. 16. Estimated position at (5, 5) using Trilateration, K-NN and Hybrid Trilateration

Table 8 shows average mean error of existing position estimation techniques and our proposed hybrid approach. The numerical results obtained from seven different points clearly indicate that, our proposed hybrid approach is better than existing position estimation techniques in terms of average mean error.

Table 8. Average mean error analysis

S. No	Position estimation Technique	Average Mean error (m)
1	K-NN	1.02
2	Trilateration	3.18
3	MinMax	2.12
4	Hybrid based on Trilateration	2.2
5	**Proposed hybrid based on MinMax**	**0.86**

5. Conclusion

This paper presented an extension of the existing hybrid position estimation technique, which integrates fingerprinting based K-NN approach with lateration based MinMax position estimation technique. The main contribution in this research work is the integration of two traditional position estimation techniques which estimated object position without considering channel modeling. Experimental results validated its accuracy compared to four different position estimation techniques using the same environment and RSSI readings. As discussed in section 3, our proposed hybrid position estimation technique is an extension of already developed hybrid position estimation technique. The main difference between existing and our proposed approach is the use of real time experimental data without the use of any kind of filtering or smoothing received signals. Another main difference is the adjustment and modeling of radio channels by optimizing radio propagation constants used in Trilateration and MinMax approach. After extensive simulation and modeling then we selected radio propagation constants for Trilateration and MinMax which improved further their position estimation accuracy but still our proposed hybrid approach performs better in terms of mean error.

Future research work is required to model the behavior of RSSI because we also observed variation in RSSI which affects position estimation. Therefore it is recommended to model the behavior of RSSI and its effect on distance estimation.

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Dr. Fazli Subhan obtained his M.Sc in Computer Science from University of Peshawar, KPK, Pakistan in 2003, and Ph.D. in Information Technology from Universiti Teknologi PETRONAS, Malaysia in 2012. Currently he is working as Assistant Professor in Department of Computer Science at National University of Modern Languages-NUML, Islamabad, Pakistan. His research interest includes, Indoor positioning systems, Wireless Sensor Networks, Machine learning and Software Engineering.

Shakeel Ahmed received Masters in Computer Science degree from Hazara University, KPK, Pakistan, in 2014. He is currently enrolled as an MPhil research scholar in Department of Computer Science at National University of Modern Languages (NUML), Islamabad, Pakistan. His areas of interest are Indoor Positioning Systems, and Wireless Sensor Networks.

Dr. Sajjad Haider received PhD in Computer Science from SZABIST, Islamabad and is working as Assistant Professor in the Department of Computer Science, National University of Modern Languages, Islamabad, Pakistan. He has also worked as Network Manager in National Institute of Electronics (RnD Organization under Ministry of Science & Tech.), Govt. of Pakistan. He has authored and co-authored many publications in reputed conferences and journals and served as paper reviewer in many International conferences and journals. His area of research includes Distributed Computing, Network Security, IoT, and Positioning Systems.

SAJID SALEEM received the Ph.D. degree from the Vienna PhD School of Informatics, Vienna University of Technology, Austria, in 2014. He is currently associated with the National University of Modern Languages, Islamabad. His research interests include image processing, computer vision, multispectral image analysis, and machine learning.

Asfandyar Khan received his M.sc Degree from University of Peshawar, Pakistan, in 2003 and received his Ph.D. degree from the Department of Computer and Information Sciences, University Technology PETRONAS Malaysia in 2011. During his PhD, he was working as Graduate Assistant in University Technology PETRONAS, Malaysia. He is currently working as a faculty member with the Department of Computer Science and IT, Institute of Business & Management Sciences (IBMS), University of Agriculture Peshawar, Pakistan. From 2011 to 2017, he has served as Assistant Professor in Department of Computer science, University of Science & Technology Bannu, Pakistan. His research interest includes Wireless Sensor Network, Topology Control Algorithms, Bioinformatics, and Medical Imaging System.

Dr. Salman Ahmed is currently working as an Assistant Professor in the CSE Department. He is a graduate of UET Peshawar (Pakistan), Universiti Teknologi Petronas (Malaysia) and University of Alberta (Canada). His research areas include multi-rate digital signal processing, optimal sampled-data control systems, multi-agent robotic systems, nonlinear control systems and networked control systems. He has received some prestigious awards in his academic career such as the university Gold Medal (UET Peshawar), Provost Doctoral Award (University of Alberta, Canada) and Research Assistantship (NSERC, Government of Canada), Graduate Assistantship (Universiti Teknologi Petronas, Malaysia). He is a Senior Member of IEEE.

Muhammad Numan received BS-Computer Science degree from Shaheed Benazir Bhutto University Sheringal (SBBU), Dir (U) KPK, Pakistan, in 2015. He is currently enrolled as an MPhil research scholar in Department of Computer Science at National University of Modern Languages (NUML), Islamabad, Pakistan. His areas of interest are Wireless Sensor Network, Internet of Things and Indoor Positioning Systems.