

Research Article

Kalman Filter-Based Hybrid Indoor Position Estimation Technique in Bluetooth Networks

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This paper presents an extended Kalman filter-based hybrid indoor position estimation technique which is based on integration of fingerprinting and trilateration approach. In this paper, Euclidian distance formula is used for the first time instead of radio propagation model to convert the received signal to distance estimates. This technique combines the features of fingerprinting and trilateration approach in a more simple and robust way. The proposed hybrid technique works in two stages. In the first stage, it uses an online phase of fingerprinting and calculates nearest neighbors (NN) of the target node, while in the second stage it uses trilateration approach to estimate the coordinate without the use of radio propagation model. The distance between calculated NN and detective access points (AP) is estimated using Euclidian distance formula. Thus, distance between NN and APs provides radii for trilateration approach. Therefore, the position estimation accuracy compared to the lateration approach is better. Kalman filter is used to further enhance the accuracy of the estimated position. Simulation and experimental results validate the performance of proposed hybrid technique and improve the accuracy up to 53.64% and 25.58% compared to lateration and fingerprinting approaches, respectively.

1. Introduction

Position estimation is the process which calculates object position with reference to some coordinate system. The position of object can be specified as absolute coordinates consisting of (latitude, longitude) and (x, y) coordinates or in a symbolic form such as room number 1 of the 2nd floor or specific location represented by name. Global positioning system (GPS) is the world first position estimation system which was originally developed by the US Department of Defense for military purpose in order to track the movement of enemies [1]. GPS was originally designed for navigation purpose to track the movement of objects from satellites. However, this technology is used for outdoor applications. The signals transmitted from GPS satellites do not penetrate inside the buildings; hence, it is not applicable for indoor environment [2]. In order to provide an alternate solution for indoor environment, the research community is focusing on low-cost and highly accurate indoor position estimation techniques which can be used for indoor environment [3].

The applications of indoor position estimation systems are different from GPS and not limited to navigation or object tracking. Also apart from this, GPS provides an accuracy from 5 to 10 meters, which is sufficient for outdoor application but for indoor environment, which comprises limited geographical area, and the accuracy required is not sufficient for indoor environment GPS [4]. Therefore, there is a dire need to develop an accurate indoor position estimation technique. In order to improve the accuracy, first of all it is necessary to identify the factors which significantly affect the accuracy of indoor position estimation systems theoretically and experimentally.

Bluetooth is a short-range wireless radio technology which uses Bluetooth-enabled electrical devices to communicate in the 2.45 GHz ISM (license-free) frequency band [5]. The communication changes the transmitting and receiving frequency 1600 times per second using 79 different frequencies. The range of Bluetooth network can be 0 to 100 meters. It is used to transmit both synchronous as well as asynchronous data. The bandwidth of Bluetooth network at

physical layer is 2.1 Mbit/s. In the domain of indoor position estimation, there are also other wireless communication standards which can be used for indoor position estimation such as wireless local area networks (WLAN) and ZigBee. However, in this paper Bluetooth technology is used for indoor position estimation due to its low cost, low power, and vast usage.

This paper presents the design of an extended hybrid technique for position estimation using the idea originally proposed in [6]. The hybrid technique combines the good features of fingerprinting- and lateration-based approaches in a simple and robust way. The proposed hybrid technique first uses fingerprinting method to calculate the nearest neighbors (NN) and then calculates the distance between each NN and anchor nodes using Euclidian distance formula. When the distance between each NN and anchor nodes is known, then the position of target node is calculated using trilateration technique. The calculated position is then given to Kalman filter to minimize the effect of noise. The next section elaborates design of proposed hybrid technique in more details. The remainder of this paper is structured as follow. Section 2 discusses the existing indoor position estimation techniques which is mainly focussed on fingerprinting- and lateration-based position estimation techniques. Section 3 presents the proposed extended hybrid position estimation technique. Section 4 presents experimental setup and data collection. Section 5 presents numerical results, and finally conclusion and future research directions are presented in Section 6.

2. Position Estimation Techniques

Positing estimation is the process to locate an object with reference to some coordinate system [2]. In RF-based wireless communication, position estimation is performed using RSS, which is the parameter used to estimate distance between mobile and anchor nodes or APs [7, 8]. The standard radio propagation models are used to convert RSS measurements into distance estimates [9]. There are generally two kinds of position estimation techniques, that is, lateration and fingerprinting-based position estimation techniques. Lateration-based position estimation techniques use the radio propagation model to convert RSS measurements to distance estimates. Fingerprinting-based position estimation techniques use the pattern matching approach to estimate the position of target node. The following section provides an overview of the lateration-based position estimation techniques.

2.1. Lateration-Based Position Estimation Techniques. Lateration-based position estimation techniques are among the widely used methods to estimate the location of the target [10–12]. Lateration-based position estimation techniques estimate the target position by measuring distance between the target and anchor nodes. The standard radio propagation model is used to convert RSS measurements to distance estimates [1, 13, 14]. The conversion process requires radio propagation constants. This process requires the

characterization of radio propagation constants specific to the environment where RSS measurements are collected. The distance estimation process strongly depends on the propagation constants. Once the distance estimates are known, then the position is estimated using equation of circles [15, 16]. The following subsection discusses the well-known lateration-based position estimation techniques.

2.1.1. Trilateration and Multilateration. The term trilateration refers to the process which estimates the target position based on measurements of distances from three fixed positions. In simple words, it is a technique which estimates the point of intersection from three fixed points [17]. Trilateration refers to measurement the distance from three anchor nodes of while multilateration measures the distance from more than three anchor nodes. Trilateration and multilateration are the mostly used lateration-based position estimation algorithms, which use the radio propagation model to convert RSS measurements to distance estimates. Trilateration algorithm computes the object position by taking the RSS measurements from at least three anchor nodes, and the locations of anchor nodes which measure the RSS are already fixed. For multilateration, more than three anchor nodes are required to locate an object. Both algorithms require distances from target to anchor nodes [18]. The distance d is obtained from RSS received at the anchor nodes. The standard radio propagation model is used to convert RSS readings from target nodes to distances for estimation of target position [19, 20]. The distance between anchor nodes and fixed points depends on the radio propagation constants, which are represented in the form of numerical values required to convert RSS measurements to distance estimates [21]. The mathematical equations of trilateration and multilateration are given as follows Let $A(x_1, y_1)$, $B(x_2, y_2)$, $C(x_3, y_3)$, and $D(x_4, y_4)$ be the anchor, and be $T(x, y)$ be the target node; then distance d_i between anchor and target nodes can be obtained using the following equation [22]:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}, \quad \text{for } i = 1, 2, 3, \dots, n - 1. \quad (1)$$

The solution set of (1) using minimum mean square error (MMSE), which is a technique designed to minimize the variance of the estimation errors is as follow:

$$A\vec{x} = \vec{b} \quad (2)$$

or

$$\vec{x} = A^{-1}\vec{b}. \quad (3)$$

The estimated target position lies at the point of intersection. In ideal conditions, the circles will intersect at only one point. However, the distance estimates contain noise which produces variations in RSS measurements. Therefore, estimated position of target node may not be the unique point of intersection. In that case the MMSE technique is used to estimate the coordinates of target node with minimum position estimation error [23].

2.1.2. Maximum Likelihood Estimation. MLE is a kind of lateration-based position estimation technique. MLE is based on the statistical consideration that the set of RSS measurements comes from anchor nodes containing noise. The main idea behind this approach is to minimize the mean square error (MSE) [24]. First of all distance estimate is derived from each of the anchor node using RSS measurement. Then the estimated target node defines an error e_i which is the error between the estimated and the actual distance using the following formula [25]:

$$e_i(x_0, y_0) = d_i - \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2} \quad \text{for } i = 1, 2, 3, \dots, n-1, \quad (4)$$

where (x_0, y_0) is the unknown position of target node and (x_i, y_i) is the position of i th anchor node. The detail mathematical formulation is discussed in Section 3.4. The main objective of MLE method is to minimize the mean error. This algorithm is mainly used for large-scale indoor positioning. Unfortunately for small scale the number of measures is normally limited; therefore, for three anchors the performance of this algorithm may be unsatisfactory.

2.1.3. MinMax Algorithm. MinMax is also a kind of lateration-based position estimation technique which provides a very simple trigonometric solution for position estimation. Like other lateration-based position estimation techniques, the position estimation process requires radio propagation model to convert RSS measurements to distance estimates. In MinMax algorithm a bounding box is constructed for each anchor node using the given distance generated from propagation model. The intersection of these bounding boxes from anchor nodes will give the position of target node. The bounding box is generated for each anchor node by adding and subtracting the estimated distance d from fixed anchor nodes [24, 26]. The mathematical formula for MinMax algorithm is as follows:

$$\left(\max_{(x_i-d_i)}, \max_{(y_i-y_i)} \right) * \left(\min_{(x_i+d_i)}, \min_{(y_i+y_i)} \right), \quad (5)$$

where (x_i, y_i) is the position of anchor node and d_i is the distance between anchor and target node. Compared to trilateration approach, the mean error of MinMax approach is better in real-time scenarios. However, the MinMax algorithm is also based on radio propagation model, and the distance estimations are obtained based on the radio propagation model. On the other hand, fingerprinting-based approaches provide better accuracy [24, 27, 28].

2.2. Fingerprinting-Based Position Estimation Techniques. In the domain of position estimation, fingerprinting is a technique which determines location of a mobile terminal based on the received signal fingerprints. It is also termed as a pattern matching technique, in which RSS measurements are matched with the stored set of RSS measurements. The position estimation based on fingerprinting technique has two operational phases, the online and offline phases. The

offline phase is the training learning phase in which the RSS *fingerprints*, which are the measured signal properties against respective location coordinates of reference points (RPs), are collected empirically to build up the fingerprint database *radio map* of the concerned indoor environment. During the online positioning phase, the measured signal quantities at target location are compared with the stored fingerprints using an appropriate database correlation method (DCM). The estimated location coordinates are derived from the RPs stored in the database, which have similar signal characteristics to the target location. The popular algorithm developed by the researchers for database correlation in location fingerprinting-based technique is K -nearest neighbors (K -NN) [29]. The fingerprints of K -NN-based position estimation technique consist of average signal strengths (SS) over a time period taken at RPs.

2.2.1. K -Nearest Neighbors (K -NN). K -NN is the most popular fingerprinting-based position estimation techniques which use RSS patterns to estimate the position of target node. The term K represents the numbers of the nearest neighbors to target node. All fingerprinting-based position estimation techniques estimate the target position in two stages, that is, offline and online stage. Similarly K -NN estimates the target position in two stages; that is, in the first stage it uses an offline database which contains the RSS pattern collected at known locations. In the second stage, which is position estimation stage, it calculates the position of target node based on K -nearest neighbors. The estimated position is average value of coordinates of the NNs. Hence, the position is estimated based on the predefined value of K . The value of K is not fixed corresponding to the number of NNs. For example, if the value of K is 2, then a total of 2 NNs will be calculated. Similarly if the value of K is n , then n number of NNs will be calculated [30–32].

The position estimation process is carried in two stages, that is, offline and online. Offline stage requires a database of RSS measurements collected at known locations. This offline phase is very time-consuming because the database generation requires a lot of effort to construct the database. That is, divide the whole area into equal size grids, collect hundreds of RSS measurements at each location, calculate the mean value, and store in the database. Once the database is generated, then position estimation is performed in the online phase. The online phase requires measurement of the RSS signals from the target node. It compares RSS patterns with stored database by measuring the Euclidian distance between the measured and stored RSS value against a predefined location. The Euclidian distance formula is used to estimate the distance between observed and stored RSS measurement. The distance between observed and stored RSS measurements is calculated and based on the value of K , which is fixed; K shortest distances are calculated which is termed as NNs. When the NNs are calculated, then the target position is estimated by averaging the coordinates of the NNs [1, 7].

K -NN is considered as the most accurate indoor position estimation technique for stationary objects, but due to time-consuming offline phase, it is rarely used for dynamically

changing environments. The RSS disagreements depend on the environment where the measurements are collected. The advantage of K -NN-based position estimation techniques is the high accuracy. On the other hand, there are two main limitations of K -NN. First of all, the time required to construct offline phase makes it impracticable for indoor environment. Secondly, the position of target node is always estimated by taking the average value of NNs. In case of large-size grid, the error will be large. For example, if the calculated NNs lie at corners of a 2-square meters grid, then estimated position will be the center point of grid, which is not always the case. Hence, position estimation error depends on the grid size. If grid size is small, then the corresponding time taken to construct the offline stage will be more [33]. Therefore, based on these two drawbacks, fingerprinting-based position estimation techniques are mostly not feasible for real-time position estimations.

2.3. Hybrid Indoor Position Estimation Technique. An attempt is being made to combine the features of fingerprinting and lateration-based position estimation techniques in order to enhance the position estimation accuracy. In [6] the author proposed a hybrid indoor positioning algorithm using WLAN. The hybrid technique estimates the target position in two steps. In the first phase it uses fingerprinting algorithm to calculate the NN, and in second stage the basic trilateration approach is applied to estimate target position. However, like lateration-based position estimation techniques, an empirical radio propagation model is used to convert RSS measurements to distance estimates. This is almost similar to radio propagation model. To convert RSSI measurements to distance estimates, the authors used empirical propagation constants for different sets of environment. The author then compared position estimation accuracy with trilateration- and fingerprinting-based K -NN approach. According to numerical results obtained, the position estimation accuracy is better than trilateration approach because target node lies near the NN. After this, the distance between NNs and target node is calculated based on the radio propagation model. The numerical results obtained using WLAN show that the proposed algorithm is better than basic trilateration approach however, the position estimation error of the proposed technique is greater than K -NN algorithm [34].

The hybrid approach performs better than trilateration approach due to limited range; that is, when the NNs are calculated, then it is assumed that target node would exist somewhere near the NNs. Therefore, position estimation accuracy of the proposed hybrid approach is comparatively better than basic lateration approach. However, the accuracy is still worse than K -NN.

In [35] the authors proposed another hybrid indoor position estimation technique which worked in three stages. In the first stage it generated a database which modeled the relation between distance and RSSI. Then based on generated database, the binary search algorithm was applied to estimate distance between anchor and target node. In the third stage it used basic trilateration approach to estimate the target position. The author claims that the performance

of the proposed hybrid approach is better than the basic trilateration, while the position estimation error is almost similar to K -NN [36]. The distance between target and anchor nodes, which are fixed, was estimated using a binary search technique. The position estimation process was carried out using the basic trilateration.

In summary, both of the hybrid approaches use trilateration approach at the end to estimate target position with assumption that position of the target node lies when circles intersect at one point only. The positioning error proves that the point of intersection is not unique or position of target node lies at the projected point of intersection. The limitation of this hybrid approach is the complex binary search algorithm to estimate distance between anchor and target nodes. The position estimation process is carried out in three instead of two steps. The hybrid approach uses the modified K -NN approach in which the NNs are calculated based on probability of each K elements. The numerical results show that the hybrid approach is comparatively better than trilateration and almost similar to K -NN.

2.4. Related Work. RADAR was the first RF-based position estimation technique for user tracking developed at Microsoft Research. RADAR is basically developed utilizing wireless local area networks (WLAN) using the most popular fingerprinting-based position estimation technique, that is, K -NN [30]. The idea of using RF for indoor position estimation is experimentally verified and tested in order to estimate the stationary object. According to the experimental results the accuracy for estimating the stationary object is around 3 to 4 meters. RADAR uses RSSI as a signal parameter for position estimation together with the radio propagation model. Furthermore, the authors opened the gate to develop an RF-based position estimation technique which can estimate the user within a building. The authors claimed that the position estimation accuracy can be further enhanced by minimizing the variations in RSSI measurements. Kotanen presented local positioning system based on received power level. The accuracy obtained using extended Kalman filter was 3.76 meters with radio propagation model. This technique is based on the RX power level and used EKF for position estimation [37]. Bluetooth technology is used for position estimation using connection-based RSSI. The measurements were then converted to RX power level by establishing a relationship using radio propagation model. The conversion process was performed based on the GRPR. The author finally suggested that the accuracy of the position estimation techniques can be improved if the variations in RSSI are minimized. In [38], the authors compared lateration- and fingerprinting-based position estimation techniques and outlined the major advantages and disadvantages. Furthermore, the authors concluded that fingerprinting-based position estimation techniques provide better accuracy than lateration-based techniques however, due to the time-consuming offline stage, it is rarely used for real-time position estimation where frequent changes in the environment occur. On the other hand, lateration-based position estimation techniques; namely, trilateration approach is very simple and efficient, but due to the radio propagation

model constants, the accuracy is comparatively lesser than fingerprinting-based position estimation techniques.

In [26] the authors compared the lateration-based position estimation techniques, namely, MLH, MinMax, and multilateration. The authors experimentally compared all the techniques and concluded that MinMax performs better than trilateration- and multilateration-based position estimation techniques. Furthermore, the authors performed simulations to see the effect of increasing anchor nodes on position estimation accuracy. According to the simulation-based numerical results, the accuracy of MLH increases with the increasing number of anchor nodes compared to MinMax and multilateration approach. However, according to the concluding remarks of authors, the accuracy still depends on selection of radio propagation constants and variations in RSSI. In [39], the authors discussed the fingerprinting-based position estimation techniques and focused on the offline stage of fingerprinting-based position estimation techniques. The authors modeled the user behavior in constructing an offline stage for fingerprinting-based position estimation techniques. The authors argued that user feed is necessary to generate an offline database, which is required to design a fingerprinting-based position estimation technique in order to minimize the time-consuming offline stage in fingerprinting-based position estimation technique. In [29], the authors extended the idea of Kotanen [37] to WLAN using extended Kalman filter for real-time position estimation in indoor environment. The authors compared trilateration and fingerprinting techniques with the proposed EKF-based indoor position estimation. The numerical results obtained from the proposed EKF-based position estimation technique confirm that the mean error of EKF is better than trilateration and worse than K -NN. The authors claimed that the mean error obtained using EKF is 3.75 meters in typical indoor environments.

In [24] the authors compared the most popular lateration-based position estimation techniques, namely, trilateration, MinMax, and Maximum Likelihood (MLH), using real-time RSSI measurements. The numerical results presented confirm that, lateration-based position estimation techniques strongly depend on radio propagation constants. The authors modeled the radio propagation constants using a mathematical approach and identified the radio propagation constants empirically. Furthermore, the computational complexity of each algorithm was also calculated. Based on the real-time RSSI measurements from IEEE 802.15.4 wireless sensor networks (WSN), it is observed that MinMax algorithm performs better than trilateration and MLH for average RSSI measurement. The authors also used the concept of multiple antennas in order to improve the accuracy of position estimation. Furthermore, authors conclude that the existing lateration-based position estimation techniques can be effectively used to develop a successful indoor position estimation system, if the variations in RSSI are minimized and radio propagation model constants are accurately used.

In [2, 9, 17, 40] the authors conclude that lateration-based approaches can be effectively used to design an indoor position estimation technique, if the radio propagation constants

and variations in RSSI measurements are minimized. In lateration-based position estimation techniques, the difficult stage is to model the radio propagation constants in such a way that the effect noise, which increases variations in RSSI, is minimized.

In summary, lateration-based approaches can be effectively used to design an indoor position estimation technique, if the radio propagation constants and variations in RSS measurements are minimized. In lateration-based position estimation techniques, the difficult stage is to model the radio propagation constants in such a way that the effect noise, which increases the variations in RSS, is minimized. The majority of these works consider IEEE 802.15.4 and its successor IEEE 802.15.4a. However, these two wireless personal area networking technologies are not yet widespread. Moreover, the 802.15.4a standard is specifically designed for positioning, but UWB-based commercial systems for positioning are still at a prototyping phase. On the other hand, most of portable devices and mobile phones include a Bluetooth technology, hence, a position estimation technique based on this technology could be easily deployed with no costs for the end users. Therefore, based on the above facts, positioning system based on Bluetooth technology provides a low-cost solution for indoor position estimation.

3. Design of Proposed Hybrid Indoor Position Estimation Technique

The proposed hybrid indoor position estimation technique calculates target position in two stages. In the first stage, NNs are calculated by comparing the RSS measurements, observed at target position, with the RSS stored in a database using K -NN algorithm. When the NNs are calculated, then distance between coordinates of NNs and anchors is calculated using Euclidian distance formula. In second stage, the position of target node is calculated using trilateration technique. The calculated coordinates usually contain noise due to the variations in RSS measurements. Noise is an unpredictable phenomenon, and its values are unknown, but it can be assumed that the values belong to a probability distribution function. In the proposed hybrid technique, the properties of noise are assumed to be Gaussian and normally distributed. As the noise is assumed to be Gaussian, Kalman filter is applied to estimate position of target node and removes the effects of Gaussian noise.

The proposed hybrid estimation technique possesses features of fingerprinting and lateration-based techniques. In fingerprinting-based technique the most popular approach is K -NN, which calculates K nearest neighbors, and position of target node is calculated by averaging the coordinates of NNs. In lateration-based technique, trilateration and MinMax are the most popular position estimation techniques [24]. In this paper, the proposed hybrid approach integrates K -NN with trilateration approach. Other than trilateration approach, MinMax can also be integrated with K -NN. However, the position estimation error using MinMax is greater compared to using trilateration-based technique. The reason behind this is the use of radio propagation model, which is used

to convert RSS measurements to distance estimates. Hence, trilateration-based hybrid approach is considered as a better approach. The main contribution of the proposed technique is to completely eliminate the use of a radio propagation model, which is normally used to convert RSS measurements to distance estimates. The proposed hybrid indoor position estimation technique is completely independent of the environmental conditions as it does not consider radio propagation model. The proposed hybrid position estimation technique minimizes the time-consuming offline stage by using a model-based radio map generation utility to build the RSS map during offline stage. To achieve this, the first step is to calculate experimentally the relation between RSS and distance. The RSS measurements are collected by varying the distance between master and mobile node at a fixed step size up to maximum range of the device used. In order to accommodate orientation of device, the measurements need to be collected in different directions. The average values of measurements for each step size are required. Each RSS measurement is stored in a table against its recorded distance. The RSS map is then generated based on the relationship model developed using RSS and distance relationship. The distance between each grid and AP is calculated using Euclidian distance formula.

3.1. Stage 1 (Offline Phase). In the offline stage of fingerprinting-based approach, the whole area is divided into equal size grids. The RSS samples are collected at each grid several times. The average of measured RSS values is calculated and stored in a lookup of table with their corresponding coordinates. If the area of position estimation system is 100 square meters, then the RSSI samples are collected at 100 locations from each anchor node. This approach is very time-consuming, and a lot of effort is required to build the RSS map. Any small change in the area can affect the accuracy. The limitations of fingerprinting-based approach are the time-consuming offline stage, which requires effort to construct the radio map. Therefore, for dynamic indoor environment, where frequent changes come, fingerprinting approach is rarely used [39]. In this paper, an attempt is made to minimize the time-consuming offline stage by an automatic map generation utility, which is based on the distance to RSS relationship. The following subsection elaborates automatic map generation utility.

3.2. Automatic RSS Map Generation Utility. In order to build an RSS map, a simple method is to measure the RSS measurements from a single anchor node in all directions depending on range of Bluetooth devices. The step size is fixed to 1 meter. A minimum of two devices are required to build the map. One is considered as master node and the second as mobile node. The master node is fixed, while the mobile node is moving. The experiment was conducted in lab at Department of Computer and Information system, Universiti Teknologi PETRONAS. The RSS samples were collected by moving the slave node away from master node with a fixed step size of 1 meter to a maximum of 10 meters. The process was repeated for all directions in order to consider the orientation of master

node. At each step, a total of 50 RSS measurements were collected. Three mobile devices of the same specifications were used simultaneously to save time. For each location the average value is calculated. Based on the mean RSS measurements, the RSS map can be generated using Euclidian distance formula. Consider an example of area of 10 square meters which have 100 locations. The distance between each grid, having known coordinates from the respective anchor nodes, can be calculated using Euclidian distance formula. The minimum value of RSS value is -90 dBm which is assigned to the maximum rounded distance of 13 meters. The Euclidian distances are converted to round numbers based on the significant digit rule. Once the relationship between distance and RSS is established, the RSS map can then be generated using Euclidian distance formula. The idea of automatic map generation is useful to large area when there are many anchor nodes and the radio map generation is difficult and time-consuming. The benefit of knowing this relationship can also be worthwhile in identifying accurate radio propagation constants. Furthermore, this relationship can also help to filter RSS values. Knowing the upper and lower boundary of RSS measurements, filtering and predicting RSS values in noisy environment can be worthwhile.

3.3. Online Phase. In this stage, the proposed hybrid position estimation algorithm uses the online stage of fingerprinting-based K -NN algorithm to calculate the NN based on filtered RSS received at anchor nodes. The NNs are calculated based on the shortest Euclidian distance between the RSS obtained at target node and the corresponding RSS in database stored in the offline stage. The formula for calculating the NN is expressed as follows:

$$d = \sqrt{\sum_{i=1}^n (s_i - s_{i'})^2}, \quad (6)$$

where d shows Euclidian distance, s_i represents RSS received at the target location, and $s_{i'}$ shows the corresponding RSS in database, while n is the number of anchor nodes for which the Euclidian distance is calculated. The number of NN represents value of K . If the value of $K = 3$, then only three NNs will be calculated. In the proposed hybrid position estimation technique, the minimum value of K must be greater than 2, the number NN required to estimate position of target node. For trilateration approach at least 3 NNs are required. The coordinates of the calculated NNs are already identified, and also the coordinates of anchor nodes are fixed in advance. Hence, the position of target node can be estimated using lateration-based approach.

3.4. Stage 2 (Position Computation Using Trilateration Approach) [26]. When the K number of NNs are calculated, the distance between their respective coordinates and anchor nodes can be calculated using (6). For example $NN_1(X_1, Y_1)$, $NN_2(X_2, Y_2)$, $NN_3(X_3, Y_3)$, and $NN_4(X_4, Y_4)$ are the nearest candidate points, and locations of anchor nodes are $AP_1(X_1, Y_1)$, $AP_2(X_2, Y_2)$, $AP_3(X_3, Y_3)$, and $AP_4(X_4, Y_4)$; hence, the Euclidian distance formula is

used to calculate distance between these points. When the distances are given, then trilateration approach can be used to calculate coordinates of the target location using the following equation for circle. Consider that (x_1, y_1) , (x_2, y_2) , (x_3, y_3) , and (x_4, y_4) are the AP location and (x, y) is the target node. Hence, the equation of circle becomes

$$(x_1 - x)^2 + (y_1 - y)^2 = d_1^2, \quad (7a)$$

$$(x_2 - x)^2 + (y_2 - y)^2 = (d_2)^2, \quad (7b)$$

$$(x_3 - x)^2 + (y_3 - y)^2 = (d_3)^2, \quad (7c)$$

$$(x_4 - x)^2 + (y_4 - y)^2 = (d_4)^2. \quad (7d)$$

$$\text{Similarly } (x_n - x)^2 + (y_n - y)^2 = (d_n)^2 \quad \text{for } i = 1, 2, \dots, 4. \quad (7e)$$

To solve the above simultaneous equations in order to find the position of target node (x, y) , subtract (7d) from (7a), (7b), and (7c), respectively:

$$\begin{aligned} (x_1 - x)^2 - (x_4 - x)^2 + (y_1 - y)^2 - (y_4 - y)^2 \\ = (d_1)^2 - (d_4)^2, \end{aligned} \quad (8a)$$

$$\begin{aligned} (x_2 - x)^2 - (x_4 - x)^2 + (y_2 - y)^2 - (y_4 - y)^2 \\ = (d_2)^2 - (d_4)^2, \end{aligned} \quad (8b)$$

$$\begin{aligned} (x_3 - x)^2 - (x_4 - x)^2 + (y_3 - y)^2 - (y_4 - y)^2 \\ = (d_3)^2 - (d_4)^2. \end{aligned} \quad (8c)$$

Rearrange (7a), (7b), and (7c), respectively, to get the linear equations:

$$\begin{aligned} 2(x_4 - x_1)x + 2(y_4 - y_1)y \\ = (d_1^2 - d_4^2) - (x_1^2 - x_4^2) - (y_1^2 - y_4^2), \end{aligned} \quad (9a)$$

$$\begin{aligned} 2(x_4 - x_2)x + 2(y_4 - y_2)y \\ = (d_2^2 - d_4^2) - (x_2^2 - x_4^2) - (y_2^2 - y_4^2), \end{aligned} \quad (9b)$$

$$\begin{aligned} 2(x_4 - x_3)x + 2(y_4 - y_3)y \\ = (d_3^2 - d_4^2) - (x_3^2 - x_4^2) - (y_3^2 - y_4^2). \end{aligned} \quad (9c)$$

Rewrite the earlier equation in matrix form as follows:

$$\begin{aligned} 2 \begin{bmatrix} x_4 - x_1 & y_4 - y_1 \\ x_4 - x_2 & y_4 - y_2 \\ x_4 - x_3 & y_4 - y_3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ = \begin{bmatrix} (d_1^2 - d_4^2) - (x_1^2 - x_4^2) - (y_1^2 - y_4^2) \\ (d_2^2 - d_4^2) - (x_2^2 - x_4^2) - (y_2^2 - y_4^2) \\ (d_3^2 - d_4^2) - (x_3^2 - x_4^2) - (y_3^2 - y_4^2) \end{bmatrix}. \end{aligned} \quad (10)$$

Hence, the linear system obtained in matrix form is as follows:

$$A * \vec{x} = \vec{b}. \quad (11)$$

Simultaneous linear equations can be solved using (11), where

$$\begin{aligned} A = \begin{bmatrix} x_4 - x_1 & y_4 - y_1 \\ x_4 - x_2 & y_4 - y_2 \\ x_4 - x_3 & y_4 - y_3 \end{bmatrix}, \quad x = \begin{bmatrix} x \\ y \end{bmatrix}, \\ b = \begin{bmatrix} (d_1^2 - d_4^2) - (x_1^2 - x_4^2) - (y_1^2 - y_4^2) \\ (d_2^2 - d_4^2) - (x_2^2 - x_4^2) - (y_2^2 - y_4^2) \\ (d_3^2 - d_4^2) - (x_3^2 - x_4^2) - (y_3^2 - y_4^2) \end{bmatrix}. \end{aligned} \quad (12)$$

Equation (11) can be solved using the following Equation (13)

$$\vec{x} = A^{-1} \cdot \vec{b}. \quad (13)$$

The solution of (13) exists only if $n = m$ and A^{-1} , where $n =$ number of equations corresponding to number of anchor nodes, and $m =$ coordinates of the target node. In case of $n > m$, then the system is considered as determined system of equations, which can be solved using minimum mean square error (MMSE) method. To minimize the distance error, which occurs due to various environmental conditions and over determined system of equations, MMSE technique is used to minimize the mean square error [26]:

$$\begin{aligned} \|Ax - b\|_2 \longrightarrow A^T Ax = A^T b, \\ x = (A^T A)^{-1} A^T b. \end{aligned} \quad (14)$$

The position estimation using trilateration approach assumes that target node lies at the point of intersection. In ideal condition the solution set of (13) will exist only if all the three or four circles intersect at only one point. Then the solution set will be existing, but in real-time scenarios, the circles do not intersect. Therefore, based on the real-time scenarios this hybrid algorithm is designed. As hybrid algorithm first calculates the NNs and then measures the distance between fixed anchor nodes and NNs using Euclidian distance, therefore it is clear that the circles will not intersect. Equation (13) calculates the position of target node based on projected point of intersection similar to basic trilateration approach. Normally in an area of 100 square meters, if there are four anchor nodes, there is only one point where all the circles will intersect. Therefore, the proposed hybrid indoor position estimation algorithm considers measuring distance between anchor nodes and NN. Hence, to minimize the effect of position estimation error, Kalman filter can be used to estimate position of target node [41].

3.4.1. Kalman Filter. Kalman filter is a standard filter developed by Rudolf Kalman in 1960 which removes noise from a series of data [42]. Kalman filter is widely used in control systems to estimate the state of a process in presence of noisy measurements. It estimates the states of a process by minimizing mean square error between the ideal and real system states. Kalman filter estimates the states of a process in two steps, that is, time update step (also known as prediction) and measurement update step (also known as correction). Let

a linear time-invariant system be represented by the following equations [43]:

$$\begin{aligned} X_{t+1} &= Fx_t + \text{noise}(Q), \\ Y_t &= Hx_t + \text{noise}(R), \end{aligned} \quad (15)$$

where F represents the system matrix, X represents state at time t , and Y represent, observations of at time t , where F and H represent the system matrices and Q and R are covariance of measurement noise. Consider that an object is moving with a constant velocity. The new estimated position is the old position plus velocity and noise. Hence the matrices become

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}. \quad (16)$$

As the position of target node is estimated using orientational space, therefore state size is 4 and observation size is 2, because we are only estimating the position of the target node. The measurement parameters of Kalman filter equations are tuned to adjust to the value of Q and R in order to minimize error in position estimation. After repeated processing, the numerical values adjusted are $Q = 0.01$ and $R = 11.6$. The numerical values are selected after extensive simulations studies in order to adjust the values based on the mean error between actual and estimated position.

4. Experimental Setup and Data Collection for Real-Time Analysis

An experiment was performed to collect the RSS measurement in order to verify the proposed hybrid position estimation technique. The location of testbed lies in second floor of Department of Computer and Information Sciences, Wireless Communication Lab. The dimension of lab is (14.20 m × 16 m) having an area of 227.2 square meters. Out of this, an area of (10 m × 10 m) was selected for the experiment. The devices which were used in the experiments are Bluetooth USB dongles from Cambridge Silicon having class 1 specifications. Four anchor nodes, which represented the master nodes, were used to collect RSS measurements. All the anchor nodes and mobile devices had the same specifications. The whole area was divided into grids having size equal to 1 square meter. A total of 100 grids were created. The data collector program was running simultaneously on all anchor nodes using BlueZ programming language. The Secure Shell (SSH) utility was configured using WLAN IP in order to synchronize the time for data collection. At each grid, the mobile device was placed in the middle of grid, and 100 RSS measurements were collected. The data collector program was programmed for collecting RSS readings using inquiry mode. The RSS samples collected by the data collector program were stored in an excel sheet. The average values for each grid were calculated. Figure 1 shows the experimental setup with known anchor and mobile nodes. The anchor nodes were fixed, and their actual position is necessary for the proposed hybrid approach to estimate the position of mobile

node. Out of 100 grids, the mobile nodes were placed in 10 random locations as shown in the experimental setup.

The following subsection discusses a comparative analysis using real-time RSS measurements obtained from the experiment conducted.

5. Results and Discussions

The performance of proposed algorithm was tested for 10 target nodes, the positions of which were already known. Based on the mean RSS values, position of mobile nodes were estimated using trilateration, MinMax, K -NN, and the proposed hybrid indoor position estimation technique. The mean error and standard deviation of position estimation error were calculated for analysis. Table 1 shows the mean error analysis of trilateration, MinMax, K -NN, and proposed hybrid indoor position estimation technique. The position of mobile client was calculated using 3 and 4 anchor nodes. The numerical results obtained from real-time RSS measurements, using sample size of 100 RSS measurements, show that the mean error of trilateration is 3.32 and 3.02 meters, for 10 target nodes, using 3 and 4 anchor nodes, respectively. The performance of lateration-based algorithms is greatly dependent on radio propagation constants. Therefore, for radio propagation constants Bluetooth channel modeler was used which identifies the radio propagation constants through a mathematical approach. The mean error observed for MinMax is 2.93 and 2.58 meters, while mean error of K -NN is 2.46 and 1.92 meters for 3 and 4 anchor nodes, respectively. On the other hand, mean error of the proposed hybrid approach is only 1.99 and 1.40 meters for 3 and 4 anchor nodes, respectively.

Table 1 shows standard deviation of position estimation error. The numerical results indicate that standard deviation of the proposed hybrid algorithm is better than K -NN; however, compared to trilateration for 3 anchor nodes it is greater. Generally increase in number of anchor nodes decreases the mean error and standard deviation proportionally. The proposed hybrid approach uses Kalman filter to minimize the effect of noise in dynamic environment. The Kalman filter assumes that the estimated position contains Gaussian noise; therefore, output of the proposed hybrid approach is given to Kalman filter to minimize the effect of Gaussian noise. The Kalman filter further minimizes mean error of estimated position. The Kalman filter improves the accuracy of the proposed algorithm by 18%. As Kalman filter minimizes the position estimation error by 18%, hence it is observed that estimated position contains noise. Hence, based on the real-time offline RSS measurements it is confirmed that the proposed hybrid approach performs better than trilateration, MinMax, and K -NN in terms of position estimation error.

5.1. Comparative Analysis Using Simulations. To investigate performance of the proposed algorithm, simulation was performed using three and four anchor nodes. The idea behind simulation-based analysis is to see performance of the proposed hybrid approach using random RSS samples in order to validate the position estimation accuracy for larger

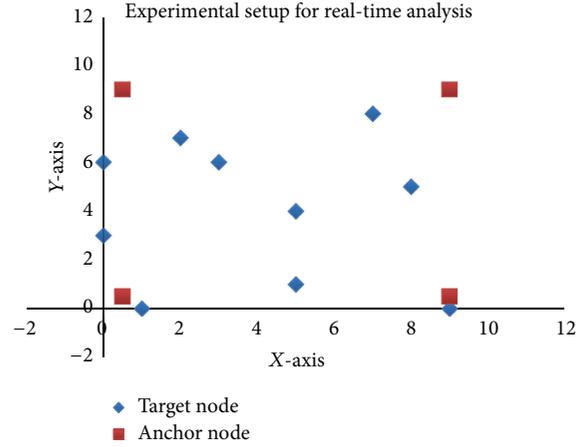


FIGURE 1: Experimental setup showing actual positions of anchor nodes and selected target nodes.

TABLE 1: Mean error (ME)/standard deviation (St. D.) analysis of trilateration, K -NN, MinMax, and proposed hybrid technique (sample size 100).

Actual position (x, y)	Trilateration (m)	MinMax (m)	K -NN (m)	Hybrid approach (m)
Anchors 3 (ME)	3.32	2.93	2.46	1.99
Anchors 4 (ME)	3.02	2.58	1.92	1.44
Anchors 3 (St. D.)	1.79	1.74	1.53	1.53
Anchors 4 (St. D.)	1.91	1.86	1.22	1.22

TABLE 2: Simulation studies: mean error (ME)/standard deviation (St. D.) analysis of trilateration, K -NN, MinMax, and proposed hybrid technique (sample size 100).

Actual position (x, y)	Trilateration (m)	MinMax (m)	K -NN (m)	Hybrid approach (m)
Anchors 3 (ME)	5.29	2.46	1.9	1.38
Anchors 4 (ME)	4.14	2.13	2.2	1.55
Anchors 3 (StD)	3.83	1.57	1.48	1.13
Anchors 4 (StD)	3.85	1.93	1.4	0.98

location. The simulation model actually depicts the variations occurring in RSS measurements in order to validate the performance of the proposed hybrid position estimation technique on large scale. According to initial experimental observation, the standard deviation of RSS measurements obtained from a stationary object is 10 dBm. Hence the methodology adopted to test performance of the proposed

technique follows real-time standard deviation of RSS. Therefore, target node is placed in middle of the anchor nodes. The actual position of target node is stored, and a total of 100 RSS random samples were generated with a standard deviation of 10 dBm. The simulation was performed using three and four anchor nodes. The position of the anchor nodes was not fixed. The simulation was repeated 3 times by changing the actual position of the anchor nodes, and each time the mobile nodes were assumed to be in the middle of the anchor nodes. The statistical parameters that were used for simulation results were mean error and standard deviation of the position estimation error. The random RSS measurements, that were generated, ignored the communication holes. The following subsection presents a comparative analysis of the proposed hybrid approach with the K -NN, trilateration, and MinMax. Table 2 shows the simulation results of trilateration, MinMax, K -NN, and proposed hybrid approach using 3 and 4 anchor nodes. As position of target node lies in the middle, therefore mean error of trilateration and K -NN algorithm is low. However, it is clear from Table 2 that the mean error of proposed hybrid approach is better than trilateration, MinMax, and also K -NN. As the proposed algorithm uses Kalman filter to minimize the Gaussian noise, therefore compared to K -NN, the mean error of proposed algorithm is better. In general, the performance of lateration-based position estimation technique increases with the increase in number of anchor nodes, but in this case the performance of lateration-based algorithm using 3 anchor nodes is better. The reason behind this is position of the target node, and also the variation is constant for all anchor nodes. According to the literature studies, the performance of MinMax algorithm is better than trilateration approach [24, 44]. Table 2 also confirms that the mean error of MinMax is lesser than trilateration approach; however, it is greater than K -NN approach. In case of increasing number of anchor nodes, the accuracy increases proportionally, but the case is different in simulations due to the fixed radio propagation constants. Hence, the mean error of MinMax for 3 anchor nodes is better than 4 anchor nodes. Therefore, based on 100 random RSS measurements with a standard deviation of 10 dBm, it is

TABLE 3: Mean error analysis of trilateration, K -NN, and proposed hybrid technique (sample size 10).

Actual position (x, y)	Trilateration (m)	K -NN (m)	Hybrid approach (m)
(0, 5)	2.00	2.07	1.65
(2, 3)	3.62	2.55	2.12
(2, 5)	1.76	1.17	0.89
(5, 0)	2.51	0.75	0.68
(5, 6)	0.53	1.45	1.44
(3, 7)	2.15	1.67	1.31
(8, 8)	1.70	1.77	0.63
(0, 8)	3.78	1	0.79

observed that the position estimation error of the proposed hybrid approach is lesser than K -NN, trilateration, and also better than MinMax. The performance of proposed hybrid technique is analyzed using two methods, that is, using offline and online RSS measurements. Offline RSS measurements mean that the RSS measurements were collected at known locations and the mean value was calculated from 100 RSS samples at each location. The performance of the proposed approach is then analyzed using mean RSS value calculated during offline phase.

While online RSS measurements mean that for each and every real-time RSS measurement obtained, the performance of proposed hybrid approach is tested and compared with trilateration, MinMax, and K -NN. In this way, the real-time RSS fluctuations are also considered.

The above numerical results demonstrate the performance of the proposed hybrid approach using offline RSS measurements based on mean RSS value. The sample size of offline measurements was 100. The following subsection presents a comparative analysis using real-time online RSS measurement for every measurement observed.

5.2. Comparative Analysis Using Real-Time RSS Measurements (Online). In order to check the performance of the proposed algorithm based on real-time online RSS measurements, an experiment was performed, and the position of target node was calculated based on online RSS measurements. The experimental setup was the same, using the same set of Bluetooth dongles. Eight random positions were selected, and the RSS measurements were observed using SSH() command to remotely access the client computers [45]. The time synchronization is important for the client computers; therefore, the data collector program was executed using LinuxSSH() command for 15 seconds. During this time, 10 samples were recorded. The RSS measurements contained the effect of noise; therefore, the measurements were filtered using extended gradient RSS predictor and filter.

Tables 3 and 4 represent a comparative analysis of proposed hybrid approach with trilateration and K -NN. A total of 8 positions were selected for mobile node, and the RSS measurements were observed for 15 seconds at each position. Table 3 shows the actual positions of mobile client. The mean error and standard deviation of the estimated position error

TABLE 4: Standard deviation of error in trilateration, K -NN, and hybrid algorithm (sample size 10).

Actual position (x, y)	Trilateration (m)	K -NN (m)	Hybrid approach (m)
(0, 5)	2.38	1.19	1.14
(2, 3)	1.57	1.14	0.77
(2, 5)	0.83	0.68	0.76
(5, 0)	1.47	0.81	0.74
(5, 6)	0.11	1.05	0.83
(3, 7)	1.93	1.82	1.07
(8, 8)	1.37	0.29	0.43
(0, 8)	1.27	0.39	0.41

were observed. In Tables 3 and 4, column 1 represents the actual position of target node, and column 2 represents the mean and standard deviation of trilateration. Similarly in Tables 3 and 4, column 3 represents mean and standard deviation of the proposed hybrid approach. According to real-time online numerical results using 4 anchor nodes, the mean error of proposed hybrid approach is better than trilateration and K -NN for each point except the middle point, that is, (5, 6). When mobile node lies in the middle of anchor nodes, then it is possible that at certain places the point of intersection is more closer than hybrid approach. As the proposed hybrid position estimation technique assumes that the point of intersection is not unique, therefore based on this assumption the position of target node is estimated by measuring the distance between calculated NN and Anchor nodes. Therefore, if the target node is placed at the center, then the position estimation accuracy is better than the proposed hybrid position estimation approach.

Table 4 shows the standard deviation of trilateration, K -NN, and proposed hybrid approach. In case of real-time online observations, the fluctuations in RSS measurements exist; therefore, it is possible that standard deviation of the proposed hybrid approach is more than the trilateration and K -NN.

Based on the numerical results presented in Tables 3 and 4, it is observed that performance of the proposed hybrid technique is better than trilateration and K -NN.

5.3. Comparison of the Proposed Hybrid Technique with Trilateration Approach. The performance of the proposed hybrid approach is further compared with trilateration approach in order to visualize the calculated position. As discussed earlier, trilateration approach assumes that target position lies at the point of intersection. The radius of circle is equal to the distance between anchor and target node. But in real-time scenarios, due to noise in RSS measurements, the circles do not intersect at one point. Therefore, the position of target node lies at the projected line of interaction from three circles. In case of hybrid approach, first of all the NNs are calculated, and then the distance between NNs and anchor nodes is calculated using Euclidian distance formula. The circles are drawn with the radii equal to the distance between NNs and anchor nodes. In all the figures the black square (if printed in

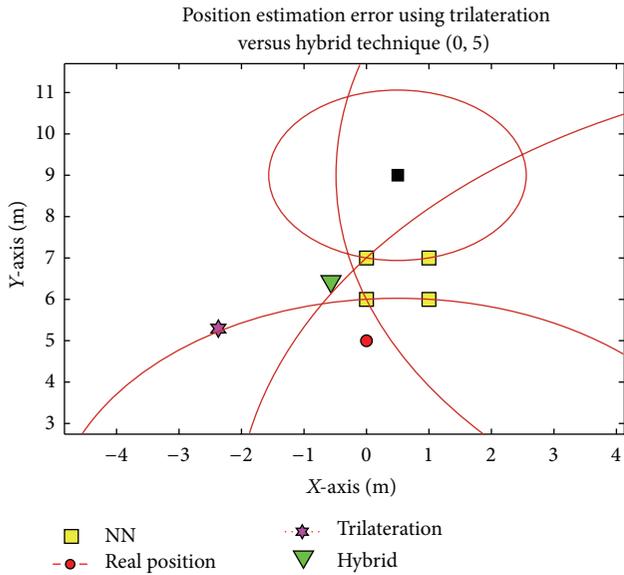


FIGURE 2: Position estimation error of trilateration and hybrid technique (0, 5).

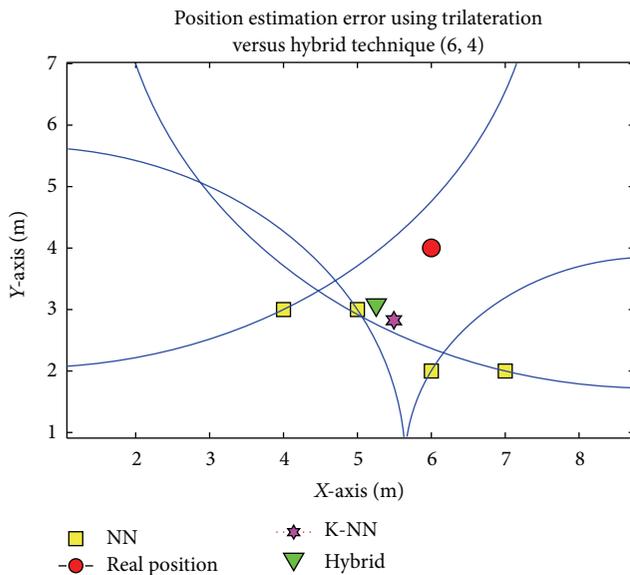


FIGURE 3: Position estimation error of trilateration and hybrid technique (6, 4).

color) represents the center of the circle. The proposed hybrid approach ensures that the estimated position will be near to NN. Following is the explanation of each case.

Figure 2 represents the case when actual position of node is at (0, 5). As indicated in Figure 2, the actual position lies at point (0, 5), the calculated NNs are very close to the actual position, and hence the estimated position using hybrid approach is also near to NN, that is, the projected point of intersection. The circumference of each circle is passing through NN. Therefore, the point of intersection and actual position are closer to each other. As shown in Figure 2, the estimated position using trilateration approach is away

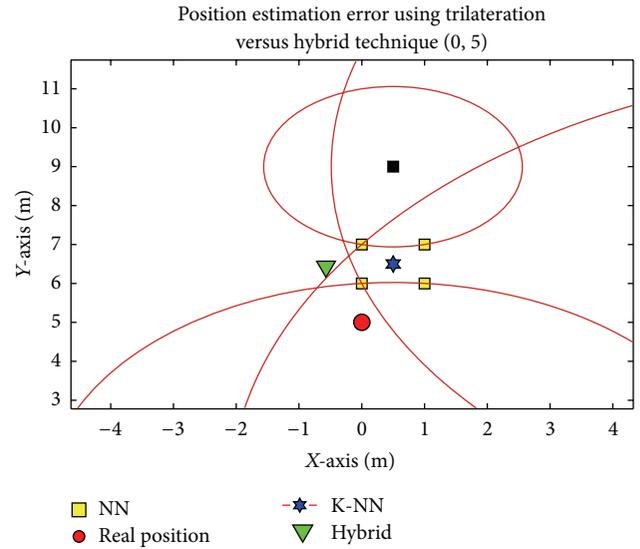


FIGURE 4: Position estimation error of K-NN and hybrid technique (0, 5).

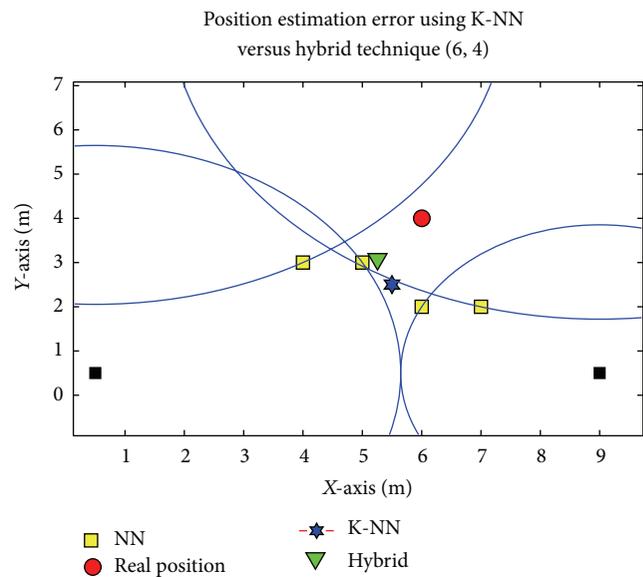


FIGURE 5: Position estimation error of K-NN and hybrid technique (6, 4).

from the actual position. It means that in case of trilateration the projected point of intersection lies away from the actual position. The calculated mean error of trilateration approach is 2.13 meters, while the mean error of proposed hybrid approach is 0.77 meters. Figure 3 shows the case, when the actual location of mobile device is (6, 4). As the point lies in the middle of the anchor nodes, so position estimation error is better than K-NN approach. The mean error of trilateration approach is approximately equal to the proposed hybrid approach, that is, 1.69 and 1.66 meters, respectively. Figure 3 shows that the proposed hybrid approach estimates the position of mobile node somewhere near to NN. This is the scenario where trilateration algorithm performs better.

Figures 2 and 3 show the comparative analysis of proposed approach with trilateration approach. The following subsection presents a comparative analysis of the proposed hybrid technique with K -NN.

5.4. Comparison of the Proposed Hybrid Technique with K -NN. The position estimation error is visualized in order to analyze the difference between K -NN approach and proposed hybrid approach. Figures 4 and 5 present the position estimation error of K -NN and proposed hybrid technique, when actual positions of the mobile node are at (0, 5) and (6, 4). As discussed earlier, K -NN algorithm computes position of target node by averaging the coordinates of NN. Figure 4 shows estimated position using K -NN approach within the middle of NN. Therefore, in case of 1 or 2 meters grid size, the position error depends on size of grid. For example, if size of grid is 2 square meters, then the target node lies at the corner of 2 square meters grid instead of center location. Figure 4 clarifies the scenario, in which the estimated position is at the middle of the anchor nodes. However, the proposed hybrid approach estimates target position based on projected point of intersection, which can be any where near NNs. The calculated mean error of the proposed hybrid approach is 0.80 meters, while the K -NN is 2 meters. Figure 5 shows the case when actual position of the mobile node is at (6, 4). This time the position estimation error is more than trilateration approach because actual position lies in the middle of anchor nodes. The mean error of K -NN is again 2 meters, which is greater than trilateration and the proposed hybrid approach.

6. Conclusions and Future Work

This paper presented an extended Kalman filter-based hybrid indoor position estimation technique. The main objective of this approach is to increase the accuracy by minimizing the mean error. Other than this, the existing gradient RSSI predictor and filter is modified based on the most recent RSS measurement in order to predict and filter the RSS in presence of communication gap termed as communication hole. In proposed hybrid approach, the filtering process is performed as a preprocessing tool to handle the variations occurring in RSS due to environmental conditions. The numerical and graphical result presented in this paper concludes that the proposed extended Kalman filter-based hybrid indoor position estimation technique improves the position estimation accuracy compared to the trilateration, MinMax, and K -NN. The novel idea presented in this paper is the elimination of radio propagation model for distance estimation which significantly improves the position estimation accuracy. A standard Kalman filter is used after the trilateration approach which further enhances the position estimation accuracy.

The proposed hybrid positioning algorithm can be easily implemented on other wireless platforms such as WLAN or ZigBee standard. The idea of automatic map generation can further simplify fingerprinting-based approach and also the time to build the radio map. Future research is needed to test the hybrid approach on other platforms and on large scale.

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