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GRNN and KF framework based real time target tracking using PSOC BLE and smartphone

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ABSTRACT

With the advancements in the mobile devices having Bluetooth Low Energy (BLE) capability, the BLE based indoor target localization is the recent trend. The majority of indoor localization methods generally rely on traditional simple techniques such as trilateration or angulation. However significant localization errors are involved with these techniques due to highly nonlinear relationship between RSSI and distance because of issues such as NLOS, multipath propagation. The Generalized Regression Neural Network (GRNN) with a one pass learning capability, is well known for its ability to train quickly. This paper proposes an application of GRNN as an alternative to these traditional techniques to obtain first location estimates of moving person using a hybrid network of PSOC BLE nodes and smartphone, which are further refined using Kalman filtering (KF) framework. Two algorithms namely, GRNN + Kalman filter and GRNN + Unscented Kalman filter are proposed in this research work. The GRNN is trained with the RSSI values from PSOC BLE nodes at various locations and the corresponding actual 2-D locations of the given monitoring area. The real time experiments prove the efficacy of the proposed algorithms over the traditional approach in the context of NLOS, multipath propagation.

1. Introduction

Several technological enhancements in radio frequency (RF) technology and embedded systems enabled the use of wireless sensor network's (WSN's) for various of new positioning, tracking and navigation applications [1–3]. Indoor localization and tracking of an individual with high level of accuracy is a very important as it can trigger variety of new applications, especially in location based services (LBS). Although, global positioning system (GPS) can offer a positioning accuracy of less than 3.5 m in the outdoor environment [4]. However, the GPS stops working on indoors environments. Therefore more efforts are being applied on GPS-less solutions which must be economical, lightweight, and easily deployable and low powered for indoor target localization and tracking. The dominant wireless technologies to realize such systems are RFID [5,6], Bluetooth [7,8] and Wi-Fi [9,10], each of which are with pros and cons.

Among these, WiFi is widely accepted because of its availability at many places and possibility of long range communication as compared to the other solutions. WiFi based fingerprinting has been the major technique for the RSSI based localization [9]. In [9], a detailed study in BLE based fingerprinting along with a quantitative comparison with WiFi based fingerprinting is provided. The fingerprinting based systems create a large database of RSSI measurements (called as RF fingerprints) between wireless devices and access points. By comparing new RSSI measurements with the fingerprint database, the corresponding new location can be estimated. The authors conclude that the drawback of WiFi based localization such as: 1) WiFi infrastructure is intended for network communication and therefore placement as well as density of access points are not generally not for the given localization problem, 2) Additionally it is a power hungry protocol. Although being low cost, RFID [6] does not have enough bandwidth for large scale LBS as well as it has short communication range (typically below 1 m). As an alternative to WiFi and RFID, the use of BLE based devices in indoor localization is the recent trend [7,8]. BLE is very cost effective with typical communication range of 20–30 m and readily available on numerous devices, especially in smartphone and laptops. It has been observed that the BLE RSSI measurements has more stability than the WiFi [9,10]. The main advantage of BLE based localization is that BLE nodes are usually easy to deploy, low powered and cheaper than Wi-Fi access points [5,6]. Being a small device with an antenna for emitting the RF signals, they can be used as WSN [11,12]. As the BLE technology uses short wavelength radio signals, data transfer is affected by number of factors, such as NLOS, multipath.

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Generally the algorithms based on RSSI use the traditional techniques such as trilateration/angulation for localization. In RF based solution, if the distance between two wireless nodes is used, it is termed as the trilateration based approach, whereas if the angle between two nodes is used, then it is termed as the angulation based approach. In practice, both trilateration and angulation methods suffer with the drawback of imperfect computations of distances and angles respectively, due to uncertain noise involved in RSSI measurements because of issues such as multipath propagation, NLOS [2,3]. Also it is observed that the position accuracy suffers due to involvement of uncertain noise in RSSI measurements due to NLOS and multipath [13]. To deal with such problems, the localization methods which are capable of filtering out the measurement noises are desired. The Artificial Neural Networks (ANN's) are capable of handling noisy measurements as well as able to learn and generalize very quickly. They are widely used when the system input-output mapping is uncertain [14,15]. Unlike the KF, in ANN based localization and tracking methods, there is no need of prior knowledge of the noise distribution [16,17]. Which is why ANN based localization solutions are very promising [18].

This research work introduce a high precision tracking system that makes use of WSN built with cheap PSOC BLE nodes and smartphone. The position of a moving person (target) is tracked using noisy RSSI measurements from PSOC BLE nodes for a dynamic indoor environment, especially in the context of issues such as NLOS, multipath propagation and presence of obstacles. A novel aspect of our approach is the design of a GRNN based framework to provide first location estimate during target motion which is then further improved with the help of KF framework. The inclusion of the GRNN framework in the proposed tracking system successfully deal with high nonlinearity in RSSI's- target location. The structure of the paper is as follows. In Section 2, we briefly review the most relevant works that address target localization and tracking techniques for target tracking WSNs. Section 3 presents the framework of localization of mobile target using general regression neural network. Section 4 describes the KF framework to be used to further refine the GRNN based target location estimates. The system design and Performance evaluation of the proposed algorithms through extensive simulation experiments are presented in Section 5. Finally, conclusions and future work are highlighted in Section 6.

2. Related work

A number of localization and tracking systems based on BLE based wireless nodes have been recently proposed in literature for indoor tracking and other location based services (LBS). Existing BLE technology based localization approaches can be broadly categorized as: trilateration with a suitable propagation model based [19–21] and fingerprinting based [9,22,23]. In trilateration, distances are estimated using the geometry of triangles and a suitable signal propagation model is used to calculate. On the other hand, in fingerprinting based approach a prior radio map is constructed using field measurements. The main drawback of first approach is the problem of selection of the appropriate signal propagation model as well as fine calibration of its parameters to perfectly characterize the given indoor environment. With the second approach the accuracy of the system is greater compared the first, but a lot of time is required for the characterization of the environment. Furthermore, it is very susceptible to any change in the given indoor environment as well as large number of fingerprint locations is must for the sufficient performance accuracy. The drawbacks of both the approaches can be smoothened by adding some other suitable technique such KF [19,24,25] or PF [22,23] to deliver improved performance for the given indoor environment.

The authors of [19] combine the propagation model with the extended KF (EKF), and reach an error rate of 2.56 m, improving the localization accuracy with sparse beacon deployment. The authors in [24] proposes a novel three-step cascaded KF (CKF) to accurately estimate the target location in the presence of the environmental dynamicity, using the BLE and an inertial measurement unit (IMU) to deal with the multipath and NLOS issues. The localization is achieved by fusing the acceleration measurements from the IMU and the trilateration estimation from the BLE. The estimated position is further refined with the Rauch-Tung-Striebel smoother. The results show that the proposed algorithm delivers high localization accuracy in the presence of the outliers due to the dynamic environment. In [22], the authors developed a mobile application using wireless communication via beacon devices. A fingerprinting technique is used to perform indoor localization, after which a PF is employed to refine the location estimates further to reduce the ambiguity in the measurements. The work in [23] present a robust tracking system named 'InLoc', in which initial location of the user is estimated with the help of RSSI values obtained from all the visible beacons deployed. The system utilizes available building floor maps to avoid the need of specially designed vector maps. This vector map can also be used in both PF based IMU tracking, and routing. The authors in [20] propose a BLE based tracking system in which KF is used to filter the noise in RSSI measurements along with the trilateration. Although the experiments conclude that trilateration and KF based fusion shows better tracking performance with an error below 0.75 m, but the considered monitoring area for experiments is pretty small. Additionally they place the BLE modules very close to each other, increasing the final cost of the solution. The authors in [25] have proposed three different techniques to enhance the precision of a BLE indoor positioning system: channel diversity, KF and a weighted trilateration method. They use KF as a way to mitigate the effects of unlikely or impossible location estimations due to wrong RSSI measurements, so that we can track the location of a device with more precision. The results conclude that the combination of all these techniques raises tracking accuracy by 43.47% in a medium sized room and by 38.33% in a big sized room as compared to accuracy without using any of the proposed techniques.

That means the application of KF or PF can improve the BLE based target localization and tracking accuracy, however the choice of the use of KF or PF must be made depending upon the amount and noise distribution in the process and measurements as well as application requirement [26,27]. These surveys on Bayesian filter implementations for location estimation in [26,27] conclude that though PF in contrast to KF, is superior in handling the nonlinearity in measurements as well it is applicable to non-gaussian and multimodal distribution, however the computational complexity of PF is predominantly higher than KF. Additionally, the large computational workload in PF is generally not suitable for giving target location estimates in a timely manner so as to suit to real time tracking applications. Although KF is a widely used algorithm for estimating the state of the moving target using RSSI measurements, the measurement noise of wireless tracking systems cannot be modeled as the Gaussian distribution due to the frequent outliers from the multipath and the NLOS. To accommodate for the changes in the dynamic conditions in the given indoor environment, the unscented Kalman filter (UKF) has been proved to be a better alternative to the standard KF and the extended Kalman filter (EKF), especially in the context of system nonlinearity [17,28,29]. In our previous work [29], a modified KF based approach of real time 2-D tracking of single moving target in WSN, is proposed to deal with uncertainties in measurement noises and abrupt changes in target velocity. These two algorithms namely, RSSI + KF and RSSI + UKF refine the estimates of the traditional RSSI based approach. Their research concludes that the RSSI + UKF algorithm better handle the

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dynamicity in the wireless environment due to the abrupt variations in target velocity, the limited set of RSSI measurements. However, the presented approach is not in the context of the BLE based indoor localization.

Though the inclusion of KF or PF framework in the BLE based indoor target tracking improve the localization accuracy, however issues the NLOS and multipath conditions have not yet been addressed fairly. That means the location estimation accuracy can't be guaranteed always with the help of KF or PF framework, if the wireless environment is highly dynamic in nature. That is why the ANN based approach can be more suitable in this context because of the ability of ANN to learn and generalize dynamic wireless environments very quickly. Very few efforts are made to employ ANN in BLE based indoor localization [30,31]. An important work is proposed in [30], in which a previously trained neural network is used to calculate the target position with the help of Bluetooth transmitters. The proposed approach is based on fingerprinting and requires two phases: an offline phase where multiple neural networks are trained using collected RSSI values, and an online phase where the system is actually being used. A neural network is selected based on the orientation of the mobile target. However the carried out research involves the computationally heavy training phase and additionally the proposed solution may not work satisfactorily on sparse data sets. The probabilistic neural network (PNN) can be good choice because of its ability to work with only few training samples as compared to the other popular neural architectures such as BPNN [32]. Additionally being very flexible, new information can be added immediately with almost no retraining. The GRNN is a highly parallel neural network which falls under PNN category [33,34]. Very few researchers have applied GRNN in localization and tracking problem [35–37]. It requires very few training samples as well as it is one-pass learning architecture. In [37], the authors proposed a GRNN based algorithm GRNNα, which is used for target location estimation. The proposed algorithm showed the capability of estimating target's position as successful as like KF algorithm in the context of zero mean Gaussian measurement noise. The performance of the GRNNα and KF algorithms are compared using simulated take-off and landing routes of aircrafts.

The main focus of this research work is to utilize the capability of both the GRNN and the KF framework simultaneously in the BLE based target tracking problem to address the dynamicity of the given indoor environment. As discussed in the previous section, the GRNN architecture gives the first location estimate of the moving target which is then further refined with the help of KF framework in this research work. Two target tracking algorithms are proposed namely, GRNN + KF and GRNN + UKF. The GRNN once trained with the pair of RSSI measurements and corresponding actual target position, can give position estimates of moving target directly. The main contributions of this work are summarized as follows:

- We developed the GRNN and KF based framework to track single moving target with high precision using BLE beacons and smartphone in the context of environmental issues such as NLOS, multipath propagation and the presence of obstacles
- Being a range free tracking system, the proposed approach successfully provide the solution to cope up with the problem of RSSI-distance nonlinear relationship encountered in the range based techniques such as trilateration.
- We advocate the use of the GRNN approach as an alternative to traditional localization techniques such as trilateration and angulation.

3. Localization of mobile target using general regression neural network

The GRNN is basically a kind of probabilistic neural network, commonly used for a variety of problems like prediction, control, plant process modeling or general mapping problems [33,34]. Being a variation of RBF neural network with capability of one pass learning, it can converge to the underlying regression surface very quickly. It is well known for its ability to train quickly to solve any regression problem (linear or nonlinear). The GRNN work by measuring how far a given sample pattern is from patterns in the training set.

The GRNN consists of input layer, pattern layer, summation layer and output layer as shown in Fig. 1. The role of the input layer is to receive the input signals, whereas the pattern layer does the necessary mapping of the applied input data with training data set. For the GRNN, the number of neurons in the hidden layer is usually equal to the number of patterns in the training set. The outputs of the pattern layer nodes are multiplied with appropriate interconnection weights which all are then added together at the summation layer. The output layer nodes are responsible for providing the required results on the applied input dataset.

Basically the GRNN can estimate values of M (dependent variables) for any input set of N (independent variables) in the short time determined by the propagation time the input takes to pass though the network. In this work, M is considered to be the estimated 2-D location of moving target while N represent four RSSI values from four anchor nodes as shown in Fig. 1. In GRNN, the estimated $M(N)$ (i.e. 2-D Target Location) is estimated as follows.

$$M(N) = \frac{\sum_{i=1}^{n} M_i \exp\left(\frac{-D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(\frac{-D_i^2}{2\sigma^2}\right)} \quad (1)$$

$$D_i^2 = (N - N_i)^T.(N - N_i) \quad (2)$$

The σ is the GRNN smoothing factor and n is the number of samples in the input data. It is believed that the selection of proper smoothing factor is important to the accuracy of both PNN and GRNN. The high smoothing factor raises the network's generalization ability to the problem at hand, and vice a versa. Therefore care has to be taken decide the appropriate value of the smoothing parameter.

The estimate $M(N)$ is the weighted average of all the sample observations M_i, where the weight for each observation is the exponential of the squared Euclidian distance between sample $N$and N_i. The GRNN network in MATLAB environment can be created by 'newgrnn' function [38]. In the carried out research work, the inputs to GRNN architecture are the RSSI values of the signals received from the anchor nodes at a specific time instance, while the output of GRNN represent the estimated x and y coordinates of the mobile node at that time instance as shown in Fig. 1. The designed GRNN architecture for the proposed tracking system is trained with the set of 70 samples and is successfully validated with a blind testing data set of 35 set of RSSI samples.

4. Kalman filtering framework

4.1. Standard Kalman filtering

The target motion model for the standard KF can be given as [16,17]:

$$X_k = AX_{k-1} + Bu_{k-1} + w_{k-1}, \quad (3)$$

Where,

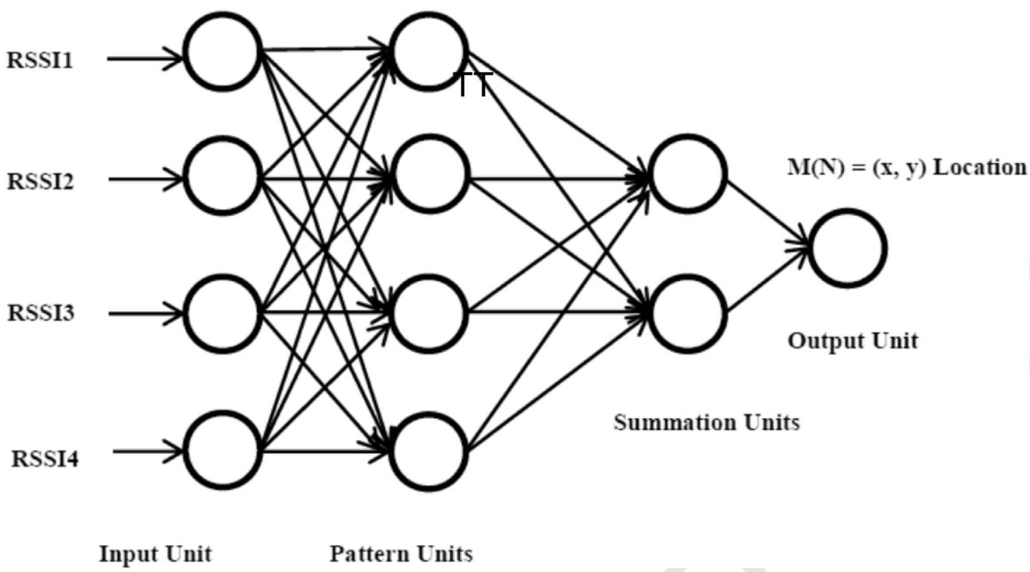

Fig. 1. The developed GRNN architecture for the proposed target tracking algorithms.

- X_k is the state vector containing the terms of interest for the system (e.g., position, velocity, acceleration) at time k.
- u_{k-1} is the vector containing any control inputs (steering angle, throttle setting,..etc).
- A is the state transition matrix which applies the effect of each system state parameter at time $k-1$ on the system state at time.
- B is the control input matrix which applies the effect of each control input parameter in the vector u_{k-1} on the state vector.
- w_{k-1} is the vector containing the process noise terms for each parameter in the state vector. The process noise is assumed to be drawn from a zero mean multivariate normal distribution with covariance given by the covariance matrix $Q_k (w_k \sim N(0, Q_k))$.

The measurement model is given as,

$$z_k = H(X_k) + \upsilon_k, \tag{4}$$

Where,

- z_k is the vector of measurements (e.g. RSSI, position, velocity, acceleration,..etc). In this research work, it is target position estimates from the GRNN algorithm.
- H is the transformation matrix that maps the state vector parameters into the measurement domain.
- υ_k is the vector containing the measurement noise terms for each observation in the measurement vector. It assumed to be normally distributed zero mean white Gaussian with covariance $R_k (\upsilon_k \sim N(0, R_k))$.

The noise terms w_{k-1} and υ_k are assumed to be uncorrelated. For the constant velocity model the matrices in Eqs. (3) and (4) are given as follows.

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2}dt^2 & 0 \\ 0 & \frac{1}{2}dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}, H = I_{4\times4} \tag{5}$$

The operation of KF can be described in two simple steps: predict and update. The predict step utilizes the estimate of the state vector X from the previous time step $k-1$ to produce an estimate of X for the current time step k. Whereas in the update step, measurements from the current time step are exploited to refine the prediction of predict step to improve it.

Prediction:

$$\bar{X}_k = A\hat{X}_{k-1} + Bu_{k-1} + w_{k-1} \tag{6}$$

$$P_k^- = AP_{k-1}A_k^T + Q_k \tag{7}$$

Update:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^- \tag{8}$$

$$\hat{X}_k = \bar{X}_k + K_k(z_k - H_k\bar{X}_k) \tag{9}$$

$$P_k = (I - K_k H_k)P_k^- \tag{10}$$

The variable K is termed as Kalman's gain matrix and I is identity matrix ($I_{4\times4}$). The $\hat{X}_k$ represents the estimated value of the target state vector at time step of k. Notice in Eqs. (6) and (7), given the initial state variable X_{k-1} and its process covariance matrix P_{k-1}, the target state vector and its process covariance matrix can be predicted for the next time step k. These estimates can be further refined (updated) with the help of measurement at time step k using Eqs. (8)–(10). The standard KF and UKF are two extremes of the basic KF framework. If the system dynamics is highly nonlinear, then the standard KF as well as EKF doesn't give optimum estimations. In this research these two extreme implementations are utilized to test highly nonlinear system dynamics.

4.2. Unscented Kalman filtering framework

However as the motion and measurement models for the given indoor environment are highly nonlinear in practice. As mentioned in the previous section, if the system dynamics is highly nonlinear, then the high tracking accuracy with standard KF and EKF is almost rare possibility [16,17]. In such scenario, the UKF is a better option for the optimum results. The UKF basically employs unscented transform (UT) in which idea is to utilize a minimal set of sample points (called sigma points) around the mean of the state vector with considering covariance matrix P (See Eq. (11)). These sigma points are then propagated through the non-linear functions space. As compared to KF and EKF, the main advantages of the UT used in UKF is that it does not use linearization for computing the state and error covariance matrices resulting in a more accurate estimation of the parameters of a noisy signal.

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Like the standard KF, the UKF operation can also be described in two steps: predict and update. The sigma points χ_{k-1} can be computed by properly initializing the state vector and P as given by Eq. 11. Prior to prediction and update steps, the noise covariance matrix Q and measurement noise covariance matrix R must be selected carefully for the given indoor environment.

$$\chi_{k-1} = [\hat{X}_{k-1} \quad \hat{X}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{X}_{k-1} + \lambda\sqrt{P_{k-1}}] \tag{11}$$

The mathematics behind the predict step and the update step are given by Eqs. (12)–(17) and Eqs. (18)–(22) respectively.

Prediction:

$$\chi^*_{k/k-1} = f(X_{k-1}, u_{k-1}) \tag{12}$$

$$\hat{X}_k = \sum\nolimits_{i=0}^{2L} w_i^m \, \chi^*_{k/k-1} \tag{13}$$

$$P_k = \sum_{i=0}^{2L} w_i{}^c \left[z_{i,k/k-1} - \hat{z}_k\right]\left[z_{i,k/k-1} - \hat{z}_k\right]^T + \mathrm{R} \tag{14}$$

$$\chi_{k-1} = [\hat{X}_{k-1}\,\hat{X}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{X}_{k-1} + \lambda\sqrt{P_{k-1}}] \tag{15}$$

$$z_{k/k-1} = H\chi^*_{k/k-1} \tag{16}$$

$$\hat{z}_k = \sum\nolimits_{i=0}^{2L} w_i^m \, z_{i,k/k-1} \tag{17}$$

Update:

$$P_{X_k, z_k} = \sum_{i=0}^{2L} w_i{}^c [z_{i,k/k-1} - \hat{z}_k][z_{i,k/k-1} - \hat{z}_k]^T + R \tag{18}$$

$$P_{X_k, z_k} = \sum_{i=0}^{2L} w_i{}^c \left[X_{i,k/k-1} - \hat{X}_k\right]\left[z_{i,k/k-1} - \hat{z}_k\right] + R \tag{19}$$

Kalman gain:

$$K_k = P_{X_k, z_k} \, P^{-1}_{z_k, z_k} \tag{20}$$

Emendation state estimate:

$$\hat{X} = \hat{X}_{k-1} + K_k(z_k - \hat{z}_k) \tag{21}$$

Error covariance matrix updates:

$$P_k = P_{k-1} - K_k P_{z_k, z_k} K_k^T \tag{22}$$

$$w_0^m = \lambda/(L+\lambda), \; w_0^c = \lambda/(L+\lambda) + (1 + \alpha^2 + \beta) \tag{23}$$

where, w_0^m is weights of mean, w_0^c is weights of covariance, λ is a scaling parameter. L is the dimension of augmented state,α is a measure of the spread of the sigma points around $\hat{X}$ and is usually set to a small positive value (typically $\alpha = 10^{-3}$) while β (typically $\beta = 2$) is used to incorporate prior knowledge of the distribution of X. The typical values of above parameters are used in this research work.

5. System design and performance evaluation

5.1. System assumptions and design

The objective of this research work is to track the person moving in a lab of area 150 m^2 (10 m by 15 m) using PSOC BLE nodes and smart phone, as shown in Fig. 2 and a base station outside (not shown in figure). In this research work mobile target is assumed to carry one smartphone (Motorola G4 Plus), which receives RF signal broadcasted by all BLE nodes for every time step k.Four BLE nodes are deployed at almost the corner of the lab, at the points of (1 m, 4 m), (9 m, 4 m), (1 m, 12 m), and (9 m, 12 m). The BLE nodes and smartphone are at a height of approximately 35 cm and 50 cm respectively from the floor, Due to the difference in the height between nodes and smartphone, there is NLOS between them. Additionally as the given indoor environment consists of walls, various electronic gadgets, furniture such as benches, stools and the presence of people, the multipath propagation will also be a crucial factor during the target tracking. In each experimental trial, the person is moved along the same track for a total time period of $T = 35$ sThe results discussed in this paper are the average of 10 trails so as to avoid any wrong conclusion. In each experimental trial, the moving person starts from position (2 m, 1 m) and stops at (8 m, 2 m). The research work utilizes RSSI measurements received using periodic broadcasted signals from four PSOC BLE nodes with transmission power of 0 dBm. Regarding the deployment of the PSOC BLE nodes, two arrangements are possible: One based on a set of the nodes that transmit RF signals to the mobile target to be located, and another where the nodes receive the signals from the mobile target to track. Our research proposal follows the first approach. The collected RSSI values from all the nodes at each time step are dispatched to outside base station. The base station attached with a laptop (Core i5, 1.70 GHz, 4GB RAM) is supposed to run all the algorithms to be analyzed namely, traditional trilateration, trilateration + KF, trilateration + UKF, GRNN, GRNN + KF and GRNN + UKF algorithms.

Fig. 2. The Indoor target tracking experiment with PSOC BLE nodes and smartphone carried out in Project Laboratory of Amrutvahini COE, Sangamner, India.

The target state vector at time instant k is defined as $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$, where x_k andy_k specify the position, $\dot{x}_k$and $\dot{y}_k$ specify the speed in x and y directions respectively at k^{th} time instance. The initial target state vector is assumed as [2, 1, 0, 0]. For $k > 0$, the motion of target during T in the given indoor environment is according to constant velocity model and is described by Eqs. (24) and (25). The motion of person in the given laboratory is according to constant velocity model during T as given by Eqs. (26)–(28) and is illustrated in Figs. 3 and 4. Here the positive velocity and negative velocity values indicate the movement in the front and backward directions respectively.

$$x_k = x_{k-1} + \dot{x}_k dt, \tag{24}$$

$$y_k = y_{k-1} + \dot{y}_k dt, \tag{25}$$

Where, dt is discretization time step between two successive time instants such that $dt = k - (k-1)$.

$$\dot{x}_k = 0, \quad \dot{y}_k = 1, \quad \text{for } 0 < k \le 15 \text{ s}, \tag{26}$$

$$\dot{x}_k = 1, \quad \dot{y}_k = 0, \quad \text{for } 16 \le k \le 21 \text{ s}, \tag{27}$$

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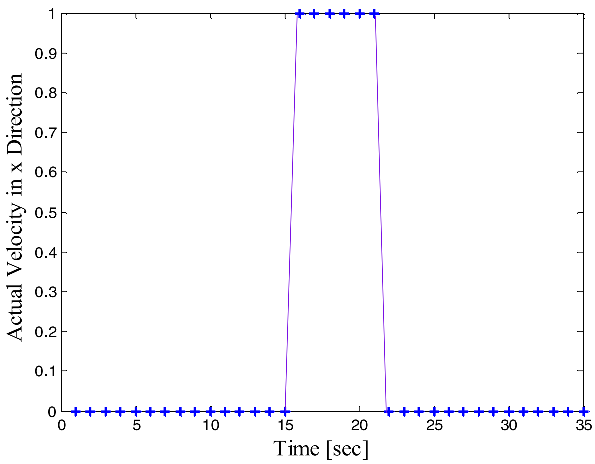

Fig. 3. This figure shows the variation in velocity in x direction during target motion.

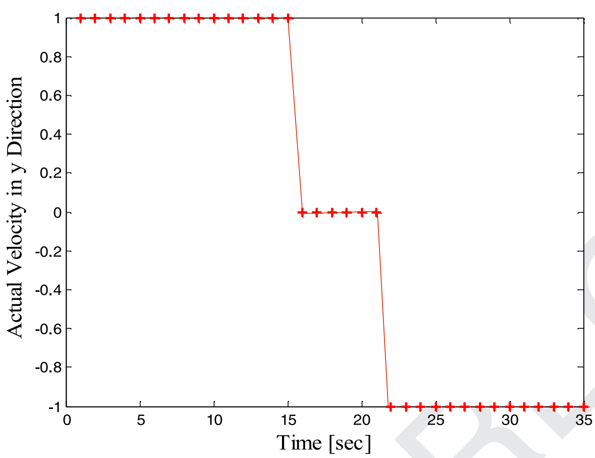

Fig. 4. This figure shows the variation in velocity in y direction during target motion.

Table 1
System parameters for the proposed algorithms.

Symbol	Parameter	Value
X_0	Initial target state at $k=0$	[12, 15, 0, 0]
dt	Discretization time step	1 s
T	Total simulation period	35 s
F	Frequency of operation	2.4 GHz
σ	GRNN spread factor	2.5
_	RF transmit power	0 dBm

$$\dot{x}_k = 0, \quad \dot{y}_k = -1, \quad \text{for } 22 \leq k \leq 35 \text{ s}. \tag{28}$$

The system parameters for the proposed algorithms are taken as given in Table 1.

The R, P_0 *and* Q matrices for this research work are taken as

$$R = \begin{bmatrix} 2.2 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}, P_0 = \begin{bmatrix} 0.25 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix},$$
$$Q = I_{4\times4}. \tag{29}$$

The research work is carried out in two phases as described below. It is to be noted that the indoor environmental setup in experiments for both the Phases is exactly same.

- Phase I: Comparative analysis of traditional trilateration technique and the GRNN approach for indoor target tracking

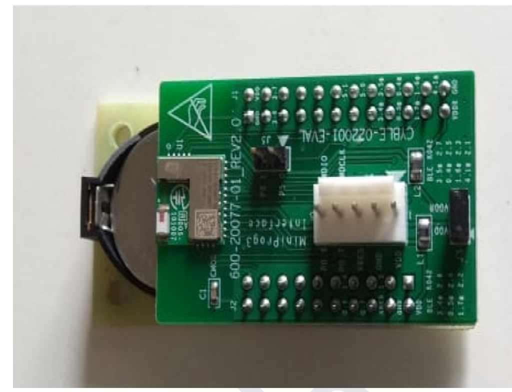

Fig. 5. PSOC BLE (Model: Cypress CYBLE-022001-00) based Wireless Sensor Node.

- Phase II: Comparative analysis of traditional trilateration technique with KF framework and the GRNN approach with KF framework for indoor target tracking

The objective of the Phase I is to determine the optimum value of the GRNN spread factor σ for the given indoor environment by trial and error method as well to compare the tracking performances of traditional Trilateration based estimation and GRNN algorithm. As described later on the GRNN approach is far more superior to that of trilateration. Whereas the major objective of the Phase II is to investigate the efficacy of the combination of the GRNN along with KF framework as well as to compare it with the combination of the trilateration along with KF framework for the same indoor environment. The details of outcome from both the phases are discussed in Section D in detail.

In this work, a hybrid WSN consisting of four static Cypress CYBLE-022001-00 BLE nodes and smartphone (Motorola G4 Plus) (carried by the moving person) is used. The CYBLE-022001-00 includes on-board crystal oscillators, chip antenna, passive components, and Cypress PSoC 4 BLE [39]. It has a very small footprint area of $10 \times 10 \times 1.80$ mm with transmit output ranging from –18 dBm to +3 dBm, RSSI with 1-dB resolution and a chip antenna with frequency range of 2400–2500 MHz and average gain of −0.5-dBi. The Cypress PSoC 4 BLE is a combination of a 32 bit microcontroller (Arm® Cortex®-M0) with an integrated BLE 4.2 support and maximum communication range of 30 m (See Fig. 5). It is powered by a small coin cell 3 V battery (Maxtel CR 2032). These small, low power nodes broadcast RF signals at regular interval of 1 s that can be received as RSSI by CyMobile app installed on smartphone (See Fig. 6) [40]. A dedicated a wearable microcontroller based transceiver could also be used in place of the smartphone to dispatch the received RSSI values to the base station.

5.2. Performance metrics

Based on the RSSI input from deployed four PSOC BLE nodes, the proposed algorithms (to be run at the base station) estimate the person locations during T and finally the estimated locations are compared to the real locations to compute the localization errors for all the algorithms. The performance metrics used for the performance assessment are Average Localization Error and root mean square error (RMSE). The Average Localization Error (See Eq. (30)) and Average RMSE (See Eqs. (31)–(33)) represent the closeness between estimated target location $(\hat{x}_k, \hat{y}_k)$ and given actual target location(x_k, y_k) over T respectively. Lower the values of these two metrics, better is the estimation of location of moving target and thereby better would be the tracking accuracy.

Table 2
GRNN + KF and GRNN + UKF algorithms description.

I. Offline GRNN Training Stage
Step 1: The GRNN is trained with 70 pairs of RSSI values from BLE nodes and corresponding actual position of the moving target.
II. Online Position Estimation using GRNN
Step 2: The moving target receive RSSI values from all PSOC BLE nodes for every k^{th} instance using carried smart phone. These RSSI values are dispatched to Base station.
Step 3: The base station run GRNN algorithm to compute the position estimate of moving target at every k^{th} instance.
III. Online Position Estimation using KF framework
Step 4: The base station refines GRNN based position estimates using KF and UKF algorithm.
For sampling instants $k = 1, 2, ...T$
Step 5: Steps from 2 to 4 are repeated for each next time step for the period T.
IV. Computation of performance metrics
Step 6: The RMSE and correlation coefficients of all the four approaches (Traditional RSSI, GRNN, GRNN + KF and GRNN + UKF are computed.

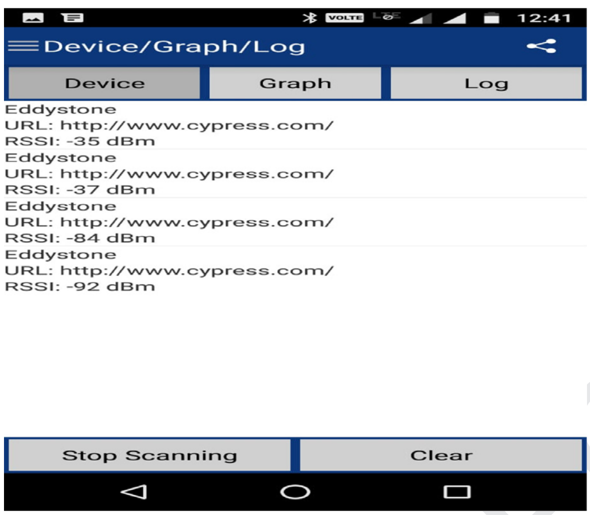

Fig. 6. This figure shows how RSSI values from four PSOC BLE nodes can be received on smartphone using CyMobile app.

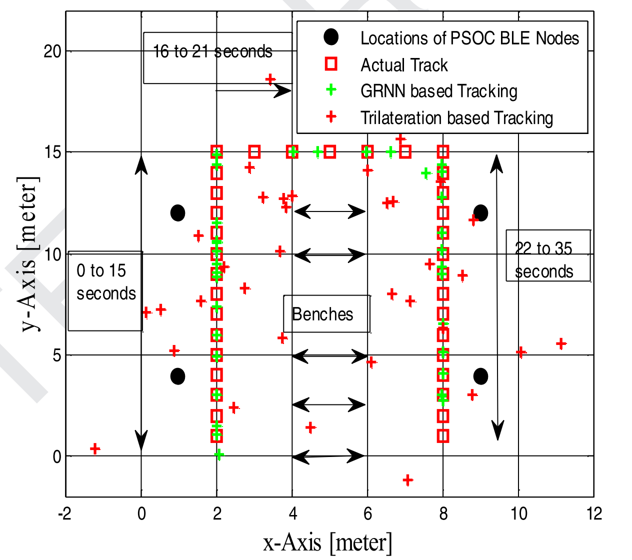

Fig. 7. Actual target trajectory and estimated trajectories by the traditional trilateration and GRNN algorithms ($\sigma = 3$).

1 Average Localization Error (Error in x–y estimates):

$$\textit{Average Localization Error} = \frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2} \tag{30}$$

2 Root mean squared error (RMSE):

$$RMSE_x = \sqrt{\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2}{T}} \tag{31}$$

$$RMSE_y = \sqrt{\sum_{k=1}^{T}\frac{(\hat{y}_k - y_k)^2}{T}} \tag{32}$$

$$RMSE_{avg} = \frac{(RMSE_x + RMSE_y)}{2} \tag{33}$$

5.3. Flow of proposed algorithm

The complete simulation for one time step k consists of three parts. The first part is offline GRNN Training Stage, the second part is Online Position Estimation using GRNN (to be run at the base station), while the third part is Online Position Estimation using KF Framework (to be run at the base station). The detailed flow of the proposed algorithms for one time step $k$is as given in Table 2.

5.4. Discussion of results

One of the most important advantages of using the GRNN architecture over the other ANN architectures and the traditional trilateration approach is that it has only one control parameter. That is its spread factor σ whose optimum value is set by trial and error method in this research. An attempt is made to find out the optimum value of σ for the given indoor environment in the lab for the Phase I. The σ value is varied from 0.5 to 6 in the step of 0.5 at the base station for 10 experimental trails of the proposed GRNN architecture and the corresponding average RMSE values are noted down. From this experiment it is found that the σ value of 3 demonstrates better tracking performance for the considered indoor environment. Next the comparison of the GRNN algorithm with $\sigma = 3$ is the traditional trilateration for the target tracking problem at hand is carried out in the Phase I. The Fig. 7 shows that the GRNN based estimated track is much close with the actual target track as compared to the traditional trilateration based estimated track. The Figs. 8–10 illustrate the localization errors during T for both the implementations for x, y and x–y estimations respectively. In these figures only the markers of localization errors of the trilateration algorithm are joined by a solid red line for the ease of understanding. One can easily note that both the Average Localization Error as well as Average RMSE is below 1 m in case of GRNN algorithm. The Average Localization Error and the Average RMSE is reduced by 59% and 48% with the GRNN based approach as compared to the trilateration approach (See Table 3). However many LBS demand higher accuracy than what is achieved with the GRNN algorithm. Therefore the GRNN based estimates are refined with the help of KF framework in the Phase II.

In the Phase II, both the trilateration and the GRNN approaches are tried with the KF framework. We have assigned names to these combinations as trilateration + KF, trilateration + UKF, GRNN + KF

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Table 3
Phase I: Comparison of tracking performances of trilateration and GRNN algorithms (Phase I).

Name of algorithm	Lowest localization error [meter]	Highest localization error [meter]	Average localization error [meter]	RMSE in *x* estimation [meter]	RMSE in *y* estimation [meter]	Avg. RMSE in *x*–*y* estimation [meter]
Trilateration	0.1887	2.5368	1.4344	1.3806	2.2857	1.8332
GRNN	0.0365	1.4635	0.5940	0.4553	1.4199	0.9646

Table 4
Phase II: Comparison of tracking performances of trilateration + KF, trilateration + UKF, GRNN + KF and GRNN + UKF Algorithms.

Name of algorithm	Lowest localization error [meter]	Highest localization error [meter]	Average localization error [meter]	RMSE in *x* estimation [meter]	RMSE in *y* estimation [meter]	Average RMSE in *x*–*y* estimation [meter]
Trilateration + KF	0.1552	2.0973	0.7563	1.1654	0.7720	0.9437
Trilateration + UKF	0.0986	0.4866	0.1248	0.1865	0.0914	0.1390
GRNN + KF	0.1983	1.4898	0.7391	0.8080	1.0444	0.9262
GRNN + UKF	0.07892	0.2867	0.0603	0.0899	0.0769	0.0834

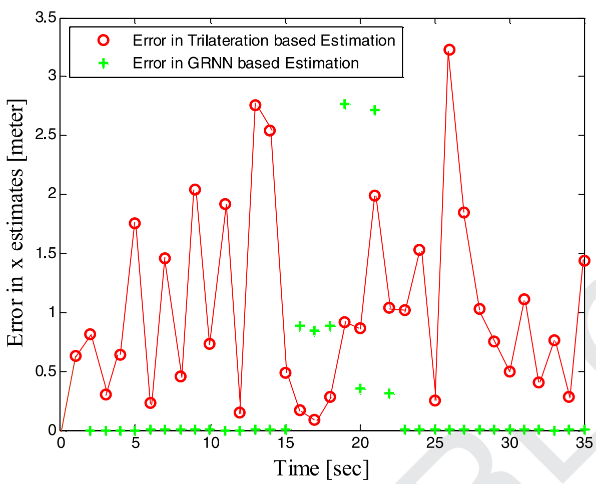

Fig. 8. Comparison of localization errors in *x* estimates in traditional trilateration and GRNN algorithms ($\sigma = 3$).

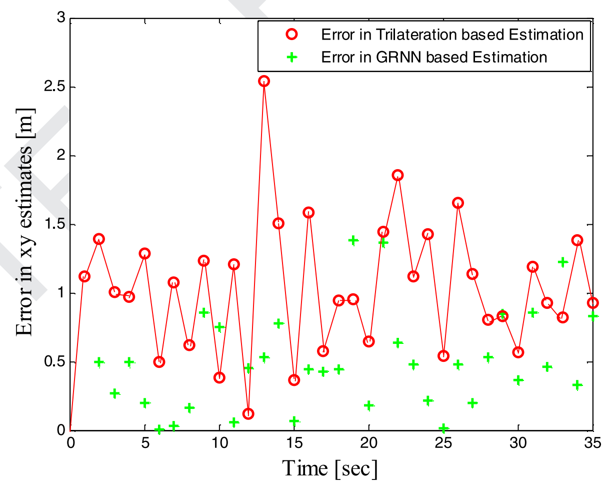

Fig. 10. Comparison of localization errors in *x*–*y* estimates in traditional trilateration and GRNN algorithms ($\sigma = 3$).

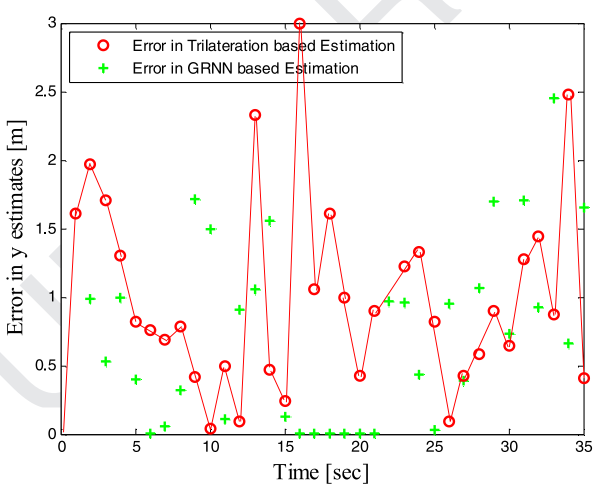

Fig. 9. Comparison of localization errors in *y* estimates in traditional trilateration and GRNN algorithms ($\sigma = 3$).

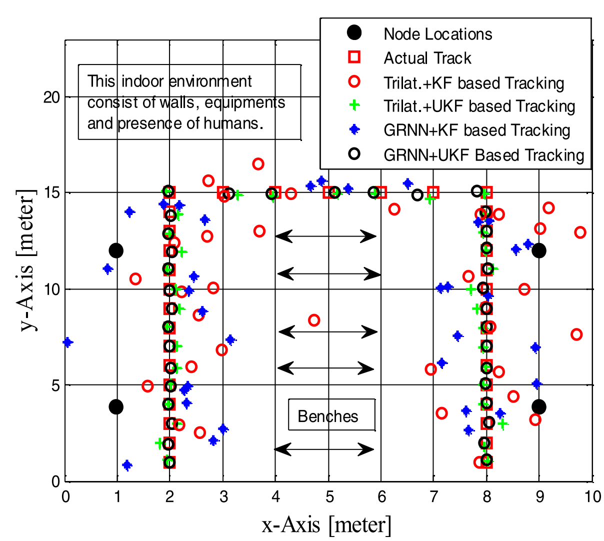

Fig. 11. Actual target trajectory and estimated trajectories by the traditional Trilat. + KF, Trilat. + UKF, GRNN + KF and GRNN + UKF algorithms ($\sigma = 3$).

and GRNN + UKF. The Figs. 11–14 and Table 4 show the comparison of target tracking performances of all these algorithms. The black filled squares represent PSOC BLE nodes, whereas red unfilled squares, green plus symbols, red plus symbols, blue plus symbols and unfilled black circles represent actual target position, trilateration + KF, trilateration + UKF, GRNN + KF and GRNN + UKF based estimated positions respectively during *T* in Fig. 11. The Figs. 12–14 illustrate the localization errors during *T* for all the above mentioned implementations for *x*, *y* and *x y* estimations respectively. In the Figs. 12–14, only the markers of localization error of

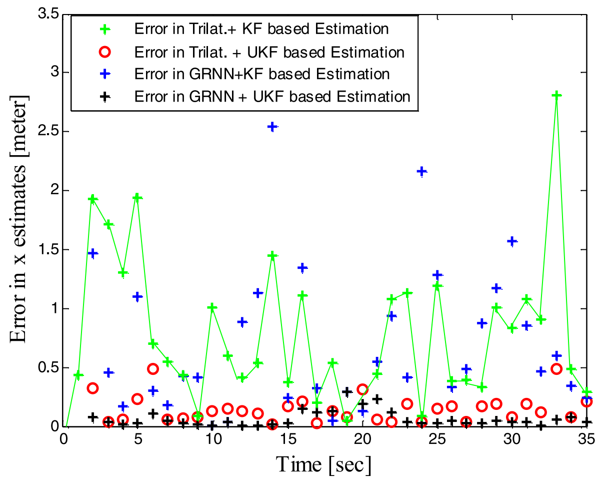

Fig. 12. Comparison of localization errors in *x* estimates in traditional Trilat. + KF, Trilat. + UKF, GRNN + KF and GRNN + UKF algorithms ($\sigma = 3$).

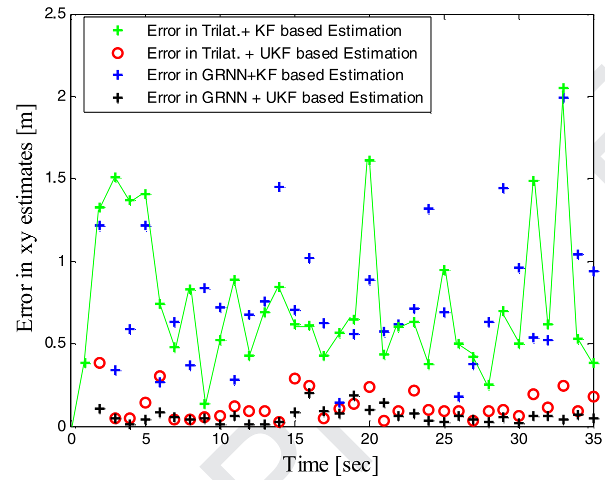

Fig. 14. Comparison of localization errors in *x–y* estimates in traditional Trilat. + KF, Trilat. + UKF, GRNN + KF and GRNN + UKF algorithms ($\sigma = 3$).

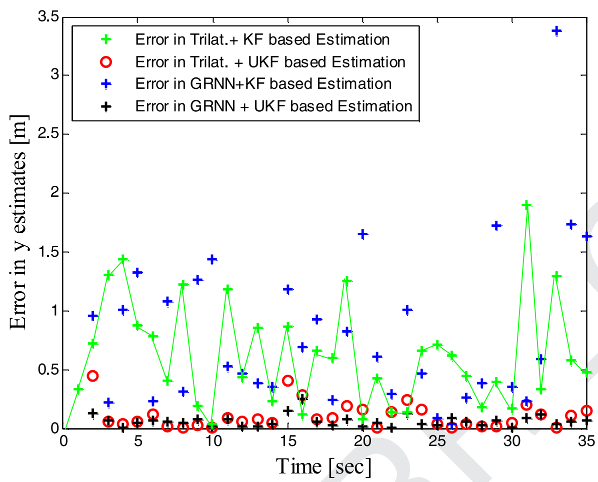

Fig. 13. Comparison of Localization Errors in *y* estimates in Trilat. + KF, Trilat. + UKF, GRNN + KF and GRNN + UKF algorithms ($\sigma = 3$).

the trilateration + KF algorithm are purposefully joined by a solid green line for the ease of understanding to avoid confusions.

One can see in Fig. 11 that irrespective of the presence of the various obstacles in the given wireless environment such as benches, various equipment's and the walls on all four sides of the lab, the tracking performance of the proposed algorithms is better than the traditional RSSI and GRNN algorithms. From the results it is clear that even though the RSSI measurements are noisy for considered indoor environment due to the issues such as NLOS and multipath propagation, the fusion of GRNN and KF approach can provide very high tracking accuracy of centimeter scale. In other words, the proposed GRNN and KF based framework successfully compensate the localization errors arising out of dynamicity in the given wireless environment. Out of the two proposed algorithms, the Average Localization Error and the Average RMSE is lowest for the GRNN + UKF algorithm. It is to be noted that the average RMSE of GRNN + UKF algorithm is reduced by approximately 92%, 40% and 90% respectively as compared to that of the trilateration + KF, trilateration + UKF and GRNN + KF algorithms respectively (See Table 4).

From the research presented in this section we can reach some important conclusions. Some of the studies as mentioned in the Related Work Section characterized the given indoor environment in order to obtain a higher tracking accuracy in their results. This characterization was done through the implementation of a fingerprinting method or through the calibration of the signal propagation model variables. The major drawback with these approaches is that resulting systems can only be used for the considered indoor environment for which the environment characterization was done. They can't be immediately deployed in other indoor environments because a learning phase is always needed to collect all the relevant data. This means that an extra investment of time and resources will be necessary. Though some of the past researches had used KF framework in their algorithms, the inclusion of the GRNN along with KF framework in this work perform fairly better against the dynamicity of the given wireless environment. Another important aspect that stands out in most of the researches is that though their implementations shows higher tracking accuracy but the underlying implementation didn't consider issues such as NLOS, multipath propagation and the presence obstacles. Although the system we propose require the characterization of the indoor environment through the training of the GRNN architecture, but the amount of time involved for training is very less as compared with the other existing solutions.

6. Conclusions and future work

This study introduces the GRNN based approach for improving real time 2-D target tracking performance in KF framework using the hybrid WSN built of the PSOC BLE nodes and smartphone. The study demonstrated that the GRNN is superior over the trilateration technique in the context of dealing with the highly nonlinear relationship between RSSI's and locations of the mobile target. The two GRNN based algorithms namely GRNN + KF and GRNN + UKF, are presented for efficient tracking of single moving target in WSN. The overall tracking performance is assessed in terms of RMSE, and Average Localization Error. The experimental results confirm the higher tracking accuracy (in the scale of few centimeters) irrespective of the dynamicity of the considered indoor environment due to NLOS, multipath propagation and the presence of obstacles. The results also conclude that the GRNN + UKF based approach is highly superior option in case of highly nonlinear system dynamics as compared to the other solutions for the BLE based indoor tracking problem. The research work advocates the suitability of GRNN architecture over traditional trilateration method for various real time LBS.

The presented work can be extended along various dimensions such as tracking of multiple moving targets, increasing the node density, testing the proposed approach for larger indoor areas and investigation of the proposed algorithms for the abrupt variations in the target velocity.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adhoc.2018.09.017.

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