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Research Article

Energy-Constrained Target Localization Scheme for Wireless Sensor Networks Using Radial Basis Function Neural Network

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The indoor object tracking by utilizing received signal strength indicator (RSSI) measurements with the help of wireless sensor network (WSN) is an interesting and important topic in the domain of location-based applications. Without the knowledge of location, the measurements obtained with WSN are of no use. The trilateration is a widely used technique to get location updates of target based on RSSI measurements from WSN. However, it suffers with high location estimation errors arising due to random variations in RSSI measurements. This paper presents a range-free radial basis function neural network (RBFN) and Kalman filtering- (KF-) based algorithm named RBFN+KF. The performance of the RBFN+KF algorithm is evaluated using simulated RSSIs and is compared against trilateration, multilayer perceptron (MLP), and RBFN-based estimations. The simulation results reveal that the proposed RBFN+KF algorithm shows very low location estimation errors compared to the rest of the three approaches. Additionally, it is also seen that RBFN-based approach is more energy efficient than trilateration and MLP-based localization approaches.

1. Introduction

The wireless technologies such as WiFi, Bluetooth, infrared, Zigbee, Bluetooth, Bluetooth Low-Energy (BLE) modules, wireless sensor network (WSN), and GPRS are basic building blocks of Internet of Things (IoT) [1, 2]. The IoT technologies can be integrated with various combinations to extract the location updates of various objects in the surrounding environment. Location-based service (LBS) is a dominant application of IoT, wherein attaining high localization accuracy is a key aspect. Out of these IoT technologies, the WSN is most appealing technology of the 21st century as it paved the way for many day to day applications such as elderly monitoring, wildlife tracking, and environmental monitoring [3]. The key strength with the use of WSN technology is the high possibility of scalability of the network through large number of tiny sensor nodes which can configure themselves in ad hoc manner. These sensor nodes have very good self-networking capability which can lead to automatic coordination among them to solve the given problem in hand. Out of all the applications, the localization of objects using the WSN is widely researched topic as the precise knowledge of node locations is key to success to many LBS. The radiofrequency- (RF-) based target localization is far superior to that obtained infrared (IR), acoustic, and ultrawideband- (UWB-) based systems. The RF can easily penetrate walls, glass, or many other barriers during signal communication. The received signal strength (RSS) that we discuss in this paper are a type of RF signal. The RSS is also referred as RSSI. Generally, all the wireless transceivers have inbuilt RSS circuitry which can directly give us RSS measurements. That is why the RSSI-based localization is simple and inexpensive as well as has lower energy consumption compared to other techniques [4, 5]. However, due to issues of reflection, refraction, reflection, and attenuation, the RSSI-based localization methods suffers with low localization accuracy. Therefore, a lot of research is going on to address fluctuating nature of RSSI measurements. Additionally, energy consumption is also very crucial constraint in WSN-based applications and thus to use the limited energy efficiently is the key design objectives in WSN-based applications. In WSN, its transceiver, processor, and sensor components work in a cooperative fashion to execute the given task, and this cooperation impact the overall energy consumption in any WSN-based application. This issue has been adopted in node energy model which can compute sensor node energy consumption accurately [6].

In the WSN area, the target moves and it generally carries a receiver. The sensor nodes broadcast the RF signal in the WSN which the target is supposed to receive. These received values are nothing but RSSI measurements. The role of object localization is to find out the unknown target locations using these RSSI measurements during its motion. Obviously, the localization system needs some advanced signal processing technique. The target localization solutions can be classified into range-based techniques and range-free techniques, each of with its pros and cons [7]. If the localization technique involves range calculation, it is termed as range-based technique, while the localization scheme that does not involve range calculation is called as range-free technique. The state estimation techniques such as Kalman filter (KF) or particle filter (PF) are generally used in target localization using WSN. However, the selection of KF or PF for target localization relies on the dynamicity in the RSSI measurements (i.e., nature and noise level) and application demands [8, 9]. As compared to PF, the KF is simple to use and computationally less expensive. Therefore, the application of KF in target localization is generally employed in WSN. Although the KF-based localization approach can offer high localization performance than traditional trilateration technique, the KF system model used for locating the moving target cannot perfectly match with the actual scenario. That means fine tuning KF parameters to match with the actual environmental scenario is very tough. The KF alone cannot guarantee low localization error alone due to high dynamicity in the RSSI measurements. Hence, more advanced technique need to be fused with KF-based localization.

The artificial neural network (ANN) can be adopted to model any nonlinear system dynamics [10, 11]. Many ANN architectures have been used for target localization in the past. For instance, the generalized regression neural network (GRNN) can be used for target localization [12, 13]. It can get trained using the training dataset. The multilayer perceptron (MLP) had also been proposed to solve target localization problem. The GRNN and MLP are supervised learning architectures and can be trained using dynamic RSSI measurements obtained for a specific indoor environment. In [14], the problem of tracking of mobile sensors in the uncertain, and the harsh indoor environment is presented in detail. This research work proposes two MLP-assisted localization schemes with two hidden layers, and these schemes are compared with trilateration-based scheme. The simulation results show localization superiority of the proposed MLP-based schemes with respect to that with trilateration-based scheme. The research work in [15] studied object localization using various neural networks such as MLP, radial basis function network (RBFN), and recurrent neural networks (RNN). In this work, the authors collected the RSSI fingerprints are collected from known locations to create an RF fingerprint map of the given indoor setup. Then, the RBFN architecture is utilized to map any random online RF fingerprint to object location coordinates. A clustering scheme is developed to lower down the computational complexity of the proposed RBFN structure. The results of localization experiment prove that the proposed RBFN-based localization scheme offers sufficient object localization accuracy to the scale of 5 meter.

Although some state estimation technique (such as KF) or some other machine learning-based approach (such as GRNN or MLP or RBFN) alone can achieve sufficient localization accuracy around 5 meters, the localization accuracy demand of some applications is around 1 meter. Thus, it is quite interesting to fuse these two approaches together to check whether such combination yield high localization accuracy or not. The major research findings for this proposed work are as follows:

(1) We proposed a robust localization scheme of fusion of RBFN and KF to locate a moving target in indoor using RSS measurements. We named the proposed fusion scheme as RBFN+KF. This scheme yields the localization accuracy around 1 meter

(2) The proposed RBFN+KF scheme is verified against dynamicity in RSS measurements and abrupt target motion using simulations. To realize RSSI measurement dynamicity, the RSS measurement noise is set to 3 dBm. The results obtained through simulations prove that that the proposed RBFN+KF-based scheme successfully solve target localization problem with the fluctuating RSS field measurements as well as abrupt target mobility as compared to trilateration, MLP, and RBFN so far as target localization (or tracking) accuracy is concerned

(3) We also found that as against trilateration and MLP-based localization frameworks, the RBFN-based scheme has very less energy consumption during tracking process of given mobile target

In this research paper, Section 2 enlists various existing target localization solutions with their pros and cons. Section 3 focuses on fundamentals of RSSI-based localization along with the implementation details of the proposed localization system with underlying assumptions. The results obtained through simulations of all the considered localization schemes are illustrated and compared briefly in Section 4. The proposed research work is concluded finally in Section 5.

2. Related Work

The indoor target localization using RSSI measurements can be broadly classified into ML-based methods and filter-based methods. The ML-based methods are based on supervised learning principles through RF fingerprinting. The popular ML-based L&T solutions in the literature are radial basis function (RBF), KNN (*k*-nearest neighbor), extreme learning machine (ELM), multilayer perceptron (MLP), recurrent neural network (RNN), CNN (convolutional neural network), and SVM. Once these models are trained offline with dataset containing RSSI values and target locations, they are tested with random RSSI measurements in the online location estimation step. In [16], the authors propose kernel online sequential ELM scheme for target localization in offline stage. In online location estimation stage, KNN is utilized. For IoT-sensor system [17], CNN was fed with RSSI measurements for target localization. Here, the authors are successful to shift complexity in online estimation stage to offline training stage. The proposed scheme yield 2 meter localization accuracy. One more CNN-based target localization scheme with RSSI measurements as inputs is proposed in [18]. Here, thousands of RSSI fingerprints are taken for a 12.5 meter × 10 meter area from deployed APs for half a month. The average positioning errors obtained with the proposed HW fingerprint-based approach are 4.1681 meter, 4.1145 meter, and 3.9118 meter using KNN, SVM, and CNN, respectively. The major drawback with CNN-based target L&T schemes is the requirement of fine tuning of hyperparameters of CNN, namely, activation function, threshold, and learning rate, and is very time-consuming task. This makes CNN accurate for specific indoor conditions, but less accurate for rest of the other indoor setups. In [19], the authors propose kernel ELM- (K-ELM-) based target L&T using 68,500 RSSI measurements obtained from indoor area of 32 meter × 16 meter with eight sensor nodes. The proposed K-ELM-based scheme is compared with KNN, Bayesian, ELM, and online sequential ELM (OS-ELM) schemes, and it is found that the proposed scheme yield 8.125 meter accuracy which is quite high as against remaining techniques for same indoor setup. The authors also used BPNN for target L&T, but it involves the need of large number of iteration for converging to the optimum solution [20].

KF is an optimal state estimator for Gaussian process filtering especially when the target model is prior known and the target state parameters do not mutate (i.e., system is linear) [21, 22]. In [21], a novel distributed consensus-based adaptive KF algorithm is proposed to track a mobile target. The authors adopted two-stage fusion structure and policy of dynamic cluster selection to achieve accurate location estimates. The authors in [23] presented an algorithm to locate target in indoor environments. The indoor environment is divided the targeted area into several sectors, and then, RSS measurements are used for target location estimation. The authors in [24] combined the extended Kalman filter (EKF) and PF together to alleviate the problem of particle degradation. The probability density function (PDF) is approximated using randomly selected particles from posterior probability. A multimodel five-degree cube KF (IMM5CKF) is proposed in [25]. The proposed algorithm processes system models through Markov chains to improve the target tracking error. The simulation experiments reveal that the proposed IMM5CKF algorithm has stable and fast switching performance while dealing with various maneuver models.

In the filter-based target L&T, state estimation techniques such as KF and particle filter (PF) are major schemes, which involves two steps: prediction, and measurement. The research works presented in [11, 26] demonstrate online semisupervised SVR- (OSS-SVR-) based localization to reduce the need of amount of the labeled data in training set. Further, the proposed OSS-SVR results are fused with KF. It is found that the proposed OSS-SVR scheme is robust enough for variations in system noise and need very smaller amount of labeled data during training. The SVR-based target localization model can also be fused with KF to smoothen the target location estimates [27]. The proposed SVR model utilizes linear, Sigmoid, RBF, and polynomial kernel functions to estimate the moving target locations in indoor. The proposed target localization model is also energy efficient as compared to the traditional trilateration model. In [12] also, trilateration-based estimates are applied as input to KF for tracking of mobile target in WSN to present two range-based algorithms: RSSI+KF and RSSI+UKF. In this research work, the issues such as uncertainties in RSSI noise, impact of variation in anchor density, and abrupt variation in target velocity with the proposed technique. The simulation results confirm the efficacy of both presented algorithms in spite of RF environmental dynamicity. However, due to need of computing distances between the transmitter and receivers frequently, although the proposed algorithms show localization errors below 1 meter, they have large computational complexity as compared to other range-free localization solutions. Two range-free algorithms GRNN+KF and GRNN+UKF are proposed in [12, 13]. In these research works, the GRNN architecture is adopted to estimate the target location, which is then fed to KF in order to deal with RSSI noise uncertainty. In this work, the GRNN is trained with only four RSSI values and corresponding target locations in the given indoor environment. The location estimations achieved with GRNN are provided to KF and UKF in order to get more refined location estimate. Most of the works discussed in this section either concentrate on target localization (or tracking) accuracy or energy efficiency or robustness to environmental dynamicity. As against these recent works, this research work attempts to address all of these issues simultaneously by providing fairly accurate, energy efficient, and robust range-free localization solution using WSN.

3. Localization of Mobile Target Using Proposed RBFN+KF Architecture

The proposed localization scheme assumes eight static anchor (sensor) nodes located at random locations in 1000 square meters area as illustrated in Figure 1. The target is supposed to carry WSN node set in transmitting mode. This

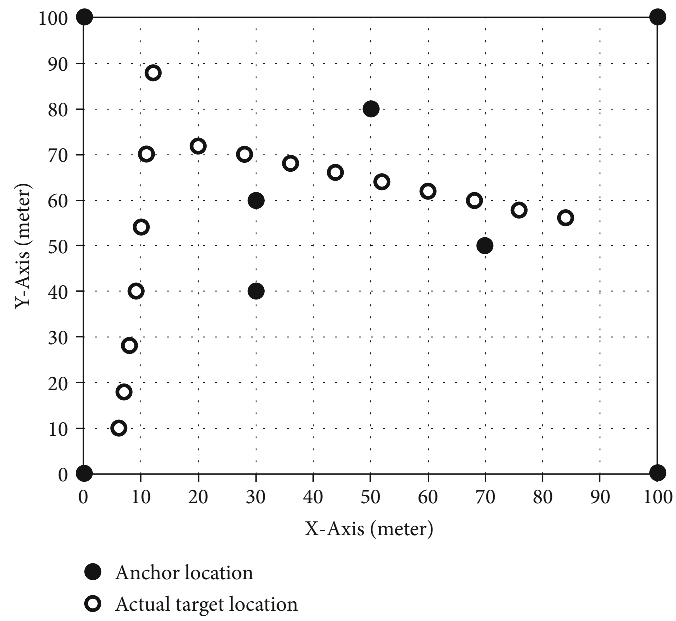

FIGURE 1: Deployment of anchor nodes and actual target trajectory in considered indoor environment.

node broadcasts signal RF for each time step k. Thus, all eight anchor nodes receives RSSI measurements according to equation (1) at each time step k. Using these RSSI measurements the trilateration, MLP, RBFN, and the proposed RBFN+KF algorithms estimate target location for each time step k. The target state vector at each time instance will be $x_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$, where x_k and y_k are the positions and $\dot{x}$ and $\dot{y}$ are target velocities in x and y directions, respectively [13]. The time duration in two time events is set to $dt = k - (k-1)$.

$$z_{\ell j,k} = P_r(d_0) - 10n \log \left(d_{lj,k}/d_0\right) + X_\sigma, \tag{1}$$

where $(z_{\ell j,k})$ is the RSSI received at the node N_ℓ with coordinates $(x_{\ell k}, y_{\ell k})$ at time k, η is the path loss exponent, $P_r(d_0)$ is the RSSI at receiver at distance d_0, and X_σ is the normal random variable representing noise in RSSI.

The four RSSI measurements $(z_3, z_2, z_3, \text{and}\, z_4)$ that are required as an input to the MLP+KF system are given using [13]:

$$\begin{aligned}
z_1 &= P_r(d_0) - 10n_1 \log\left(\frac{d_1}{d_0}\right) + X_\sigma,\\
z_2 &= P_r(d_0) - 10n_2 \log\left(\frac{d_2}{d_0}\right) + X_\sigma,\\
z_3 &= P_r(d_0) - 10n_3 \log\left(\frac{d_3}{d_0}\right) + X_\sigma.\\
z_4 &= P_r(d_0) - 10n_4 \log\left(\frac{d_4}{d_0}\right) + X_\sigma.
\end{aligned} \tag{2}$$

The average path loss exponent is then calculated as shown below.

$$n_{\text{avg}} = \frac{(n_1 + n_2 + n_3 + n_4)}{4}. \tag{3}$$

Using above value of (n_{avg}), equation (1) can be reconfigured using

$$z_{lj,k} = P_r(d_0) - 10n_{avg} \log\left(\frac{d_{lj,k}}{d_0}\right) + X_\sigma. \tag{4}$$

The RBFN is a type of ANN, which is widely used for the problems of supervised learning such as classification and regression [10, 12]. It is basically a universal approximation tool. It may be utilized for approximation of any continuous function. Its unique features are good approximation ability, fast rate of convergence, and fast learning speed. It is basically a feed-forward neural network as depicted in Figure 2. The value transition from input layer to hidden layer is found to be nonlinear using RBF function, whereas transition from hidden layer to output layer is supposed to be linear. Figure 3 presents MATLAB view of the RBFN neural network-based localization architecture. In this, we can see that four RSSI field measurements are fed to input layer terminal of the proposed model, and we get coordinates of estimated target position at the output layer terminal. In between these two terminals, two hidden layers have been used.

The important building block of the proposed RBFN +KF algorithm is the RBFN architecture designed specifically for localization using four RSSI field measurements. The RBFN architecture is trained using set of 100 vectors consisting of RSSI field measurements (input vector) and corresponding real 2-D locations of target (output vector).

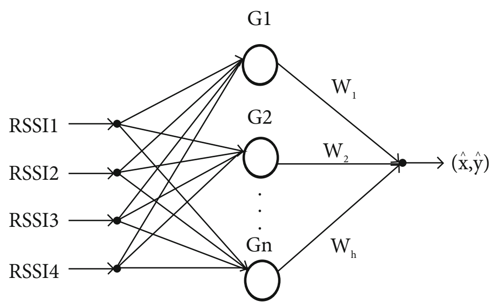

Figure 2: Proposed RBFN structure for target localization.

The training set consisting of 100 input vectors and 100 corresponding output vectors is obtained through some trial of target motion. After training the proposed RBFN architecture, it can be utilized for any given input vector with RSSI's obtained during target motion for each time step k.

The proposed RBFN architecture has two operational stages, namely, unsupervised learning phase and application of concept of least squares. In the first stage, the width parameters and the center vector in Gaussian function with hidden node are computed with the help of the input samples. The radial basis function used in RBFN is generally Gaussian function as defined below in [10, 12]

$$G(X - c_i) = \exp\left(-\frac{1}{2\sigma_i^2}\|X - c_i\|^2\right), \tag{5}$$

where $X = [\text{RSSI}_1, \text{RSSI}_2, \text{RSSI}_3, \text{RSSI}_4]$, $\|X - c_i\|$ is the Euclidean distance, and c_i is the Gaussian function for the central vector of the j^{th} hidden node.

The estimated target location using RBFN can be given as follows:

$$(\hat{x}, \hat{y}) = \sum_{i=1}^{h} w_h \exp\left(-\frac{1}{2\sigma_i^2}\|X - c_i\|^2\right), \tag{6}$$

where $w_i(i = 1, 2, \cdots h)$ is the weight between the hidden layer to the output layer and $(\hat{x}_k, \hat{y}_k)$ is the estimated target location.

As discussed in the Section 1, RBFN alone is not sufficient to guarantee high localization accuracy due to dynamicity in the indoor environment and high noise in RSSI measurements. In other words, if the system dynamics is highly nonlinear and uncertain, the RBFN location estimated must be improved further with advanced state estimation technique such as KF. Therefore, the RBFN estimates are fed as an input to KF. The generalized framework for the RSS measurement and target motion models for the KF is given below in

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \tag{7}$$

$$z_k = H(x_k) + v_k, \tag{8}$$

where A, B, and H are the state transition matrix, control input transition matrix, and RSSI input vector transition matrix, respectively (see equation (9)). The values of A and B matrices in equation (7) considered for this research work are given in

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2}dt^2 & 0 \\ 0 & \frac{1}{2}dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}, H = I_{4\times4}. \tag{9}$$

The KF algorithm execute in two steps: predict step and update step. The mathematics behind predict and update stage is described below in

$$\begin{aligned} \bar{x}_k &= A\hat{x}_{k-1} + Bu_{k-1} + w_{k-1}, \\ P_k^- &= AP_{k-1}A_k^T + Q_k, \\ K_k &= P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k\right)^-, \\ \hat{x}_k &= \bar{x}_k + K_k(z_k - H_k\bar{x}_k), \\ P_k &= (I - K_kH_k)P_k^-, \end{aligned} \tag{10}$$

where K is called Kalman gain matrix and I is identity matrix $(I_{4\times4})$..

The $R, P,$ and Q values in this research work are as follows:

$$R = \begin{bmatrix} 1.2 & 0 & 0 & 0 \\ 0 & 0.2 & 0 & 0 \\ 0 & 0 & 0.6 & 0 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}, P = \begin{bmatrix} 0.15 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.1 \end{bmatrix}, Q = I_{4\times4}. \tag{11}$$

The loss function for our proposed RBFN-based target localization scheme can be explained using performance evaluation parameters. These parameters must assess how far the estimated target locations from the real-time locations of the mobile target. The performance evaluation parameters used in this research work are average localization error and RMSE. For the successful localization performance the metrics of these loss functions must be as low as possible. These performance evaluation parameters can be defined as

$$\begin{aligned} \text{Average Localization Error} &= \frac{1}{T}\sum_{k=1}^{T} \frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2}, \\ \text{RMSE} &= \sqrt{\frac{1}{T}\sum_{k=1}^{T} \frac{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2}{2}}, \end{aligned} \tag{12}$$

where (x_k, y_k) is the actual target track and $(\hat{x}_k, \hat{y}_k)$ is the estimated target track.

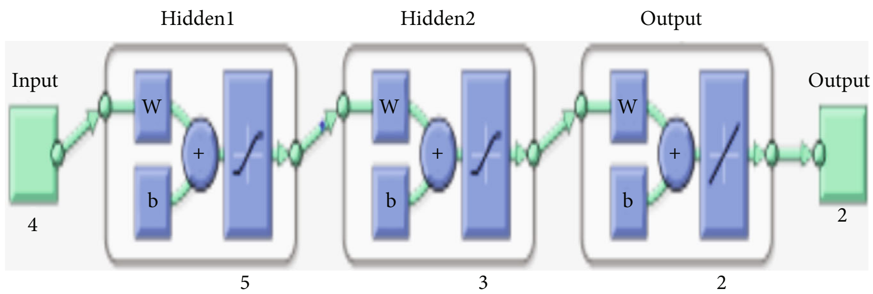

Figure 3: MATLAB view of RBFN neural network-based localization architecture.

In this paper, we have adopted the node energy model proposed by Garcia et al. [6]. According to this model, the sensing module is assumed to be operating in periodic mode and it is matching with our system setting. This model also assumes the sensing module alternately goes in "on" and "off" state. Considering energy consumptions during "on" and "off" states are constant, the energy consumption of wireless sensor (E_{sensor}) can be computed by

$$\begin{aligned} E_{\text{sensor}} &= E_{\text{on-off}} + E_{\text{off-on}} + E_{\text{sensor-run}} \\ &= N(e_{\text{on-off}} + e_{\text{off-on}} + V_s I_s T_s), \end{aligned} \tag{13}$$

where $e_{\text{on-off}}$ is the one-time energy consumed to switch sensor from "on" to "off" state, $e_{\text{off-on}}$ is the one-time energy consumed to switch sensor from "off" to "on" state, $E_{\text{sensor-run}}$ is the energy consumed during sensing wireless signal, V_s is the working voltage of sensor, I_s is the working voltage of sensor, T_s is the time period required for sensing operation, and N is the total number of "on" to "off" and "off" to "on" operations.

4. Discussion on Results

The RBFN and the proposed RBFN+KF-based localization architectures are trained using 100 sets of four RSS measurements (input vectors) and 100 corresponding actual locations (output vector) each. As the proposed RBFN architecture is trained, it is now ready for target localization by using random set of four RSSI vectors obtained in real-time motion of the target. Once the location estimates with RBFN architecture are obtained, these are fed to the KF framework to refine them further for each time step. The training samples (RSSI measurement vector and corresponding target locations) are presented to the proposed RBFN architecture during training, based on which it gets adjusted according to its error. The validation samples are used to measure generalization ability of the proposed RBFN and to stop training if generation stops further improvisation, whereas the testing samples (real-time RSSI measurement vector) are provided to the RBFN to evaluate the localization accuracy of the proposed RBFN during online estimation. Figure 4 shows the results of validation performance with the proposed RBFN+KF algorithm. The mean squared error (MSE) represents the distance between the model's estimate for test values and the actual test value. This plot is useful to give rough idea about how your model behaves for training dataset, test dataset, and validation dataset. The model validation is checked generally to know about suitability of your model at guessing out-of-sample values. From Figure 4, it is clear that MSE is very less, moderate, and high for training dataset, test dataset, and validation dataset, respectively. We get best validation performance at epoch 12; thus, the proposed model takes less epochs to get generalized.

Figure 5 shows the results of model training state using parameters such as gradient, Mu, and validation checks with the proposed RBFN+KF algorithm. The gradient error between the estimated target location values and the actual target location values is minimized using the back-propagation algorithm and is achieved to be 1.6313 at epoch 18. The mu is the control parameter used to train the neural network, whereas the validation check is a parameter to be observed when you do not have huge amount of training dataset. This is most beneficial when you do not have huge amount of data. The values for mu and validation checks at epoch 18 are $1e-11$, and 6, respectively. It simply means the proposed model performs best at epoch 18.

We know that the regression R represents the correlation between estimated output and desired target. It varies between 0 (high correlation) and 1 (high correlation). From Figure 6, it is evident that training of the proposed RBFN architecture has R value of 0.99988, validation has R value of 0.99452, test has R value of 0.86539, and all has R value of 0.96279. It can be inferred that there is close relationship between estimated results and desired results by adopting the proposed RBFN+KF algorithm. In each simulation experiment, the mobile target starts its motion from (10, 10) and stops at (85, 55). The RMSE and average localization errors presented in Table 1 are obtained by averaging of 40 simulation trials. Figure 7 illustrates comparison of localization accuracy with trilateration, RBFN, and RBFN+KF schemes. From Figure 7, it is evident that the estimated target locations with the proposed RBFN+KF algorithm almost coincide with the actual target track during its motion.

Figure 8 presents the comparison of variation of estimation errors in localization in x location estimate with trilateration, MLP, RBFN, and RBFN+KF-based localization schemes. As far as estimation of target x coordinate during its motion is concerned, the x coordinate estimation error is highest with the traditional trilateration-based localization technique as compared to the rest. The x coordinate

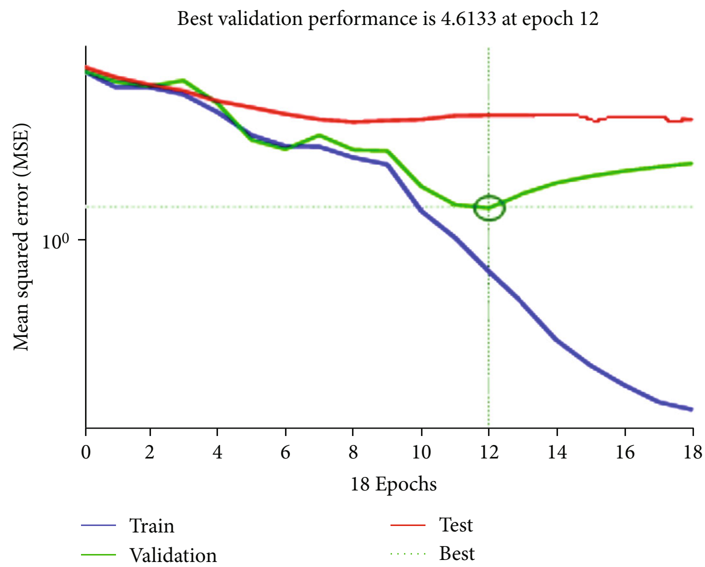

FIGURE 4: Results of validation performance with the proposed RBFN+KF algorithm.

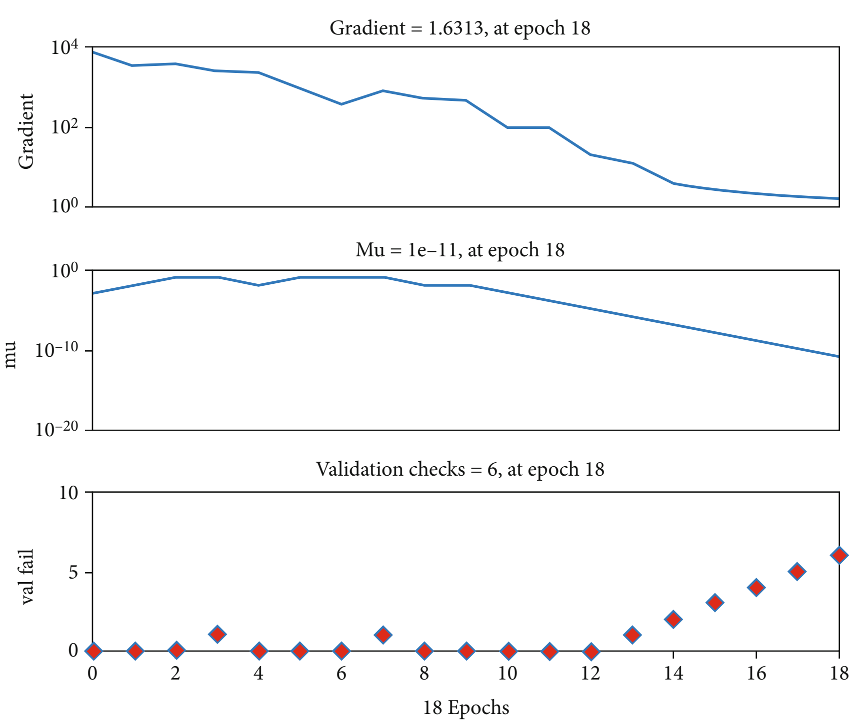

FIGURE 5: Results of gradient, Mu, and validation checks with the proposed RBFN+KF algorithm.

estimation errors are different for different target locations during its motion. The same logic is applicable for y coordinate estimation errors, and x-y coordinate estimation errors illustrated in Figures 9 and 10, respectively. The highest error with trilateration, MLP, RBFN, and RBFN+KF are approximately 20 meters, 10 meters, 5.8 meters, and 1.7 meters, respectively. Thus, the proposed RBFN+KF model target localization performance is very high for the given indoor setup as compared to that with the rest of the other techniques.

Figure 9 illustrates the comparison of variation of estimation errors in localization in y location estimate with trilateration, MLP, RBFN, and RBFN+KF-based localization schemes. As far as estimation of target y coordinate during its motion is concerned, the y coordinate estimation error is highest with the traditional trilateration-based localization technique as compared to the rest. The highest error with trilateration, MLP, RBFN, and RBFN+KF are approximately 18 meters, 10 meters, 5 meters, and 2 meters, respectively. Thus, the proposed RBFN+KF model target localization

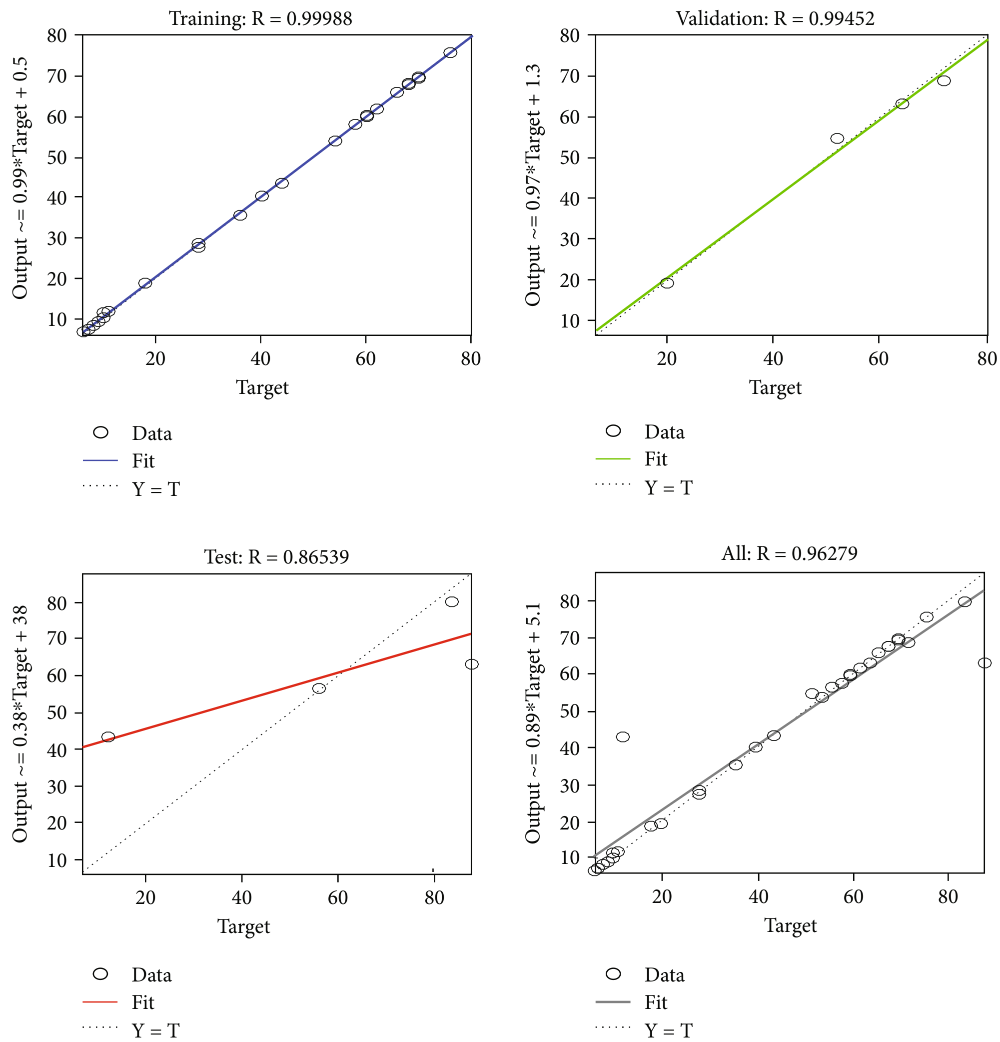

FIGURE 6: Results of regression during training, validation, and testing with the proposed RBFN+KF algorithm.

TABLE 1: Average localization error, RMSE, largest and smallest localization errors with trilateration, RBFN, and RBFN+KF schemes in meters.

Algorithm	RMSE (meter)	Average localization error	Smallest localization error in x-y estimation	Largest localization error in x-y estimation
Trilateration	12.4312	6.7076	0.5487	19.7849
MLP	7.0431	3.1076	0.4723	11.6523
RBFN	6.1756	2.4682	0.7450	8.2512
RBFN+KF	1.4874	0.8991	0.2130	1.9732

performance is best for target y coordinate estimation also as compared to that with the rest of the other techniques.

Figure 10 demonstrates the comparison of variation of estimation errors in localization in x-y location estimate with trilateration, MLP, RBFN, and RBFN+KF-based localization schemes. This graph of target x-y location estimate is obtained by taking average of x location estimate and y location estimate. Here, also, the x-y coordinate estimation error is highest with the traditional trilateration-based localization technique as compared to rest of the others. The highest error with trilateration, MLP, RBFN, and RBFN+KF are approximately 14 meters, 8 meters, 7.7 meters, and 1.8 meters, respectively. Thus, the proposed RBFN+KF model target localization performance is the best for target x-y coordinate estimation also as compared to that with the rest of the other techniques.

It is also observed that RMSE for the proposed RBFN +KF is lowered down by around 88%, 79%, and 75% as compared with that of trilateration, MLP, and RBFN, respectively (see Table 1). Additionally, the average localization error for the proposed RBFN+KF is lowered down by approximately 86%, 71%, and 63% as compared with that of trilateration, MLP, and RBFN, respectively. The largest

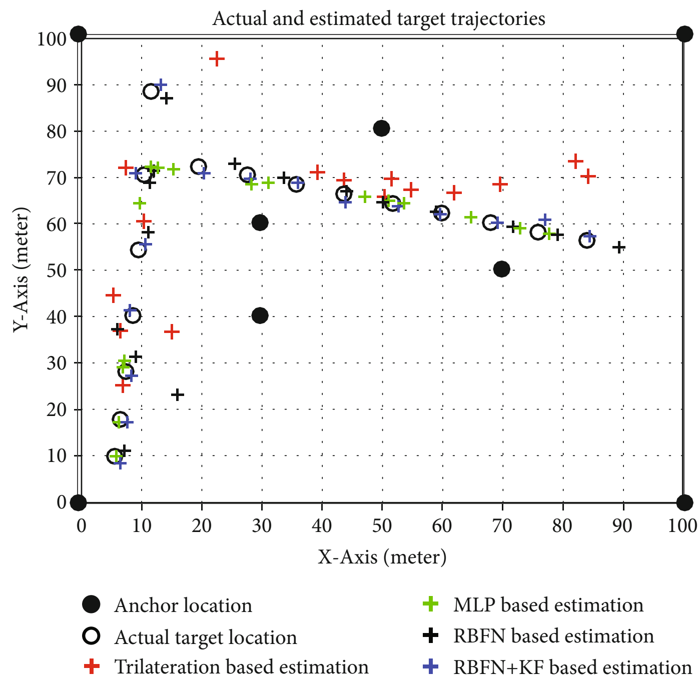

Figure 7: Comparison of trilateration, MLP, RBFN, and proposed RBFN+KF-based localization estimation.

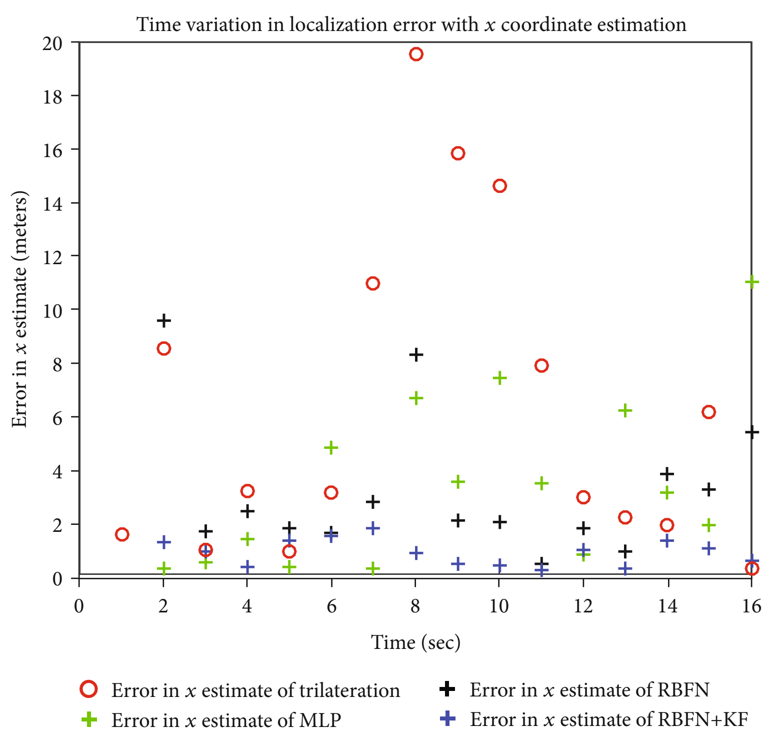

Figure 8: Comparison of variation of estimation errors in localization in x location estimate with trilateration, MLP, RBFN, and RBFN+KF-based localization schemes.

possible localization error in the x-y location estimation with the RBFN+KF scheme is 1.9732, and it is very much less than that with the RBFN and trilateration-based localization schemes. Thus, from all these results discussed so far, it can be easily concluded that target localization accuracy is lowest, moderate, and highest with trilateration, MLP, RBFN, and the proposed RBFN+KF schemes, respectively.

From Figure 11, it is clear that the energy consumption (in Joules) during target tracking is lowest with the proposed RBFN-based framework, moderate with MLP-

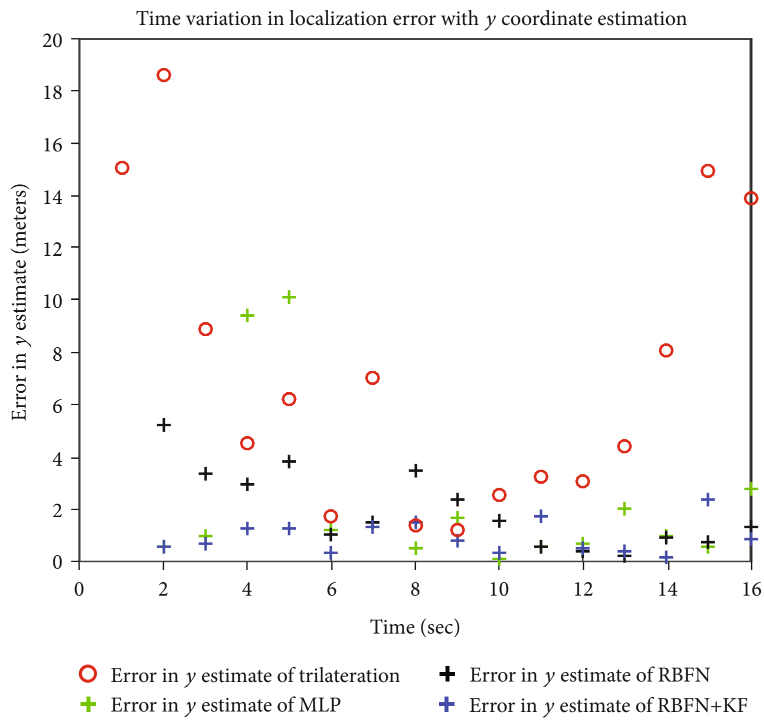

FIGURE 9: Comparison of variation of estimation errors in localization in y location estimate with trilateration, MLP, RBFN, and RBFN+KF-based localization schemes.

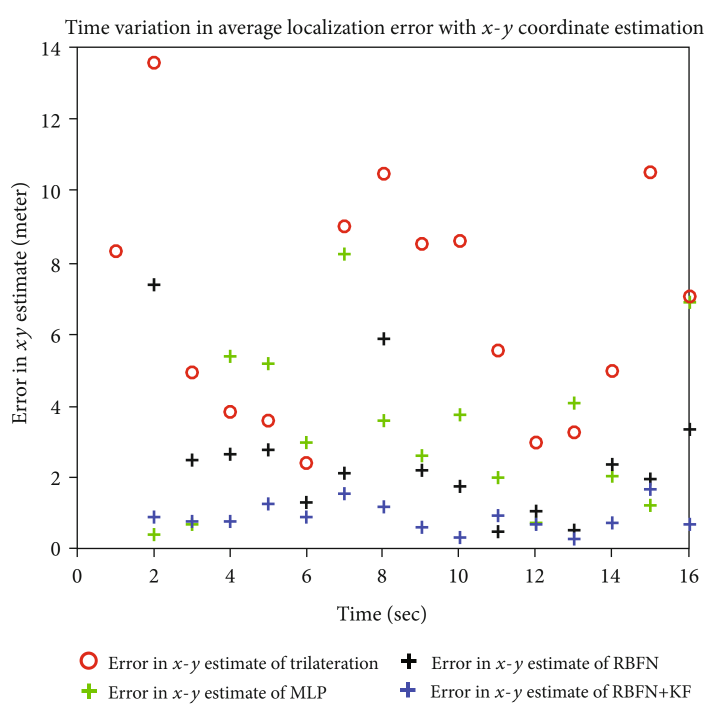

FIGURE 10: Comparison of variation of estimation errors in localization in x-y location estimate with trilateration, MLP, RBFN, and RBFN +KF-based localization schemes.

based framework, and highest with trilateration-based scheme. Looking at Figure 11, it is also clear that the proposed RBFN+KF scheme also comparatively consume much less energy than that with the classical trilateration-based scheme for our given indoor setup. We also believe that this energy consumption will vary from indoor setup to

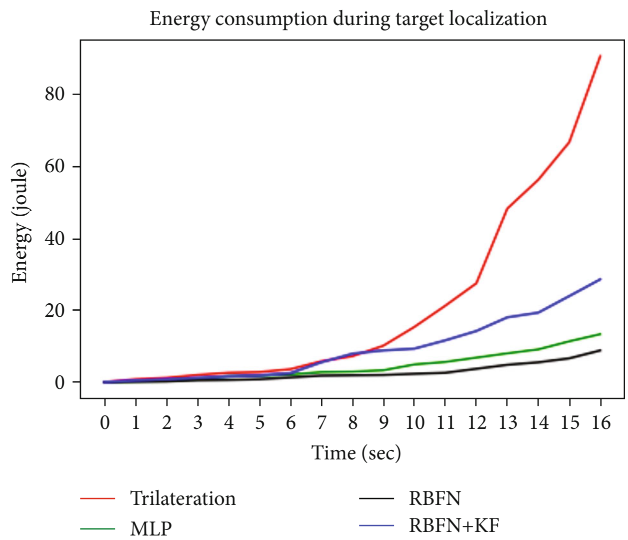

FIGURE 11: Comparison of energy consumptions during target localization with trilateration, MLP, RBFN, and RBFN+KF-based Localization schemes.

setup. Thus, the proposed RBFN+KF scheme is found to be superior than remaining other localization schemes. It is quite clear that the target tracking accuracy will vary for different target trajectories as well as for different WSN areas say $1000\,\mathrm{m} \times 1000\,\mathrm{m}$. For such different operating environments, one needs to use more customized training dataset of RSSI measurements. We believe that if a custom training dataset is generated using simulations, the proposed RBFN-based target tracking scheme may yield good target tracking performance.

5. Conclusion

This work proposes novel RSS measurements based target L&T algorithm, namely, RBFN+KF. It is basically a fusion of RBFN and KF techniques. The results obtained through simulations prove that our proposed RBFN+KF target localization scheme provides improved target location estimates as against trilateration, MLP, and RBFN-based solutions. The RBFN+KF scheme successfully deals with the dynamicity in the given RF channel for indoor target L&T. To realize RSSI measurement dynamicity, the RSS measurement noise is set to 3 dBm. It is also revealed that the proposed RBFN+KF scheme successfully address the problem of fluctuations in RSS field measurements as well as abrupt motion of mobile target against trilateration and RBFN in the context of tracking accuracy. In the future, we intend to apply proposed fusion-based RBFN+KF localization scheme to solve multitarget tracking (MTT) problem. We also believe that the variation in the total number of anchor nodes or in the number of input RSSI measurements to the proposed RBFN model may yield variation in target localization accuracy as well as total energy consumption.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Authors' Contributions

Conceptualization was done by V.K.K. and A.S.J. Methodology was provided by A.S.J. Software was acquired by U.N.D. and B.V.R. Validation was done by J. L and A.S.J. Formal analysis was performed by J. L and A.S.J. Investigation was conducted by A.S.J. Writing—original draft preparation was done by U.N.D and A.S.J. Writing—review and editing was done by U.N.D, A.S.J., and B.V.R. Supervision was provided by J.L. Project administration was done by J.L. Funding acquisition was done by J.L. All authors have read and agreed to the published version of the manuscript.

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