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Kalman Filtering Framework based Real Time Target Tracking in Wireless Sensor Networks using Generalized Regression Neural Networks

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Abstract**—**Traditional received signal strength indicators (RSSI's) based moving target localization and tracking using wireless sensor networks (WSN's) generally employs lateration/angulation techniques. Although this method is a very simple technique but it creates significant errors in localization estimations due to nonlinear relationship between RSSI and distance. The Generalized Regression Neural Network (GRNN) being a one-pass learning algorithm is well known for its ability to train quickly on sparse data sets. This paper proposes an implementation of GRNN as an alternative to this traditional RSSI based approach, to obtain first location estimates of single target moving in 2-D in WSN, which are then further refined using kalman filtering (KF) framework. Two algorithms namely, GRNN + kalman filter (KF) and GRNN + unscented kalman filter (UKF) are proposed in this research work. The GRNN is trained with the simulated RSSI values received at moving target from beacon nodes and the corresponding actual target 2-D locations. The precision of the proposed algorithms are compared against traditional RSSI based, GRNN based approach as well as other models in the literature such as traditional RSSI + KF and traditional RSSI + UKF algorithms. The proposed algorithms demonstrate superior tracking performance (tracking accuracy in the scale of few centimeters) irrespective of nonlinear system dynamics as well as environmental dynamicity.

Index Terms**—** General Regression Neural Network (GRNN), Kalman Filter (KF), Received Signal Strength Indicators (RSSIs), Target Tracking, Unscented Kalman filter (UKF), Wireless Sensor Networks (WSNs).

I. INTRODUCTION

Several technological enhancements in radio frequency (RF) technology and embedded systems have made possible the use of wireless sensor network's (WSN's) for a variety of new monitoring and control applications [1],[2]. The target localization and tracking is one of the fundamental research areas of WSN with diverse military and civilian applications. Originally developed for military applications, today it is being an integral part of plenty of civilian applications such as locating moving objects in building, tracking people inside building, wildlife tracking, environmental monitoring as well as various location based services (LBS). The prime objective of localization and tracking is to estimate the locations of the moving targets (localization problem) and their trajectories (tracking problem) by exploiting the field measurements at regular intervals of time [3],[4]. That means the tracking problem can be described as the solution of a set of localization problems at successive time intervals. The performance of such applications requires the target tracking accuracy as high as possible. Although localization can be done with sufficient accuracy by using GPS with the help of satellites. Although, GPS performs well for line of sight (LOS) to several satellites, maintaining LOS is generally a rare possibility especially for indoor environments. Target tracking based on data from a low cost WSN is more economical approach as compared to the use of GPS. Consequently, the research trend is to develop WSN based (GPS-less) solutions, especially under constraints of limited resources of WSN's. The WSN based localization can be broadly classified as range-based or range-free. To estimate target location the range based solutions rely on computing distance between wireless sensor nodes and target whereas range free solutions use information such as connectivity between wireless sensor nodes (i.e. information other than distance).

Looking at the technological aspects, the target localization and tracking in WSN, can be achieved with the help of RF, infrared (IR), video, acoustic and ultra wideband (UWB) [4]. The RF technology (which dominantly exploiting RSSI measurements) as compared to rest of the others is widely used because of its ability to penetrate smoke, nonmetallic barriers and walls, making it a better choice for localization applications. RF signals from WiFi access points can also be employed for indoor localization [5]. With the release of the Bluetooth Low Energy (BLE) technology, the BLE beacons have also attracted considerable attention for the indoor localization [6]. In the context of RSSI based localization, the traditional methods such as lateration/angulation are generally used. If the distance between two sensor nodes is used for localization, it is termed as the lateration based approach, whereas if the angles of arrival between two sensor nodes are used for localization, then it is termed as the angulation based approach [4]. However to determine angle of arrival of the RF signals in case of angulation approach, WSN nodes are required to be equipped with array of at least two directional antennas. In practice, both lateration and angulation methods suffer from the problem of imperfect computations of

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distances and angles respectively. This imperfection is due to abrupt variations in target velocity and uncertain noise involved in RSSI measurements because of signal attenuation, multipath fading, orientation of antenna, and height to the ground and shadowing effects. Especially, it is very difficult for lateration based system to handle highly nonlinear RSSI-distance relationship. To deal with such environmental dynamicity, 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 mapping between the input and output values of a system is unclear or subject to noise [7]-[9]. Unlike the KF, in ANN based localization and tracking methods, there is no need of prior knowledge of the noise distribution. Which is why ANN based localization solutions are very promising. Noisy distance measurements along with the actual node locations can be used directly to train the ANN. The main objective of this research work is to deal with high nonlinearity in RSSI's-target location relationship using a suitable neural network architecture and further refine these location estimates with the help of KF framework. Excluding the traditional method from localization and tracking, the proposed approach will avoid the process of lateration/angulation and thereby computations of distances/angles between the sensor nodes. 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.

II. RELATED WORK

Many research efforts have been reported in target tracking literature to deal with dynamicity in RSSI measurements. The dominant approach to account this dynamicity is to fuse RSSI measurements with a suitable recursive bayesian framework based filters such as kalman filter (KF) [8],[11],[12], and partical filter (PF) [13],[14]. The choice of KF or PF based system depends mainly on the statistics such as the amount and distribution of noise in the process and measurements as well as application requirement. In [14], the authors carried out a rigorous survey of various bayesian filter implementations for location estimation. These surveys 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, the computational complexity of PF is predominantly higher than KF. The unscented kalman filter (UKF) has been proved to be a better alternative to KF and the extended Kalman filter (EKF), especially in the context of system nonlinearity [16], [17]. In [17], UKF based location and tracking algorithm is proposed which employs a dynamic model of human walking along with a number of sensor measurements to track target position and velocity.

A comparison of localization performance using various ANN families such as Multi-Layers Perceptron (MLP), Radial Basis Function (RBF) and Recurrent Neural Networks (RNN) along with the two variants of the KF, is done by [18]. The simulation area considered by the authors is 26x26 meters with 8 anchor nodes deployed on its edges. Although the experiment concludes that the localization performance of RBF is highest than other ANN approaches, the MLP shows the best trade-off between accuracy and computational resource requirements. The KF shows fewer localization errors but the magnitudes of errors are quite high, which is generally due to the process noise of the simulated target motion with non-gaussian characteristics. The research concluded that the KF requires several iterations to reduce the localization error as against various neural network architectures presented.

Stella et al. [19] developed an indoor WSNs positioning system based on location fingerprinting and ANN, showing an average accuracy of 1.79 meters. A neural network is employed to establish the relations between different levels of received signal strength and the location of wireless sensors in an indoor environment. The method proposed in [20] combines machine learning with a KF for tracking of a target moving with some acceleration. The kernel-based ridge regression and the vector output regularized least squares are used in the learning process. In this experiment, radio fingerprints of RSSI's are first collected over the surveillance area. This radio fingerprints are then used with machine learning algorithms to compute a model that estimates the position of the target using only RSSI information. The presented algorithm computes a first position estimate of the moving target, which is then further refined using KF. The efficacy of the proposed approach is evaluated for different target tracks as well as it is compared with other contemporary target tracking algorithms in the literature.

BPNN has also been successfully applied to the indoor localization problem [21]. However the major drawback of BPNN is that it generally takes a large number of iterations to converge to the desired solution. The Probabilistic Neural Network (PNN) can be a good alternative to overcome the limitation of BPNN [22]. The major advantage of PNN is very flexible architecture as well as it works with only few training samples. The GRNN is a highly parallel neural network which falls under PNN category [23],[24]. Very few researchers have applied GRNN in localization and tracking problem [25]-[27]. In [27], the authors proposed a GRNN based algorithm GRNNα, which is used for estimating the target position in 3-D measurement environment. 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.

In our previous research work [28], 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

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estimates of the traditional trilateration based approach. The proposed algorithms address the important real time problems such as abrupt variations in target velocity, the limited set of RSSI measurements and the variation in the anchor density. The results confirmed that as compared to the traditional RSSI based algorithm, the proposed approach achieve better tracking accuracy and real time performance, irrespective of environmental dynamicity. However being range based algorithms, the presented approach involves the time consuming computations of distances based on noisy RSSI values. Although the algorithms achieve tracking accuracy of centimeter scale, due to high nonlinearity involved in the RSSI-distance relationship, the higher target tracking accuracy is not guaranteed all the time. This issue gives a motivation to address this important issue further with the help of the GRNN based approach.

To deal with high level of nonlinearity involved in the RSSI-distance relationship, two target tracking algorithms are proposed in this paper namely: GRNN+KF and GRNN+UKF. As against our previous work in [28], in this research the traditional RSSI based position estimation technique is replaced by GRNN, so as to get GRNN + KF and GRNN + UKF algorithms. The GRNN once trained with the pair of RSSI measurements and corresponding actual target position, can give position estimates of moving target directly. In this RSSI based position estimates of GRNN are inputted to KF and UKF to get further refinements. Both the proposed algorithms take into account these real time problems (uncertainties in measurement noises and abrupt changes in target velocity) and are evaluated through MATLAB simulations. The major contribution of our work is: 1) we designed a KF and UKF based approach to refine the GRNN based position estimates of a moving target to deal with uncertainty in measurement noise, 2) The proposed algorithms successfully bypass the computations of RSSI based distances, path loss exponent and environmental calibration, 3) we critically analysed the proposed algorithms for abrupt changes in target velocity.

III. LOCALIZATION OF MOBILE TARGET USING GENERAL REGRESSION NEURAL NETWORK

The discrete-time target motion model and observation model can be generalized to the forms:

$$X_k = f(X_{k-1}, u_{k-1}, w_{k-1}), \tag{1}$$

$$z_k = h(X_k) + v_k \ , \tag{2}$$

where X_k is the target state vector $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$ and z_k is the observation vector (RSSI measurements from anchor nodes) at the current time step k, u_{k-1} is control input vector, while w_{k-1} and v_k are white noise, mutually independent from each other. In general, f and h are non-linear functions. The RSSI values are generated according to log normal shadow fading model. The RSSI $(z_{\ell j,k})$ received at the node N_ℓ with coordinates $(x_{\ell k}, y_{\ell k})$ at time k, after being transmitted from the node N_j with coordinates (x_{jk}, y_{jk}), propagates as follows [29]:

$$z_{\ell j,k} = P_r(d_0) - 10n\log(d_{lj,k}/d_0) + X_\sigma, \tag{3}$$

Where, $P_r(d_0)$ is RSSI measured at receiver node located at reference distance d_0 (it is generally 1 meter) from transmitter, and X_σ is normal random variable (a measure of shadowing effect which generally ranges from 3 to 20 dBm). In this research it is set with variance of 3 dBm and standard deviation of 1 dBm such that $X_\sigma \sim N(3,1)$.

With capability of one pass learning, the GRNN can converge to the underlying (linear or nonlinear) regression surface very quickly. It is well known for its ability to train quickly on sparse data sets and is especially useful for continuous function approximation. The GRNN work by measuring how far a given sample pattern is from patterns in the training set. The algorithmic form can be used for any regression problem in which an assumption of linearity is not justified.

The GRNN basically consist of input layer, pattern layer, summation layer and output layer (see Fig. 1). The input layer receives the input signals while the pattern layer possesses a nonlinear transformation applied on the data from the input space to the pattern space. For the GRNN, the number of neurons in the hidden layer is usually equal to the number of patterns in the training set. The summation layer performs the sum operation where outputs of the pattern layer nodes are multiplied with appropriate interconnection weights to sum up for producing the output of the network. The output layer nodes are represented by a GRNN individual output. 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.

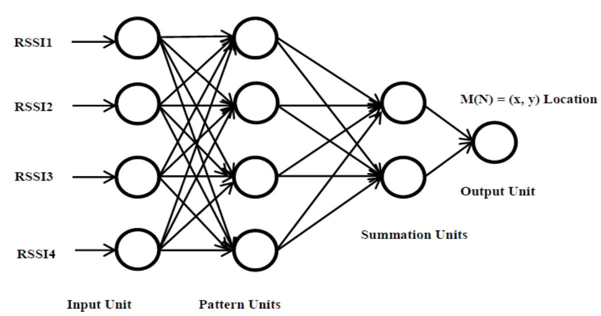

Fig. 1 Block Diagram of GRNN Architecture for the proposed Target Tracking Algorithms.

Basically the GRNN can estimate values of M (dependent variables) for any new value of N (independent variables) in the short time determined by the propagation time through the multilayer network. In this research, The GRNN architecture is adopted for the target tracking problem at hand. In this work, M is considered to be the estimated 2-D

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location of moving target while N represent four RSSI values from four anchor nodes as shown in Fig. 1. The M_i and N_i are sample values of M and N respectively. It can be noted that 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. Using the proposed GRNN architecture, the $M(N)$ (i.e. 2-D Target Location) is estimated as follows:

$$M(N) = \frac{\sum_{i=1}^{n} M_i \exp(\frac{-D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} \exp(\frac{-D_i^2}{2\sigma^2})} \tag{4}$$

$$D_i^2 = (N - N_i)^T .(N - N_i) \tag{5}$$

The σ is the smoothing factor and n is the number of sample observations (or the dimension of input vector). As the input to the developed GRNN architecture is four RSSI values, hence in this work $n = 4$. It is believed that the selection of proper smoothing factor is important to the accuracy of both PNN and GRNN [45]. The high smoothing factor increase the network's ability to generalize, conversely the low smoothing factors degrade the network's ability to generalize. Therefore care has to be taken decide the appropriate value of the smoothing parameter.

It can be noted that 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 compressive strength can be calculated from GRNN by scaling the input parameters such as the standard deviation of all the input variables are similar and choosing a proper sigma value. The GRNN network in MATLAB 2013a environment can be created by 'newgrnn' function [30].

IV. Kalman Filtering Framework

A. Standard Kalman Filtering

KF provides the optimal bayesian estimator when the underlying system is linear and noises in system dynamics are gaussian with zero mean [8],[12],[16]. The target motion and measurement models for the standard KF can be written respectively as:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \tag{6}$$

$$z_k = H(x_k) + v_k, \tag{7}$$

where A, B and H are state transition, control input transition and measurement transition matrices respectively as given below. The matrix B relates the optional control input vector u_{k-1} to the state. Here w_{k-1} and v_k are the process noise and observation noise respectively, and are assumed to be normally distributed zero mean white gaussian with covariance Q_k ($w_k \sim N(0, Q_k)$) and R_k ($v_k \sim N(0, R_k)$) respectively. These two noise are assumed to be independent of each other or in other words they are uncorrelated. For the constant velocity model the matrices in equations (6) and (7) are given as follows.

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2}dt^2 & 0 \\ 0 & \frac{1}{2}dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}, H = I_{4\times4} \tag{8}$$

The operation of KF can be described in two simple steps: predict and update. The predict step utilizes the estimate from the previous time step $k-1$ to produce an estimate of 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 :

$$\bar{x}_k = A\hat{x}_{k-1} + Bu_{k-1} + w_{k-1}. \tag{9}$$

$$P_k^- = AP_{k-1}A_k^T + Q_k. \tag{10}$$

Update :

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^- . \tag{11}$$

$$\hat{x}_k = \bar{x}_k + K_k(z_k - H_k\bar{x}_k) . \tag{12}$$

$$P_k = (I - K_k H_k)P_k^- , \tag{13}$$

where the matrix K is called Kalman's gain matrix and I is identity matrix $(I_{4\times4})$. The superscript "^" above indicates the estimate of the state vector. Notice in equations (8) and (9), given the initial state variable x_{k-1} and its process covariance matrix P_{k-1}, the state variable and its process covariance matrix of next time step k can be predicted. These estimates can be further refined (updated) with the help of measurement at time step k using equations (11)-(13).

B. Unscented Kalman Filtering Framework

Generally in practice motion model and measurement models are nonlinear. The EKF and the UKF are techniques aimed at relaxation of the linearity requirement in contrast to KF [17],[18]. The EKF is based on model linearization and however it is highly sensitive to higher model nonlinearities. The UKF can effectively cope up these higher model nonlinearities. The UKF basically employs unscented transform in which idea is to deterministically sampling pick a minimal set of sample points (called sigma points) around the mean. These sigma points are then propagated through the non-linear functions and the covariance of the estimate is then recovered. The result is a filter which more accurately captures the true mean and covariance.

In UKF prior to prediction and update steps, one need to carefully define noise covariance matrix Q and measurement noise covariance matrix R, initialize x and the covariance matrix P and calculate sigma points as given by equation (14).

$$\chi_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{x}_{k-1} + \lambda\sqrt{P_{k-1}}]. \tag{14}$$

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The estimate from the previous time step (k-1) are used to produce an estimate of the current time step k in the predict step, as given by equations (15)-(20).

Prediction :

$$\chi^{*}_{k/k-1} = f(x_{k-1}, u_{k-1}) \quad (15)$$

$$\hat{x}_k = \sum_{i=0}^{2L} w_i^m \chi^{*}_{k/k-1}. \quad (16)$$

$$P_k = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k]\,[z_{i,k/k-1} - \hat{z}_k]^T + \mathrm{R}. \quad (17)$$

$$\chi_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{x}_{k-1} + \lambda\sqrt{P_{k-1}}]. \quad (18)$$

$$z_{k/k-1} = H\chi^{*}_{k/k-1}. \quad (19)$$

$$\hat{z}_k = \sum_{i=0}^{2L} w_i^m z_{i,k/k-1}. \quad (20)$$

In the update phase, measurement information from the current time step is used to refine this prediction to arrive at a new more accurate estimate, as given by equations (21)-(25).

Update :

$$P_{xk,zk} = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k]\,[z_{i,k/k-1} - \hat{z}_k]^T + \mathrm{R}. \quad (21)$$

$$P_{xk,zk} = \sum_{i=0}^{2L} w_i^c [x_{i,k/k-1} - \hat{x}_k]\,[z_{i,k/k-1} - \hat{z}_k]^T + \mathrm{R}. \quad (22)$$

Kalman Gain :

$$K_k = P_{xk,zk}\, P_{zk,zk}^{-1}. \quad (23)$$

Emendation state estimate:

$$\hat{x} = \hat{x}_{k-1} + K_k(z_k - \hat{z}_k). \quad (24)$$

Error covariance matrix updates:

$$P_k = P_{k-1} - K_k P_{zk,zk} K_k^T, \quad (25)$$

Where, w_0^m is weights of mean, w_0^c is weights of covariance, λ is a scaling parameter, as given by equation (26). L is the dimension of augmented state. The general values of α=10^{-3}, k_i=0 and $\beta = 2$.

$$w_0^m = \lambda/(L+\lambda),\ w_0^c = \lambda/(L+\lambda) + (1+\alpha^2+\beta), \quad (26)$$

Where, α is a measure of the spread of the sigma points around $\hat{x}$ and is usually set to a small positive value, while β is used to incorporate prior knowledge of the distribution of x.

V. SYSTEM DESIGN AND PERFORMANCE EVALUATION

A. System Design

The proposed system consists of a set of static anchor nodes at known coordinates, deployed in simulation area of 100 meter by 100 meter, the mobile target, as shown in Fig.4 and a base station outside (not shown in figure). The mobile target is assumed to carry one WSN node, which receives RF signal broadcasted by all anchor nodes for every time step k. The collected RSSI values from all anchors at each time step are transmitted to outside base station. That means the target is assumed to be acting as a transceiver whereas anchor nodes as transmitters with perfectly isotropic antennas. The base station attached with a laptop (Core i5, 1.70 GHz, 4 GB RAM) is supposed to run all the algorithms to be analyzed namely, traditional RSSI, GRNN, GRNN + KF and GRNN +UKF algorithms. For simplicity, we limit this work to estimation of a single target. The system is considered to run for a total time period of T, which is divided into several time slots dt. Variety of state mobility models are previously described in the literature such as random walk, constant-velocity, constant-acceleration, polynomial models, singer acceleration model, mean-adaptive acceleration model [31], [32]. In this work, we choose a constant velocity model.

The state of moving target at time instant k is defined by the vector $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$, where x_k and y_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. In this research work the motion of mobile target is defined by following equations.

$$x_k = x_{k-1} + \dot{x}_k\ dt, \quad (27)$$

$$y_k = y_{k-1} + \dot{y}_k\ dt, \quad (28)$$

Where, dt is discretization time step between two successive time instants such that $dt = k-(k-1)$. The target motion undergoes the variation in velocity during T seconds as given by equations (29)-(32) and illustrated in Fig. 2 and Fig. 3. Here negative velocity value indicates that target is moving to a location with smaller coordinate value as compared to that at previous time instance.

$$\dot{x}_k = 2,\quad \dot{y}_k = 5,\quad \text{for } 0 < k < 9 \text{ s}, \quad (29)$$

$$\dot{x}_k = 5,\quad \dot{y}_k = 2,\quad \text{for } 9 \le k \le 15 \text{ s}, \quad (30)$$

$$\dot{x}_k = 0,\quad \dot{y}_k = 0,\quad \text{for } 16 \le k \le 17 \text{ s}, \quad (31)$$

$$\dot{x}_k = 2,\quad \dot{y}_k = -3,\quad \text{for } 18 \le k \le 35 \text{ s}. \quad (32)$$

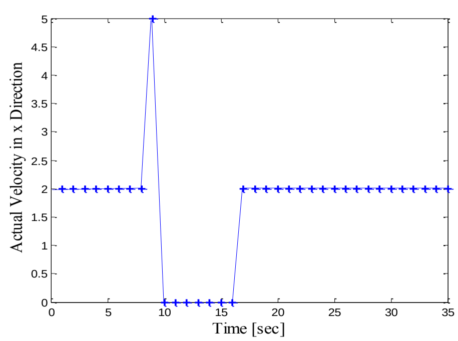

Fig.2. Actual Speed of target. This figure shows abrupt variation in velocity in x direction during motion.

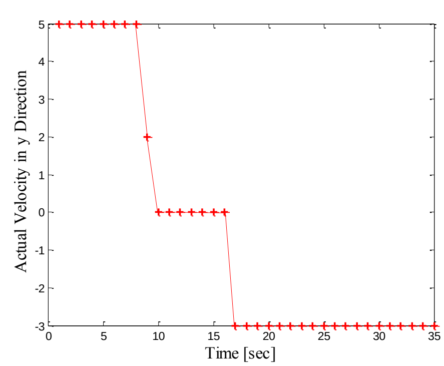

Fig.3. Actual Speed of target. This figure shows abrupt variation in velocity in y direction during motion.

In this research, the target velocities ($\dot{x}_k$ and $\dot{y}_k$) is estimated by dividing distance covered by the target with the time it takes to cover that distance. The communication range of the sensor nodes is assumed to be 100 meters. The transmitter and receiver antenna gains are set to 1 dB. The transmission power is set to 1 millwatts. It is quite logical that higher the density of anchors, better would be the target tracking performance. However the higher anchor density will increase hardware cost and additional maintenance. As reported in our previous work [39], by raising the anchor density, the tracking performance gets improved in almost all the algorithms. To focus more upon the proposed GRNN based approach, number of anchors are restricted to four in this research work. The R, P_0 *and* Q matrices are taken to be,

$$R = \begin{bmatrix} 2.2 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}, P_0 = \begin{bmatrix} 0.25 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix}, Q = I_{4\times 4}. \qquad (33)$$

TABLE 1
Simulation Parameters for 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
X_σ	Normal Random Variable	~N(3, 1)
η	Average Path Loss Exponent	2.84
σ	Spread Factor	3.5

This research work is carried out for two phases:

Phase I : Analysis of Tracking Performances of Traditional RSSI, GRNN, GRNN+KF and GRNN+UKF based algorithms,

Phase II : Analysis of Tracking Performances of Traditional RSSI+KF, Traditional RSSI+KF, GRNN+KF and GRNN+UKF based algorithms.

B. Performance Metrics:

We have used two metrics to evaluate the performance of the proposed algorithms namely, Average Localization Error and root mean square error (RMSE). The Average Localization Error and RMSE represent the closeness between estimated target trajectory $(\hat{x}_k, \hat{y}_k)$ and given actual target trajectory (x_k, y_k) over T respectively. The Average Localization Error (See equation (34)) and Average RMSE (See equation (35), (36) and (37)) represent the average of corresponding errors in x and y estimates. Lower the values of these two metrics, better is the estimation of location of moving target and thereby better would be the tracking accuracy. After every sampling instance k, the error in x estimate $(\hat{x}_k - x_k)$, error in y estimate $(\hat{y}_k - y_k)$, for the traditional RSSI, GRNN algorithms, and the proposed GRNN + KF and GRNN + UKF algorithms, are computed.

1]Average Localization Error (Error in x-y Estimates) :

$$\textit{Average Localization Error} = \frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2}, \qquad (34)$$

2] Root Mean Squared Error (RMSE) :

$$RMSE_x = \sqrt{\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2}{T}}. \qquad (35)$$

$$RMSE_y = \sqrt{\sum_{k=1}^{T}\frac{(\hat{y}_k - y_k)^2}{T}}. \qquad (36)$$

$$RMSE_{avg} = \frac{(RMSE_x + RMSE_y)}{2} \qquad (37)$$

C. Flow of Proposed Algorithm

The complete simulation for one time step k consists of three parts. The first part is offline GRNN Training Stage which involves the training of GRNN. The second part is Online Position Estimation using GRNN (to be run at the base station), whereas the third part is Online Position Estimation using KF Framework (to be run at the base station). Values of performance metrics for both simulation phases in Table 4 to Table 5 are average values of 50 simulation trials. The detailed flow of the proposed algorithms for one time step k is as given in Table 2.

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 anchors and corresponding actual position of the moving target.

II. Online Position Estimation using GRNN

Step 2: The moving target receives RSSI transmitted from all anchor node for every k^{th} instance. 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. The errors in x and y position estimates are computed as well as recorded.

III. Online Position Estimation using KF Framework

Step 4 : The base station refines GRNN based position estimates using KF and UKF algorithm. The errors in x and y position estimates are computed as well as recorded.

For sampling instants $k = 1, 2, , ... T$

Step 5 : Steps from 2 to 4 are repeated for each next time steps until the completion of total simulation 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.

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D. Discussion of Results

As mentioned earlier the research work is carried out in two phases (Phase I and Phase II). Before the analyzing these two phases, a small attempt is made to find out the optimum value of σ by trial and error method for the given wireless scenario. The σ value is manually varied from 0.5 to 6 and average RMSE is noted down for all algorithms mentioned in phase I. From this experiment it is found that for the given wireless environment, σ value in the range of 3 to 4 demonstrates better tracking performance (See Table 3). The Fig. 4 to Fig. 7 and Table 4 are comparison of target tracking performances of algorithms mentioned in Phase I, while Fig. 8 to Fig. 11 and Table 5 are comparison of target tracking performances of algorithms mentioned in Phase II. In both the phases, the moving target start from position (12, 15) and stops at (97, 10).

The Fig. 4 depicts the actual and the estimated target trajectories by the traditional RSSI, GRNN, GRNN+KF and GRNN+UKF algorithms. The black filled squares represent anchor nodes, whereas red unfilled squares, green plus symbols, red plus symbols, blue plus symbols and unfilled black circles represent actual target position, RSSI based estimated position, GRNN based estimated position, GRNN + KF based estimated position and GRNN + UKF based estimated position respectively at a specific time instance k in Fig. 4. The Fig. 5 and Fig.6 illustrate the comparison of localization errors in x estimate and y estimate for all above mentioned algorithms respectively. The average performance in both x and y estimates can be obtained by taking the average of both x and y estimates, as shown in Fig. 7. The red line (joining unfilled circle symbols), the black line (joining green plus symbols) and the blue plus symbols and black plus symbols represent localization errors in traditional RSSI, GRNN, GRNN + KF, and GRNN + UKF based estimation approaches for the total simulation period T respectively. The GRNN + KF, and GRNN + UKF based estimates in Fig. 5, Fig. 6 and Fig. 7 are purposefully not joined by solid line to avoid confusions in these figures and to be able to differentiate tracking results of all these approaches easily.

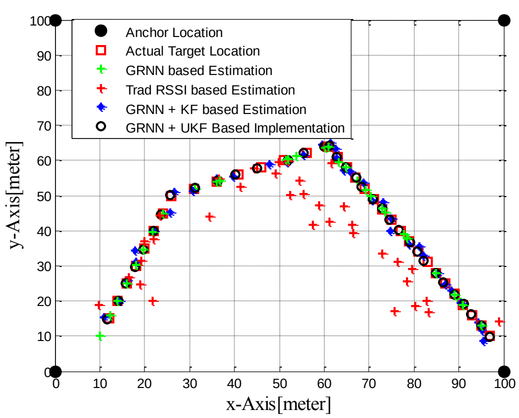

Fig. 4. Actual target trajectory and estimated trajectories by the Traditional RSSI, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

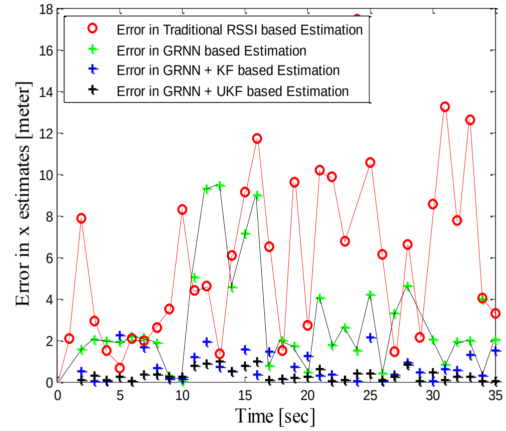

Fig. 5. Comparison of Localization Errors in x estimates in Trad. RSSI, RSSI+KF, and RSSI+UKF algorithms (σ= 3.5).

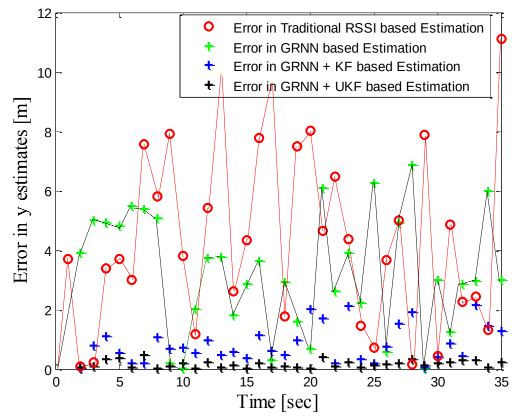

Fig. 6. Comparison of Localization Errors in y estimates in pure RSSI, RSSI+KF, and RSSI+UKF algorithms (σ= 3.5).

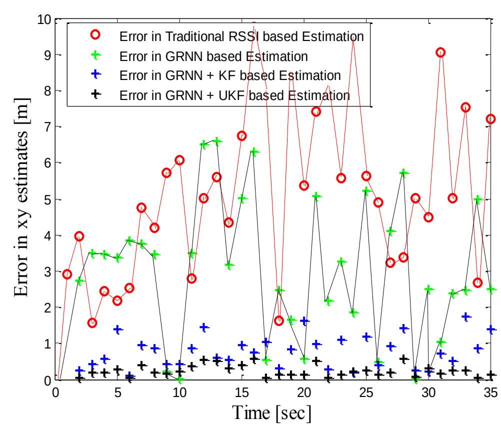

Fig.7. Comparison of Localization Errors in x-y estimates in Trad. RSSI, GRNN, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

The Fig. 4 and Table 4 reveal that our proposed algorithms closely follow the actual target trajectory. It is quite logical that whenever there is abrupt change in the target velocity, the tracking error would be higher. For instance, during the time period $16 \leq k \leq 17$, as the target velocity is suddenly dropped down to zero in both the x and y directions, the large localization error is observed in traditional RSSI and GRNN based estimation (see Fig. 5 to Fig. 7). However in this time period, the proposed algorithms show low localization errors. That means the proposed algorithms successfully

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absorb this abrupt change in target velocity as compared to the rest of the two algorithms. It is to be noted that out of all implementations of Phase I, the GRNN+ UKF results in lowest average localization error of 0.3896 meters and lowest average RMSE of 0.4973 meters. That means the GRNN + UKF better absorbs the high nonlinearity in RSSI-distance relationship, uncertain measurement noise as well as the abrupt change in the target velocity during period T. The Table 4 also shows the lowest, highest and average localization errors as well as RMSE in x and y estimation and average RMSE in x and y estimates for all the algorithms mentioned in the Phase I. It is to be noted that the average RMSE of GRNN+UKF algorithm is reduced by approximately 94%, 90% and 58% respectively as compared to that of Traditional RSSI, GRNN and GRNN+KF algorithms respectively (See Table 4).

The Phase II is also carried out for the same network environment as Phase I. As shown in Fig. 8 and Table 5, the proposed algorithms closely track the actual target track as compared to the our previously proposed algorithms (i.e. Traditional RSSI + KF and Traditional RSSI + UKF). It is to be noted that out of all implementations of Phase II, the GRNN+ UKF results in lowest average localization error of 0.3334 and lowest average RMSE of 0.4333. That means like the Phase I results, the Phase II results also conclude that the GRNN + UKF outperforms the other algorithms in the context of the considered environmental dynamicity. The Table 5 also shows the lowest, highest and average localization errors as well as RMSE in x and y estimation and average RMSE in x and y estimates for all the algorithms mentioned in the Phase II. It is to be noted that the average RMSE of GRNN+UKF algorithm is reduced by approximately 68%, 50% and 57% respectively as compared to that of Traditional RSSI+KF, Traditional RSSI+UKF and GRNN+UKF algorithms respectively (See Table 5). This considerable decrease in average RMSE for the proposed algorithms can be considered as significant achievement of the application of GRNN in place of Traditional RSSI technique. In other words the GRNN architecture is far more superior option to approximate nonlinear mapping between RSSI and 2-D location of the moving target.

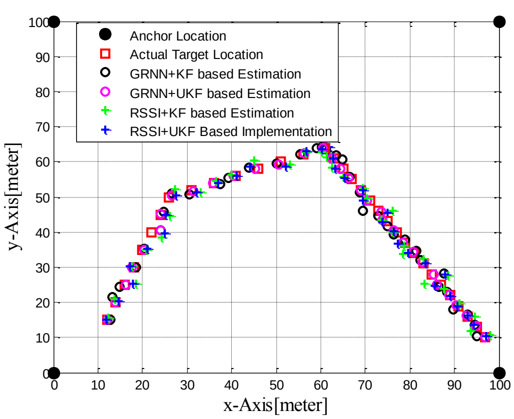

Fig. 8 Comparison of tracking performance of trad. RSSI+KF, RSSI+UKF, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

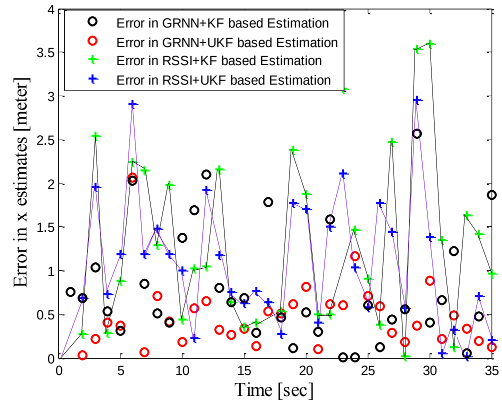

Fig. 9. Comparison of Localization Error in x estimate of trad. RSSI+KF, RSSI+UKF, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

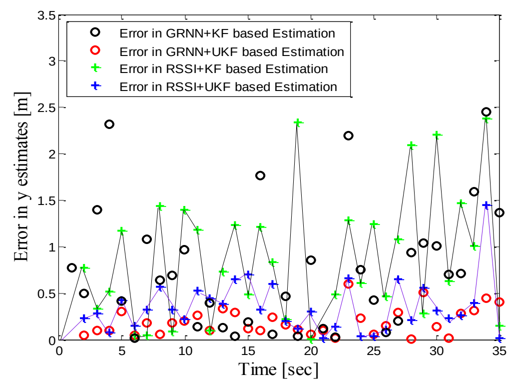

Fig. 10. Comparison of Localization Error in y estimate of trad. RSSI+KF, RSSI+UKF, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

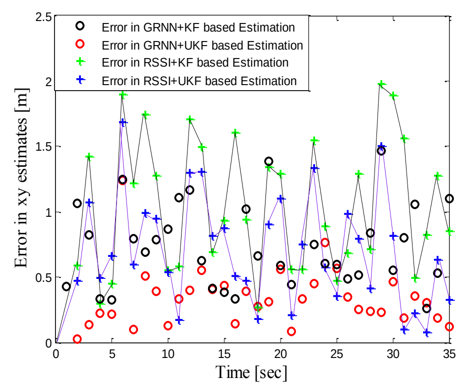

Fig. 11. Comparison of Localization Error in x-y estimate of trad. RSSI+KF, RSSI+UKF, GRNN+KF and GRNN+UKF algorithms (σ= 3.5).

It is to be noted that the experiment of the variation of smoothing parameter σ on tracking accuracy of the proposed algorithms and experiments of Phase I, are completely independent. As the simulated RSSI values are obtained in MATLAB using log normal shadow fading model, for each run the amount of noise added is different due to the parameter normal random variable X_σ in equation (3) and therefore the computed corresponding RMSE values of the algorithms are different (See Table 3 and Table 4). The same logic is applicable for experiment of Phase I and Phase II (See Table 4 and Table 5). From the carried out all the simulation experiments, it can be easily concluded that the overall tracking accuracy (average localization error and RMSE) is lowest for GRNN + UKF approach compared to rest of others. The GRNN+KF and GRNN+UKF shows the improved target tracking as compared to their traditional lateration based counterparts namely, Traditional RSSI + KF and Traditional RSSI + UKF. The GRNN along with KF framework better handles the nonlinearity associated with the target motion and the measurement models in both the phases.

VI. CONCLUSIONS AND FUTURE WORK

This study introduces the GRNN based approach for improving real time target tracking performance in KF framework in WSN with uncertain measurement noises. The study demonstrated that nonlinear function approximation of RSSI-2D location is possible through the use of the GRNN technique. The two RSSI based algorithms namely, GRNN+KF and GRNN+UKF, are presented for efficient 2-D tracking of single moving target in WSN. For tracking single mobile target, only four anchor nodes with known locations and RSSI measurements are exploited. The GRNN model was trained with 70 samples and was successfully validated with a blind testing data set of 35 samples. To study the effect of variations in target velocity, the target velocity is varied within the range of -3 to 5 (m/s) abruptly at specific time instances during simulation. The overall tracking performance is assessed in terms of RMSE, and average localization error. The results of simulation experiments demonstrated higher tracking accuracy (in the scale of few centimeters) irrespective of the abrupt changes in the target velocity, unpredictable measurement noise as well as limited set measurements available. The Simulation results show that the GRNN +UKF based approach outperforms all the others in the context of the tracking performance. The simulation result confirms the potential of GRNN architecture for the real time target tracking problem in WSN using RSSI.

There are several avenues for the further research such as tracking of multiple moving targets, investigation of various other mobility models, application of suitable optimization technique to compute the optimum value of σ for the given tracking problem. Our future work will be more focused on realizing and verifying the proposed algorithms using real RSSI values from WSN hardware.

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Table 3. Comparison of Tracking Performance of the Proposed Algorithms wrt Smoothing Parameter (σ)

Tracking Algorithm	Variation of Smoothing Parameter (σ)							
	0.5	**1**	**2**	**3**	**3.5**	**4**	**5**	**6**
Avg. RMSE of Trad. RSSI	8.7258	8.5402	7.8806	8.2426	8.1085	7.3412	8.4617	10.4850
Avg. RMSE of GRNN	5.9733	5.7797	5.1829	3.9004	3.8199	3.8479	5.1430	6.1737
Avg. RMSE of GRNN+KF	1.0730	1.0144	0.9910	1.0897	1.0157	1.0231	1.1341	1.1079
Avg. RMSE of GRNN+UKF	0.4490	0.5051	0.4857	0.3310	0.3621	0.3466	0.4572	0.5845

Table 4. Error Analysis of all the Algorithms (Phase I)

Tracking Algorithm	Lowest Localization Error in Avg. Est. [meter]	Highest Localization Error in Avg. Est. [meter]	Avg. Localization Error [meter]	RMSE in x Estimation [meter]	RMSE in y Estimation [meter]	Avg. RMSE in x-y Estimation [meter]
Traditional RSSI	1.7834	9.7812	7.0621	8.1405	7.8985	8.0195
GRNN	0.8107	6.4936	4.7437	5.0818	5.6216	5.3517
GRNN + KF	0.1263	1.8941	0.9554	1.2431	1.1618	1.2025
GRNN + UKF	0.0197	0.6325	0.3896	0.6052	0.3894	0.4973

Table 5. Comparison Error Analysis of the Proposed Algorithms in this work with that in [33] (Phase II)

Tracking Algorithm	Lowest Localization Error in Avg. Est. [meter]	Highest Localization Error in Avg. Est. [meter]	Avg. Localization Error [meter]	RMSE in x Estimation [meter]	RMSE in y Estimation [meter]	Avg. RMSE in x-y Estimation [meter]
RSSI + KF	0.0978	4.8967	1.0373	1.6244	1.0461	1.3353
RSSI + UKF	0.1913	4.4869	0.6937	1.2986	0.4547	0.8766
GRNN + KF	0.1997	1.6415	0.7788	1.0428	0.9641	1.0034
GRNN + UKF	0.0082	0.9267	0.3334	0.5944	0.2722	0.4333