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Improved Generalized Regression Neural Network for Target Localization

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Abstract
Knowledge of location is of utmost importance in many indoor Location-Based Services (LBS). Although traditional technique such as trilateration involving the use of received signal strengths (RSS's) is quite popular and simple to use for wireless sensor network (WSN) based target localization, the location estimates obtained using it are not accurate and reliable. The reason behind this is the highly fluctuating nature of RSS's due to dynamic RF environment and non-linear system dynamics. If the dataset is sparse, the concept of centroid is very useful to estimate fairly closer approximation to the underlying relationship in the given dataset. The GRNN architecture is well known for mapping any nonlinear relationship between input and output. To address the problems with the RSS based target localization and tracking (L&T) using WSN for indoor environment, a novel range free Centroid Generalized Regression Neural Network (C-GRNN) algorithm is presented in this paper. The proposed C-GRNN algorithm is formed by combining the advantages of both centroid and GRNN. In order to realize the dynamicity in given RF environment, the variance in the RSSI measurements is varied from 3 to 6 dBm. During simulation experiments, although the variance in the RSSI measurements is doubled, the average RMSE and average localization error are increased by only approximately 28.31%, and 22.28% respectively. This rise in localization errors with the proposed C-GRNN architecture is very less as compared to the trilateration as well as GRNN based technique.

Keywords Location-based services (LBS) · Received signal strength (RSS) · Wireless sensor network (WSN) · Trilateration · Centroid · Generalized regression neural network (GRNN) · Localization and tracking (L&T)

1 Introduction

Today sensor network is a basic building block in applications involving smart sensing and ubiquitous computing, and has plenty of localization and tracking (L&T) based applications [1–3]. The heavy deployment sensor nodes can scan, sense the useful physical

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parameters from the environment and send these measurements to the base station for further processing. The measurements collected are useful only if knowledge of source of data is known [4–6]. Therefore, the underlying target localization mechanism plays very crucial role in the WSN based applications. The L&T is one of the core application areas of the WSN. Although GPS is widely used for localization in outdoor environment, GPS based location estimates are not accurate and reliable for indoor environmental setup [7, 8]. The reason behind this is unavailability of GPS signals in indoor. Consequently, the indoor L&T applications require GPS-less architecture. The low cost and low power WSN technology is proved to be very useful to address the problem of indoor L&T. The WSN based localization has two major categories namely, range-free and range (distance)-based [9–11]. The range-free localization is based on relationship between inter node connectivity and network topology, whereas the range-based approach is based on computing the distances between sensor nodes. Generally, the localization accuracy is high in latter approach. Out of various measurement metrics in range-based as well as range free techniques, received signal strength indication (RSSI) or RSS is widely used in the WSN based L&T. The major reason behind this is that unlike other methods the RSSI based system do not need additional hardware in the process of localization [12, 13]. The research work in this paper utilizes RSSI measurements to locate the single target moving in WSN defined area.

The traditional trilateration technique is widely used in the RSSI based target L&T because of its simplicity in use [14, 15]. In practice, trilateration-based method of localization suffer lead to estimation of inaccurate (erroneous) locations of the target [16]–[18]. The obvious reason is due to uncertain noise involved in RSSI measurements because of signal attenuation, multipath fading, NLOS condition, and shadowing effects. Additionally, if there is an abrupt variation in velocity of mobile target, the probability of large localization error is very high. Looking the L&T problem from another perspective, the concept of centroid can be very useful to provide accurate estimate if the underlying RSSI dataset is sparse [19–23]. Recently the Weighted centroid based localization (WCL) using RSSI measurements has been found to be an attractive low complexity solution for target L&T [19, 22, 23]. The WCL based localization algorithm uses position of anchors that are in the communication radius of unknown node whose position is to be estimated. The WCL algorithm generally yields low localization accuracy, especially if the unknown node is outside a polygon established by the anchors. Some researchers have proved that by fusing the centroid concept with some other existing localization framework the localization error can be significantly reduced. The authors in [19] have proposed a fuzzy-based centroid localization (FCL) algorithm for localization. In proposed FCL, the anchor nodes are prioritized using fine-tuned weights. The results obtained with FCL method are superior than existing WCL based localization methods. In [23], the authors proposed a particle centroid drift (PCD) algorithm for large scale WSN with an objective to reduce the distance estimation errors. In PCD based system centroid algorithm is combined with particle distribution function to form in high quality particles. These high-quality particles in PCD algorithm benefits in low localization errors along with low time complexity.

We know that artificial neural network (ANN) once trained with appropriate dataset, can deal with almost any non-linear system dynamics [24]. However, choosing appropriate ANN architecture for the given indoor L&T application is very crucial. The GRNN is found to be suitable to variety of target L&T applications involving highly nonlinear system dynamics. Unlike other ANN architectures, the GRNN has only one control parameter. That is GRNN smoothing factor. We have previously used the concept of GRNN and applied it in several ways to solve the problem of single mobile target L&T [16–18]. For instance, we proposed and verified two algorithms namely: GRNN + KF and GRNN + UKF to address uncertainty in RSSI measurement noise in [16]. The proposed GRNN architecture is trained with training dataset that consists of input vectors (four RSSI measurements) and corresponding output vector (actual 2-D locations of target). Here the location estimates obtained with developed GRNN architecture are applied to KF and UKF to further smooth the GRNN location estimates. These GRNN + KF and GRNN + UKF algorithms are also validated in a real time experiment carried out in our institute laboratory [18]. In this experiment, we proved that the moving person can be tracked efficiently using wireless communication network formed using smartphone and PSOC BLE nodes. Although the algorithms presented in [16, 18] show improved localization results than that with trilateration, GRNN, RSSI + KF, and RSSI + UKF algorithms, the RSSI measurement noise is kept constant (i.e. 3 dBm). Motivated by the benefits of centroid concept, and GRNN, and, we propose a novel range free Centroid Generalized Regression Neural Network (C-GRNN) architecture for RSSI based indoor target L&T problem using WSN. The main contributions of this research work are listed below.

(1) We formulated a novel framework based on the GRNN, and centroid for the problem of RSSI based L&T of single target moving in indoor environment, namely C-GRNN. Unlike our previous GRNN architecture [16, 18], input vector dimension for the proposed C-GRNN architecture is 6. Unlike localization analysis in our previous works [16, 18], a new parameter for the evaluation of localization performance is introduced (i.e. Regression Coefficient *R*).

(2) The proposed C-GRNN algorithm is tested and verified against dynamicity in the surrounding environment (high fluctuations in RSS measurements) as well as non-linear system dynamics (abrupt variation in target velocity) through MATLAB simulations. Unlike [16, 18], we critically analyzed the proposed C-GRNN algorithm by increasing the measurement noise in RSSI from 3 to 6 dBm in steps of 3 dBm.

(3) We compared the localization performance of the proposed C-GRNN algorithm with trilateration as well as with our previously published GRNN algorithm. Simulation and numerical results demonstrate that C-GRNN algorithm better deal with the environmental dynamicity and non-linear system dynamics as compared to trilateration and GRNN.

The remaining structure of the paper is as follows. Section 2 briefly discusses the architecture of proposed C-GRNN architecture. We present system design and results obtained with proposed algorithm in detail through extensive simulations in Sect. 3 and Sect. 4, followed by conclusions at the end in Sect. 5.

2 C-GRNN Architecture for Target Localization

The RSS's used in this research work are artificially generated using log normal shadow fading model (LNSM) as given below [9, 16, 18]:

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

where ($z_{\ell j,k}$)—RSSI received at the node N_ℓ with coordinates $(x_{\ell k}, y_{\ell k})$ at time k. It is assumed to be transmitted by node N_j with coordinates (x_{jk}, y_{jk}),$P_r(d_0)$—RSSI at receiver kept at a distance d_0(1 m),η—Path loss exponent. Like [16], here also it is kept 2.84.X_σ

—Normal random variable with some value of variance, and standard deviation. Here, during analysis of the proposed C-GRNN architecture, the variance, and standard deviation are kept 3 dBm, and 1 dBm respectively in Case I such that $X_\sigma \sim N(3, 1)$. Whereas, in Case II standard deviation is kept same as 1 dBm as but variance is changed to 6 dBm. In short, it represents measurement noise in RSSI values.

It is well known that the GRNN can converge any linear or nonlinear regression surface (sparse data sets) very quickly. For estimating output, it measures the distance of given input vector from vectors used in the training dataset. The detailed study of GRNN can be found in [25]. In this work we designed the proposed C-GRNN architecture by fusing the concept of centroid in the GRNN architecture. The input to the proposed C-GRNN is (input vector consisting of any four RSSI measurements, and Centroid location), and its output is (output vector that includes estimated 2-D location) (See Fig. 1).

The location estimation given by C-GRNN architecture is given as [16, 18]:

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

$$D_i^2 = (X - X_i)^T.(X - X_i) \tag{3}$$

where M—Estimated 2-D location,X—A input vector consisting of four RSSI measurements and Centroid location),σ—Smoothing factor, and.n—Dimension of input vector. Here $n = 6$.

Choosing appropriate value of σ is very important in case of GRNN and C-GRNN for accurate output estimation [16, 18]. In order to compare our previously published GRNN architecture with the proposed C-GRNN architecture, we took $\sigma = 3.5$.

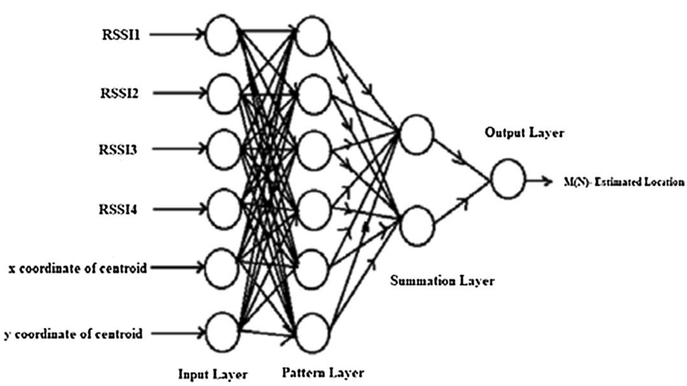

Fig. 1 C-GRNN Architecture for Target L&T

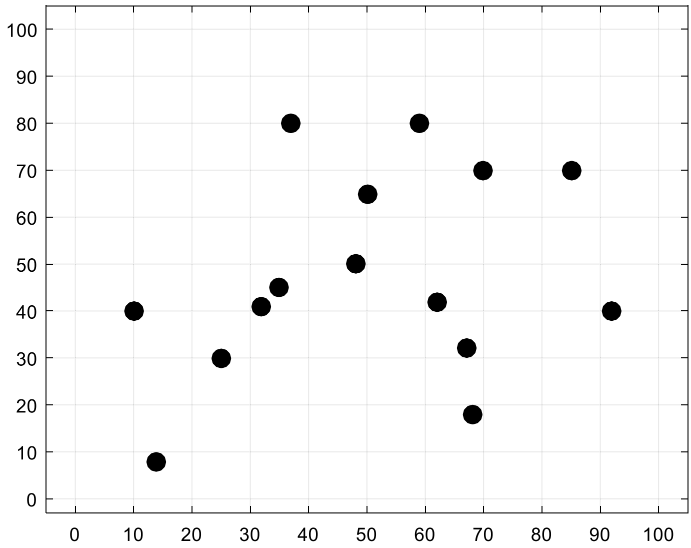

Fig. 2 Simulated Indoor Environment and Deployment of Anchor Nodes

Table 1 Deployment of Anchor Nodes in the simulations

Anchor node number	2-D location	Anchor node number	2-D location
1	(14, 8)	9	(92, 40)
2	(25, 30)	10	(68, 18)
3	(35, 45)	11	(59, 80)
4	(37, 80)	12	(48, 50)
5	(50, 65)	13	(32, 41)
6	(70, 70)	14	(10, 40)
7	(62, 42)	15	(67, 32)
8	(85, 70)		

3 System Design and Assumptions of C-GRNN Based L&T System

In this research work an indoor area of 100 m × 100 m is simulated using MATLAB 2016a as shown in Fig. 2. Total 16 WSN nodes are assumed to utilized for the proposed target L&T problem, out of which 15 are considered to be anchor nodes. The remaining 1 node is assumed to be carried by the target during motion. All of the anchor nodes are supposed to be configured in transmitter mode, whereas the node carried by the mobile target is assumed to be configured in receiver mode. The anchor nodes are deployed at locations as given in Table 1 and shown in Fig. 2. The total number of unknown target locations to be estimated during target motion in this work are 35. The location estimations are carried out using trilateration technique, GRNN algorithm and the proposed C-GRNN algorithm.

The Fig. 3 illustrates the proposed C-GRNN architecture-based target L&T system as shown below.

The GRNN and C-GRNN architectures are trained with the help of 75 sets of input vector (field measurements) and corresponding output vector (Actual 2-D location of

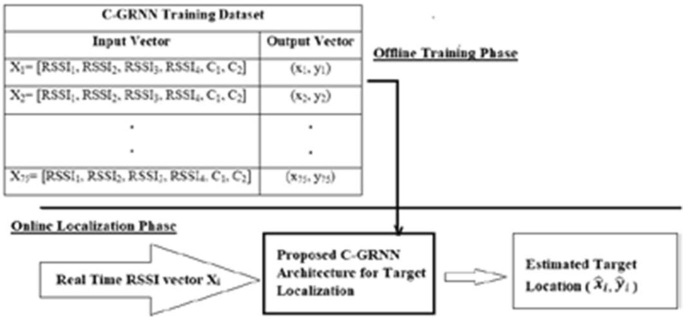

Fig. 3 System Block Diagram of C-GRNN based Target L&T System

target corresponding to those field measurements) (See Fig. 4). This training dataset (of 75 sets of input and output vectors) is obtained for $X_\sigma \sim N(3, 1)$ through some random trial of target motion as described by Eqs. (6–11). For each trial the Once the proposed C-GRNN is trained, it is ready to estimate any real time target location for input vector corresponding to that location in online localization stage. The operational difference between the GRNN architecture and C-GRNN architecture is the dimension of input vector. The input vector for GRNN architecture consists of any four random RSSI measurements, whereas input vector for C-GRNN architecture includes the same four random RSSI measurements, and centroid coordinates of anchors which produced those four RSSI measurements (See Eq. 4). Thus, the input vector dimensions for GRNN and C-GRNN architectures are 4 and 6 respectively. Although the Fig. 4 shows system block diagram of C-GRNN based target L&T system, it is also applicable for GRNN based

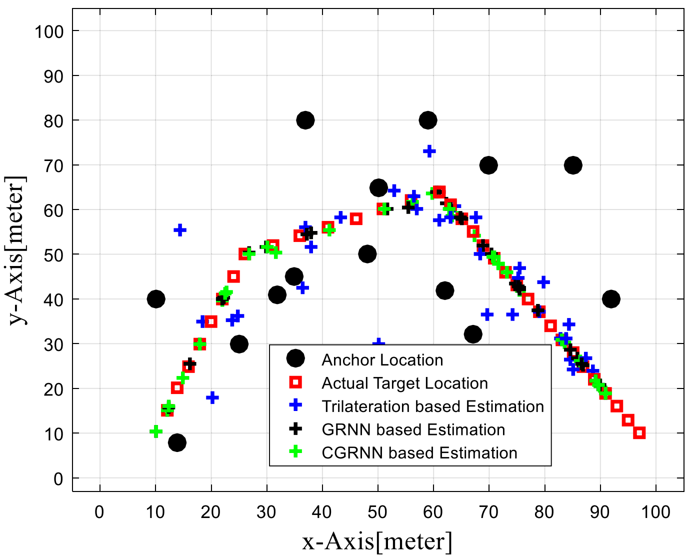

Fig. 4 Comparison of Target Location Estimations using Trilateration, GRNN and C-GRNN (case I)

L&T system. In order to visualize GRNN based L&T system all we have to replace C-GRNN architecture box by GRNN box, and remove C_1 and C_2 from X_i in Eq. (4).

$$X_i = [RSSI_1, RSSI_2, RSSI_3, RSSI_4, C_1, C_2], \quad i = 1, 2, ...75. \tag{4}$$

where X_i—ith Input vector for C-GRNN architecture,$RSSI_1$ to $RSSI_4$—RSS's obtained from four random anchors.C_1 and C_2—x and y coordinates of centroid of four anchors.

Let's consider the coordinates of anchors who generated $RSSI_1$, $RSSI_2$, $RSSI_3$, and $RSSI_4$ are $(x_1, y_1), (x_2, y_2), (x_3, y_3)$, and (x_4, y_4) respectively. Then C_1 and C_2 can be computed using coordinates of anchors who generated $RSSI_1$ to $RSSI_4$ as given below in Eq. (5).

$$C_1 = \left(\frac{x_1 + x_2 + x_3 + x_4}{4}\right), \quad C_2 = \left(\frac{y_1 + y_2 + y_3 + y_4}{4}\right) \tag{5}$$

Unlike GRNN and C-GRNN architectures, trilateration does not need such training prior to its real time application. As the target path is fixed, so we know all 35 unknown locations of target, thus 15 RSSI measurements we get for each of these locations. Out of these 15 measurements, three higher values of RSSI measurements are utilized to estimate the target location in case of trilateration. Whereas, the GRNN and C-GRNN works with any four random RSSI measurements during online estimation phase. The MATLAB simulations are carried out on hp platform with Core i5, and 4 GB RAM. The transmission power and communication radius of node is assumed to be 1 milliwatts (0 dBm) and 50 m respectively.

The state of moving target at time instant k is defined by state vector $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$, where x_k and y_k specify the x and y coordinates target, $\dot{x}_k$ and $\dot{y}_k$ specify target velocities in x and y directions respectively at k^{th} time instance.

$$x_k = x_{k-1} + \dot{x}_k \, dt \, , \tag{6}$$

$$y_k = y_{k-1} + \dot{y}_k \, dt \, , \tag{7}$$

where dt is discretization time step between two successive time instants such that $dt = k - (k - 1)$ and is kept 1 s. The target motion undergoes the variation in velocity for total simulation period of T seconds as given by Eq. (8) to Eq. (11). In this work, $T = 35$ seconds. The negative velocity means target is moving opposite direction.

$$\dot{x}_k = 2, \quad \dot{y}_k = 5, \quad \text{for } 0 < k < 9 \ \text{ sec}, \tag{8}$$

$$\dot{x}_k = 5, \quad \dot{y}_k = 2, \quad \text{for } 9 \le k \le 15 \ \text{ sec}, \tag{9}$$

$$\dot{x}_k = 0, \quad \dot{y}_k = 0, \quad \text{for } 16 \le k \le 17 \ \text{ sec}, \tag{10}$$

$$\dot{x}_k = 2, \quad \dot{y}_k = -3, \quad \text{for } 18 \le k \le 35 \ \text{ sec}. \tag{11}$$

Like previous works [9, 16, 18], in order to evaluate the localization performance of the proposed C-GRNN algorithm two parameters are considered namely, Average Localization Error (See Eq. 12) and root mean square error (RMSE) (See Eqs. 13–15. Lower the values of these two parameters, high will be the target localization (or tracking) accuracy.

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

where $(\hat{x}_k, \hat{y}_k)$—Estimated target location for k^{th} time instance,(x_k, y_k)—Actual target location at k^{th} time instance.

$$RMSE_x = \sqrt{\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2}{T}}. \tag{13}$$

$$RMSE_y = \sqrt{\sum_{k=1}^{T}\frac{(\hat{y}_k - y_k)^2}{T}}. \tag{14}$$

$$RMSE_{avg} = \frac{(RMSE_x + RMSE_y)}{2} \tag{15}$$

One more way to prove the efficacy of the proposed localization algorithm is to plot estimated (predicted) target location versus actual target location using linear regression. MATLAB provides plotregression (target,output) command to plot the linear regression of target relative to output [26]. In the corresponding result figure, we get a value of coefficient of correlation (R).R is a measure of correlation between actual and estimated value. R varies from -1 to $+1$. $R = -1$ indicates inverse correlation between target and output, whereas $R = +1$ indicates a perfectly linear positive correlation. Unlike [9, 16, 18], we have also used R for performance evaluation of all the techniques in this work.

4 Discussion on Results

In order to realize the real time indoor environment, X_σ(See Eq. (1)) is varied in Case I ($X_\sigma \sim N(3, 1)$), and Case II ($X_\sigma \sim N(6, 1)$). For each of the simulation case, the target is assumed to start from (10, 10) and stop at (97, 10). Numeric values of performance metrics for both simulation phases in Tables 2, 3, 4, 5 and 6 are average values of 50 simulation trials.

Table 2 Comparison of RMSE and Average Localization Errors with Trilateration, GRNN, and proposed C-GRNN algorithms (Case I)

Name of Localization Algorithm	RMSE for x Coordinate	RMSE for y Coordinate	Average RMSE	Average Localization Error
Trilateration	36.8601	23.1512	30.0057	12.5293
GRNN	4.4092	6.2206	5.3149	4.4640
C-GRNN	4.0421	5.4015	4.7218	3.5698

Table 3 Comparison of Estimations of Sample Target Locations with Trilateration, GRNN, and proposed C-GRNN algorithms (Case I)

Location Number	Actual Coordinate	Coordinates estimated with Trilateration	Coordinates estimated with GRNN	Coordinates estimated with C-GRNN
1	(10, 10)	(163.53, −60.70)	(10.11, 10.27)	(10.11, 10.27)
2	(12, 15)	(20.19, 18.05)	(12.09, 15.22)	(12.09, 15.22)
27	(79, 37)	(79.06, 37.18)	(83.51, 30.22)	(78.67, 37.49)
35	(95, 13)	(85.01, 24.36)	(91.04, 18.94)	(86.68, 25.47)

Table 4 Comparison of R values obtained with Trilateration, GRNN, and proposed C-GRNN algorithms through linear regression (Case I)

Name of L&T Algorithm	R for actual x coordinate and estimated x coordinate	R for actual y coordinate and estimated y coordinate
GRNN	0.98791	0.94392
C-GRNN	0.99032	0.96237

Table 5 Comparison of RMSE and Average Localization Errors with Trilateration, GRNN, and proposed C-GRNN algorithms (Case II)

Name of Localization Algorithm	RMSE for x Coordinate	RMSE for y Coordinate	Average RMSE	Average Localization Error
Trilateration	62.0431	45.8233	53.9332	27.2599
GRNN	7.7049	10.7450	9.2249	6.9534
C-GRNN	5.4556	7.7174	6.5865	4.5936

Table 6 Comparison of R values obtained with Trilateration, GRNN, and proposed C-GRNN algorithms through linear regression (Case II)

Name of L&T Algorithm	R for actual x coordinate and estimated x coordinate	R for actual y coordinate and estimated y coordinate
GRNN	0.96122	0.80126
C-GRNN	0.9821	0.90996

4.1 *Case I:* $X_\sigma \sim N(3, 1)$

As discussed earlier the objective of this research work is to evaluate the efficacy of the proposed C-GRNN architecture with our previously published GRNN architecture and traditional trilateration technique for indoor L&T problem. Figure 4 plots target track, and corresponding location estimates obtained using trilateration, GRNN, and C-GRNN methods. Figure 4 illustrates the comparison of location estimations with C-GRNN, GRNN and trilateration techniques. Here, black dark circles are anchor nodes that continuously broadcast RF signal to be received by mobile target node. The red square indicates 35 actual target locations during its motion, whereas blue plus, black plus, and green plus symbols are the location estimations with trilateration, GRNN, and the proposed C-GRNN architecture respectively against these 35 actual target locations. The overall localization error in estimating *x* and *y* coordinates of mobile target can be computed by taking average of individual localization errors in estimating *x* and *y* coordinates. The overall (average) localization error obtained with trilateration, GRNN, and C-GRNN techniques with respect to all the 35 target locations are plotted in Fig. 5.

From Fig. 4 it is clear that the estimations with the proposed C-GRNN architecture very closely match for most of the corresponding actual target locations as compared to rest of the other two techniques. It can be noted down that out of location estimations with all three techniques, the estimation results with the proposed C-GRNN based implementation is best. It is moderate and poor with GRNN, and trilateration respectively. We want to highlight few important observations regarding result in Fig. 4.

- For few locations, the estimation with C-GRNN can be seen, but the corresponding GRNN based estimates are not visible in Fig. 4. The reason behind this is that the estimations with GRNN and C-GRNN are exactly same and overlapping with each other. In order to clarify this observation, kindly check estimation results of GRNN and C-GRNN for target location 1 (10, 10) and target location 2 (12, 15) (Refer Table 2). For location 1 and location 2, the estimation results with GRNN and C-GRNN are same and are (10.11, 10.27), and (12.09, 15.22) respectively.
- Few location estimates of target with trilateration are not seen in Fig. 4. The reason behind this is that the location estimates obtained with trilateration are out of considered monitoring area (100 m × 100 m). In order to clarify this observation, kindly check estimation results of trilateration for target location 1 (10, 10) (Refer Table 2). For location 1, the location estimates obtained with trilateration is (163.53, −60.70).
- In case of estimations of few locations, trilateration performs even better than GRNN, and C-GRNN algorithms. For instance, for target location 27, the estimations obtained

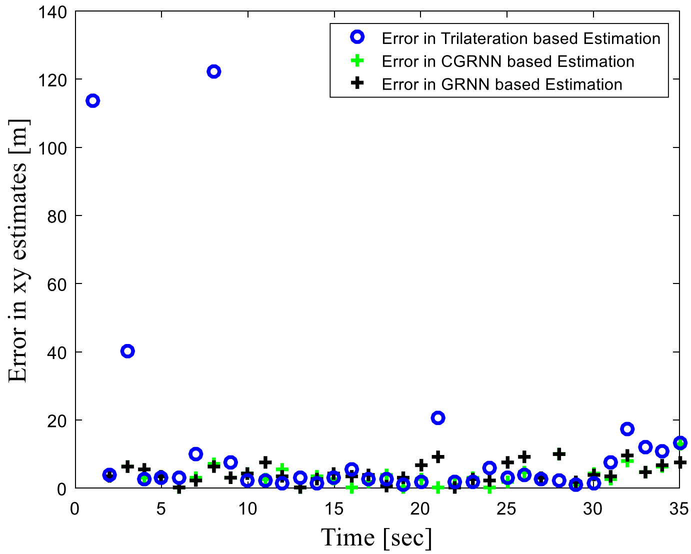

Fig. 5 Plot of Average Localization Errors in Target Location Estimation using Trilateration, GRNN and C-GRNN (case I)

with trilateration are better than GRNN and the proposed C-GRNN algorithm (Refer Table 2). However, the better localization performance of trilateration than rest of the two algorithms is only for few location estimations.

- During location estimation for few locations, GRNN works well as compared to rest of the two. Take an estimation of target location 35 (See Table 2).

As described earlier the difference in the GRNN and the proposed C-GRNN architecture is the difference in the dimension of input vector. The result in Fig. 4 clearly indicates that augmenting two extra parameters (C_1 and C_2) in input vector for C-GRNN architecture certainly improves the target localization performance as compared to that that with plain GRNN architecture. Thus, one can note that Fig. 4 plots target track with 35 locations, and corresponding target location estimates with trilateration GRNN, and C-GRNN techniques. Whereas, Fig. 5 plots average localization errors with trilateration GRNN, and C-GRNN. A significant variation in localization error is observed in case of trilateration-based estimation as compared to rest of the other methods. For instance, the average localization error with trilateration varies between 0 m to approximately 120 m. In [16], average localization error, average RMSE values obtained during simulations for $X_\sigma \sim N(3, 1)$ with the GRNN architecture are 4.7437 m, and 5.3517 m respectively. Whereas, for the same environmental setup (i.e. $X_\sigma \sim N(3, 1)$) in this work, average localization error, average RMSE values obtained with the proposed C-GRNN architecture during simulations are 3.5698 m, and 4.7218 m respectively. This proves the localization efficacy of the proposed C-GRNN architecture over GRNN architecture.

Figures 6 and Fig. 7 plot regression of x and y coordinates of actual target locations and corresponding *x* and *y* estimations of GRNN, and C-GRNN respectively. Idea behind plotting these linear regression curves here is to compare the localization performance of all of the three techniques (i.e. trilateration, GRNN, and C-GRNN) with respect to actual coordinates of the mobile target. The *R* values in the context of *x* as well as *y* coordinate estimations for case I are given in Table 3. It can be seen that the *R* values obtained with the.

proposed C-GRNN algorithm for *x* and *y* estimations are highest as compared to rest of the two algorithms. From Fig. 4 to Fig. 7, and Tables 4 to 3, it is clear that the proposed C-GRNN architecture is far more superior in target location estimation than rest of the two methods. From these figures, one can very easily observe that the localization errors on an average are high, moderate and low for trilateration, GRNN, and C-GRNN algorithms respectively. It clearly means that the proposed C-GRNN architecture is superior in dealing

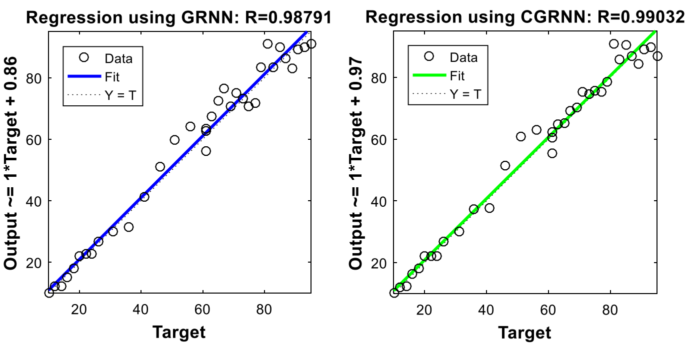

Fig. 6 Comparison of regression in x coordinate Estimation for GRNN, and C-GRNN (case I)

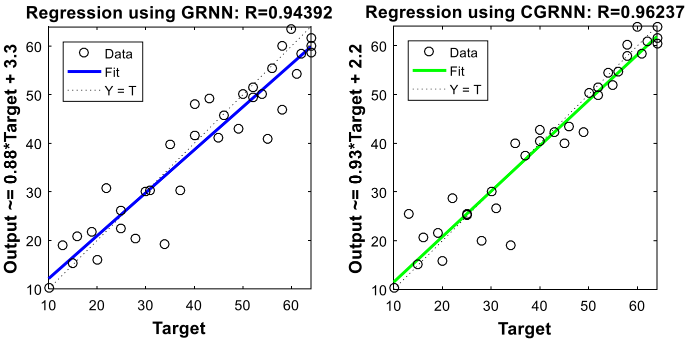

Fig. 7 Comparison of regression in y coordinate Estimation for GRNN, and C-GRNN (case I)

with the environmental dynamicity and non-linear system dynamics as compared to rest of the other two techniques.

4.2 *Case II: $X_\sigma \sim N(6, 1)$*

The case II results are illustrated with the help of Figs. 8, 9, 10 and 11. Figure 8 plots target track, and corresponding location estimates obtained using trilateration, GRNN, and C-GRNN methods. Figure 8 illustrates the comparison of location estimations with C-GRNN, GRNN and trilateration techniques. In order to better compare the results of case I, case II, and case III, the same color combination of markers is used to plot the simulation results. The red square indicates 35 actual target locations during its motion, whereas

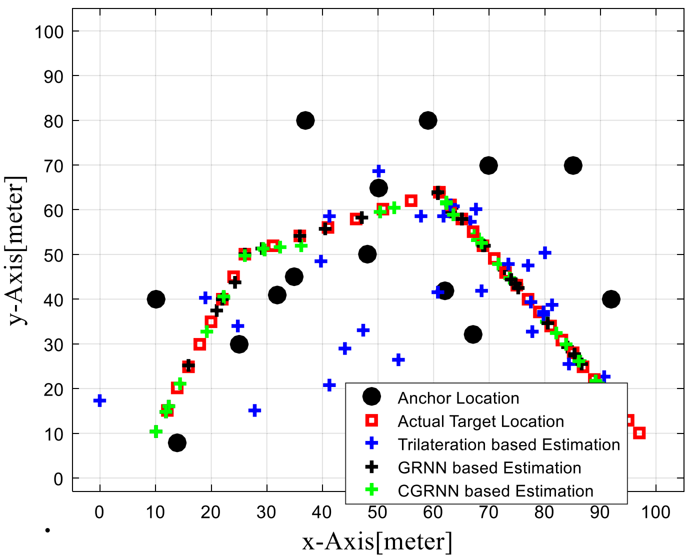

Fig. 8 Comparison of Target Location Estimations using Trilateration, GRNN and C-GRNN (case II)

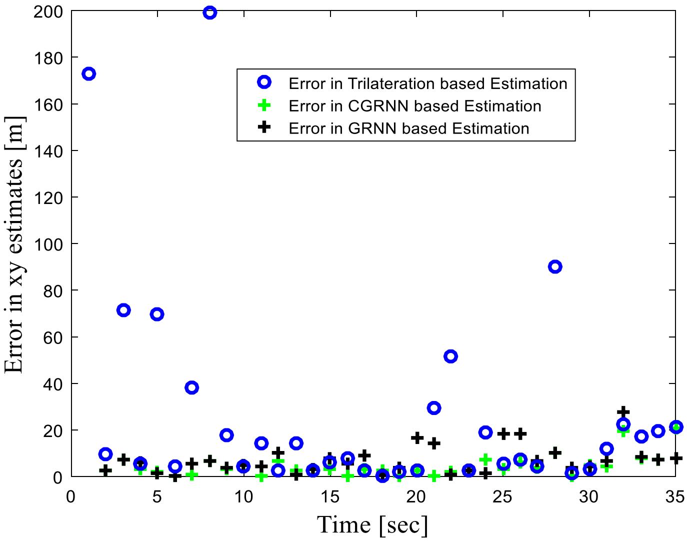

Fig. 9 Plot of Localization Errors in Target Location Estimation using Trilateration, GRNN and C-GRNN (case II)

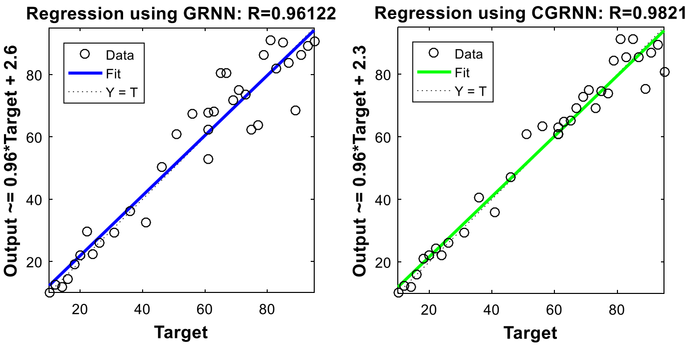

Fig. 10 Comparison of regression in x coordinate Estimation for GRNN, and C-GRNN (case II)

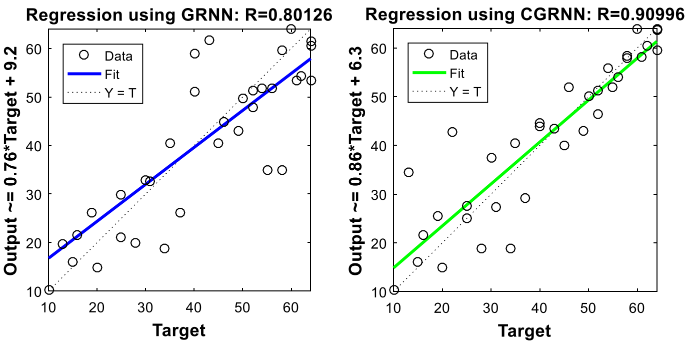

Fig. 11 Comparison of regression in y coordinate Estimation for GRNN, and C-GRNN (case II)

blue plus, black plus, and green plus symbols are the location estimations with trilateration, GRNN, and the proposed C-GRNN architecture respectively.

By comparing Fig. 8 (case II) with Fig. 4 (case I), it can be concluded that as the measurement noise in RSSI is doubled, the localization errors are also increased. However, significant rise in localization error can be noted down in case of trilateration only (See Table 5). The % rise in localization error with C-GRNN is lowest as compared to that with trilateration and GRNN. Figure 9 plots average localization errors with trilateration GRNN, and C-GRNN. The average localization error with trilateration varies between 0 m to approximately 200 m, which is approximately 20 times higher than that with rest of the two algorithms. Figures 10 and Fig. 11 plot regression of *x* and *y* coordinates of actual target locations and corresponding *x* and *y* estimations of GRNN, and C-GRNN respectively. It can be seen that the *R* values obtained with the proposed C-GRNN algorithm for *x* and *y* estimations are better than that obtained with GRNN algorithm (See Table 6). Speaking about the efficacy of the proposed C-GRNN algorithm as compared to our previous GRNN for Case I (Refer Table 4), it is observed that average RMSE, and average localization error for the proposed C-GRNN algorithm are decreased by 12%, and 20% as compared to GRNN. Whereas, average RMSE, and average localization error for the proposed C-GRNN algorithm are decreased by 20%, and 34% as compared to GRNN for Case II (See Table 5). Thus, by comparing this statistic obtained from Case I and Case II, it can be firmly concluded that as the proposed C-GRNN better deals with our previously published GRNN architecture in the context of indoor target L&T.

5 Conclusion

This paper presents an improved GRNN architecture named as C-GRNN. The proposed C-GRNN architecture yield more accurate location estimates as compared to GRNN as well as trilateration in the context of dynamic RF channel and non-linear system dynamics for the problem of indoor L&T of a mobile target. In order to realize uncertainty in the noise in RSSI measurements, the normal random variable parameter in LNSM path loss model is varied from 3 to 6 dBm in the steps of 3 dBm during simulations. The extensive simulation results indicate that the proposed improved trilateration-based C-GRNN architecture demonstrate superior localization performance as compared to trilateration as well as GRNN architecture. Although we do not claim that the C-GRNN architecture has offered the ultimate answer to all of the research questions related to RSSI based indoor target L&T, according to our opinion, it offers few interesting insights on the indoor L&T domain. Fusing the proposed C-GRNN architecture with KF framework under the same conditions of environmental dynamicity to further refine localization accuracy will be a research objective of our future work.

Declarations

Conflict of interest On behalf of all the authors, it is declared that the work has not been published and is not being considered for publication elsewhere. The authors also declare that there is no any conflict of interest involved. We also declare that this research work is not funded by any agency, and the publisher will not be held legally responsible for any kind claim for compensation. We are also ready to adhere to data transparency as well as code availability.

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