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Localizing Mobile Target using Kalman Filtering and Least Square Boosting Ensemble Learning based Approach

[1] **Mr. Mahadev Mahajan,** [2] **Dr. Narendra Bawane**
[1] mahadev.mahajan12@gmail.com,[2] narendra.bawane@yahoo.com
Jhulelal Institute of Technology, Nagpur, Maharashtra, India

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Abstract:

Trilateration-based target localization using received signal strengths (RSS) within wireless sensor networks (WSN) often results in inaccurate location estimates due to the considerable fluctuations in RSS measurements encountered in indoor environments. Enhancing the precision of RSS-based localization systems has been a primary area of interest in extensive research efforts. This study introduces two range-free algorithms, Ensemble Learning (EL) and EL+KF, which leverage RSS measurements for localization. In contrast to trilateration, the EL- based localization approach enables the direct estimation of target locations based on field measurements, eliminating the need for distance calculations. Notably, unlike other cutting-edge localization and tracking (L&T) scheme like the support vector regression (SVR), the LSBoost (Least Squares Boosting) EL based localization architecture can be trained very quickly using RSS measurements to determine the mobile target's position. Furthermore, the proposed EL-based localization scheme incorporates the Kalman filter (KF) to achieve additional refinement in target location estimates. To assess the localization effectiveness of these proposed algorithms in the presence of noisy RF channels and dynamic target motion models, rigorous simulations were conducted. Thanks to the robust generalization capabilities of EL, the simulation results reveal that the presented EL-based localization algorithms exhibit superior performance compared to trilateration and the SVR-based localization scheme, particularly in terms of indoor localization accuracy.

Keywords: Received Signal Strength (RSS); Wireless Sensor Network (WSN); Ensemble Learning (EL); LSBoost (Least Squares Boosting); localization and tracking (L&T); Support Vector Regression (SVR); Kalman Filter (KF).

1. Introduction

Target localization has been a focal point of extensive research in recent years, driven by the burgeoning demand for location-based services (LBS) across a myriad of applications [1-3]. These LBSofferings have the potential to enhance the quality of life for individuals in society in various ways. For instance, consider the convenience of a bike-sharing service, where a rider can effortlessly rent a bike via a mobile app and return it at any location once their ride is complete. To make this possible, interested riders rely on precise information about the locations of available shared bikes. Wearable devices such as smartwatches provide their owners with valuable services like activity monitoring, tracking, and emergency alerts. In the retail industry, localization technology can significantly boost profits by identifying customer locations and guiding them to products of interest, creating an improved shopping experience for customers and generating increased revenue for businesses. Another intriguing example of LBS is location-based flow management (LBFM), where location data from public spaces like metro stations, airports, and rail stations are harnessed to analyse passenger statistics, optimize their organization, and provide essential guidance. In industrial settings, logistics, productivity, and safety can be markedly improved through the application of LBS concepts. While the Global Positioning System (GPS) has long been a popular choice for outdoor location estimation, its accuracy and reliability falter in indoor environments due to the absence of GPS signals [4], [5]. Hence, GPS-independent localization and tracking (L&T) systems are imperative for achieving high target localization accuracy indoors. Wireless Sensor Networks (WSNs) have emerged as a dominant wireless communication technology over the last three decades, offering a cost-effective, energy- efficient, and smart sensing solution that is ideal for indoor localization applications [6-8].

Signal propagation within a wireless medium, connecting a transmitter to a receiver, hinges on location-specific data that can be harnessed for target localization. This data is derived from various signal measurement metrics, including Received Signal Strength (RSS), Time-of-Arrival (TOA), Time-Difference-of-Arrival (TDoA), Angle-of-Arrival (AOA), or combinations thereof [9]. Among these metrics, the RSS-based approach holds particular favor within Wireless Sensor Network (WSN)-based Localization and Tracking (L&T). Unlike the others, RSSI-based localization systems do not necessitate additional hardware components with the sensor nodes [10]. In the realm of localization techniques, two predominant methods are range-based localization and range-free localization. In range-based localization, the calculation of the distance between a transmitter and a receiver ispivotal, while range-free localization dispenses with distance calculations. RSS plays a pivotal role in both these approaches. However, it's worth noting that RSSI measurements are inherently noisy and subject to significant fluctuations due to the intricate RF environment found indoors [11], [12]. These RSSI measurements contend with a variety of indoor interferences, multi-path effects, noise sources, and the ever-changing channel conditions characteristic of dynamic indoor environments. Consequently, meticulous attention must be paid when designing an RSSI-based target Localization and Tracking algorithm to mitigate the risk of substantial localization errors.

One of the most basic and traditional methods within RSSI-based target Localization and Tracking (L&T) is trilateration [13], [14]. Trilateration involves the direct conversion of RSSI measurements into distances between the transmitters and receivers involved. Subsequently, the target's location can be estimated with the aid of at least three of these distance measurements. However, the trilateration technique tends to suffer from error propagation and struggles to effectively adapt to dynamic environmental conditions, resulting in notably poor localization accuracy. In intricate indoor environments where signal interference, reflection, and refraction compound the challenges, fingerprint-based methods, leveraging machine learning (ML), often outperform trilateration in terms of localization accuracy. These methods rely on data matching algorithms utilizing a curated set of reliable RSSI data extracted from a pre-established fingerprint database [15]. Among various data processing techniques, ML algorithms stand out as highly promising. Their adaptive nature lends them the ability to cope with changing indoor conditions, reducing the need for extensive redesign efforts. In the offline phase of the process, a target localization model is trained using a suitable dataset to learn the intricate relationship between RSSI measurements and their corresponding reference positions. Once this model is trained, real-time RSSImeasurements can be input into it during the online phase to estimate the corresponding target's location. Support Vector Machine (SVM), a pivotal ML variant, boasts superior data fitting capabilities, global optimality, and fewer control parameters [16-18]. Thanks to its exceptional generalization prowess, SVM, when adapted for regression estimation problems (referred to as Support Vector Regression or SVR), has become a favored choice over popular ML models like the Back Propagation Neural Network (BPNN), Radial Basis Function (RBF) Neural Network, Multilayer Perceptron (MLP), and Generalized Regression Neural Network (GRNN), showcasing superior forecasting performance [15]. The regression capability of the LSBoost (Least Squares Boosting) ensemble learning model is a notable feature that makes it suitable for solving regression problems. LSBoost is an ensemble learning method that combines the predictions of multiple weak learners, typically decision trees, to create a strong regression model. It is particularly well-suited for tasks where the goal is to predict a continuous numerical output, such as predicting stock prices, housing prices, or any other real-valued target variable. It focuses on minimizing the loss (usually least squares) by iteratively adjusting the model's parameters. SVR models tend to be simpler and more interpretable. They aim to find the best linear fit in the transformed feature space, which can be easier to understand. Whereas, LSBoost models can be highly complex due to the combination of multiple decision trees. While this complexity can lead to high accuracy. the choice between LSBoost and SVR depends on the specific characteristics of your dataset and your goals. LSBoost is often favored when high predictive accuracy is the primary objective and when nonlinear relationships need to be captured.

SVR, on the other hand, is a good choice when you need a simpler and more interpretable model, and when robustness to outliers is crucial. It's important to experiment with both methods andassess their performance on your data to make an informed decision. The research objective of this work is to harness the potential benefits of the proposed EL model to address the challenges of indoortarget localization. The research conducted in this paper unfolds in two distinct phases, and its key contributions are as follows:

1) We have introduced an innovative target localization framework based on LSBoost EL model to tackle the challenges associated with locating a single moving target in an indoor environment using Received Signal Strength Indicator (RSSI) measurements. In Phase I of our work, we conducted simulations to compare the performance of the proposed LSBoost EL-based approach with both the conventional trilateration technique as well as SVR based localization model.
2) In addition, we have extended our proposed EL model by integrating it with a standard Kalman Filter (KF) to create an enhanced target localization framework, and is named as EL+KF. In the Phase II of our study, we conducted simulations to compare the performance of the EL+KF scheme with the previously introduced SVR-based approach and the traditional trilateration scheme. Remarkably, the EL+KF scheme achieved target localization accuracy to the scale of few meters.
3) In both Phase I and Phase II of our study, we considered scenarios where the target exhibited maneuverable trajectories with high variations in its velocity during motion. It's important to note that we maintained constant noise levels in the RSSI measurements and maintained the same target motion statistics in both phases. The simulation results from both phases unequivocally illustrate the efficacy of our proposed SVR-based approaches in effectively handling noisy RSS measurements and dynamic target motion, outperforming both trilateration and GRNN methods.

The manuscript is structured as follows: In Section 2, we delve into recent literature on RSSI- based target Localization and Tracking (L&T). Section 3 introduces our proposed LSBoost EL based architecture for localization. The overall system design is outlined in Section 4, while Section 5presents a detailed discussion of the results obtained. Finally, in Section 6, we summarize the key findings of our research.

2. Related Work

Indoor localization methods that utilize RSSI field measurements can be broadly categorized into two main branches: Machine Learning methods and Filters-based methods. The first approach primarily employs supervised learning techniques for target Localization and Tracking (L&T) through RF fingerprinting. Several possibilities exist within this approach, including K-Nearest Neighbor (KNN), Radial Basis Function (RBF), Multilayer Perceptron (MLP), Extreme Learning Machine (ELM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN),Backpropagation Neural Network (BPNN), and Support Vector Machines (SVM). These methods involve a training phase where the relationship between RSSI measurements and corresponding target locations is established. This allows the adjustment of model parameters specific to the indoor RF environment. Once the model is trained, real-time target locations can be estimated from random RSSI field measurements during the offline phase. For instance, in [19], an RF fingerprint is created using RSSI measurements in an indoor environment with a moving target. During the online location estimation phase, the k-nearest positions are calculated using the least squares method, and the target location is determined by averaging these k-nearest positions. In [20], the authors proposed a scheme called Kernel Online Sequential Extreme Learning Machine (KOS-ELM), which combines RF fingerprinting and trilateration for target localization in the offline stage. The KNN framework is thenemployed for target localization during the online estimation phase. In another study by Wafa et al. [21], a CNN-based localization framework for an IoT-Sensor System was developed for target localization. This work transformed the 2D localization problem into a 3D tensor identification problem. Constructing a 3D image tensor from a 2D matrix of RSSI measurements resulted in an average localization accuracy of 2 meters. Another approach utilizing CNN and hybrid wireless fingerprint localization was proposed in [22], where RSSI ratios from various access points (APs) wereused. Large numbers of RSSI fingerprints were collected over a 12.5m x 10m area from deployed APs for fifteen days. The average localization errors for KNN, SVM, and CNN-based approaches were found to be 4.1681 meters, 4.1145 meters, and 3.9118 meters, respectively. While CNN showed superior performance, it relies on parameters such as learning rate, activation function, and threshold process, which must be fine-tuned for high localization accuracy. This parameter tuning can be time- consuming and makes CNN-based localization suitable for specific system conditions but not idealfor general applications. In [23], the authors proposed an RSSI-based robot indoor positioning schemebased on the Kernel Extreme Learning Machine (K-ELM) algorithm. They collected 68,500 samples of RSSI measurements over a 32m x 16m area using eight APs. The fingerprint-based localization scheme was evaluated using the proposed K-ELM scheme as well as Bayesian, KNN, classic ELM, and online sequential ELM (OS-ELM) algorithms. The K-ELM-based scheme achieved a localization accuracy of 8.125 meters, surpassing other considered methods. Additionally, Backpropagation Neural Networks (BPNN) can also be employed for indoor target localization [24]. However, BPNN has a notable limitation in that it requires multiple iterations to converge to the optimal location estimation.

The authors in [25] introduced a localization scheme based on Support Vector Machines (SVM) for target localization in ad hoc networks. This scheme operates under the assumption of full connectivity among all network nodes, and it requires prior knowledge of anchor node positions. The classification model is constructed using field measurements collected by these anchor nodes, whichis then employed for real-time target localization. It is worth noting that this SVM-based scheme performs optimally in networks with densely distributed sensors. The research work in [26] demonstrated an analysis of the SVM-based localization scheme proposed by Nguyen et al. for Wireless Sensor Networks (WSN)-based target localization. In their study, the authors established an upper bound for the localization error. Leveraging this upper bound, they improved target localization accuracy through an advanced optimization technique based on the concept of mass- spring. In another study by a different group [16], a multi-class SVM trained with RSSI field measurements was proposed for zoning localization. This SVM-based framework was trained using datasets collected from two real-world scenarios, a laboratory building, and a hospital. The results showed that this model outperformed an Artificial Neural Network (ANN)-based scheme in terms of estimation accuracy. Furthermore, an indoor target localization model based on two types of measurements, namely RSSI and Channel State Information (CSI) features, was introduced by authorsin [27]. In the offline stage, dimension reduction was achieved using Principal Component Analysis (PCA) through CSI measurements. Subsequently, SVM was employed to create a location-based regression function, enabling target locations to be estimated with an accuracy of approximately 1 meter. In a different context, a scheme for RF-based beacon localization was proposed by authors in [17], which involved an Unmanned Aerial Vehicle (UAV) guided by the pure pursuit guidance law. This scheme, based on Support Vector Regression (SVR), directly located the beacon using RSSI measurements. Simulation results demonstrated that the proposed SVR-based localization scheme achieved position accuracy within 2 meters. The authors in [18] introduced a Least Squares Support Vector Regression (LSSVR) localization scheme that utilized RSSI-based ranging values as inputs. To address fluctuations in the RSSI measurements, a queue was employed to store the most recent valueswhile removing older ones. The average of all RSSI values was computed to ensure queue stability over the RSSI sampling period. During LSSVR-based localization, optimization was conducted for target localization error, RBF kernel function parameters, and the grid width parameter of LSSVR to enhance target localization accuracy. The results indicated that the average localization error of the proposed LSSVR algorithm, without SVR parameter optimization, was 21.82%, and with SVR parameter optimization, it improved to 11.70%.

In the realm of filter-based localization approaches, Kalman Filtering (KF) and Particle Filtering (PF) stand as pivotal techniques offering a wide array of solutions for target localization challenges. As state estimation methods, filter-based localization involves two fundamental steps: prediction and measurement. A study presented in [28] introduces an innovative approach known as online semi-supervised Support Vector Regression (OSS-SVR) for target positioning, with the goal of minimizing the need for labeled training data. Additionally, this proposed algorithm is fused with KF and compared against semi-supervised manifold learning, online Gaussian process, and online semi- supervised localization techniques. Simulation results clearly demonstrate the robustness of the OSS- SVR algorithm in the face of varying system noise, highlighting its capacity to accurately estimate locations with minimal reliance on labeled training data. In a different investigation detailed in [29], the authors explored various Machine Learning (ML) techniques, including Recurrent Neural Networks (RNN), Multilayer Perceptrons (MLP), Radial Basis Functions (RBF), and compared them with KF within the context of indoor target localization. The simulated environment covered an area of 26x26 meters and involved the deployment of eight anchor nodes at the area's edges. The results of the simulations revealed that RBF outperformed the other techniques, although MLP exhibited a favorable balance between computational complexity and localization accuracy. The study also concluded that KF demonstrated lower average localization error but required multiple iterations to achieve a similar level of accuracy compared to the other presented architectures. Furthermore, in a previous research endeavor [30], the authors integrated Generalized Regression Neural Networks (GRNN) with KF to develop a robust localization system for moving targets in Wireless Sensor Networks (WSN). The proposed algorithms, GRNN+KF and GRNN+UKF, effectively addressed the challenge of uncertainty in RSSI measurement noise. In this approach, the GRNN architecture was trained with input vectors comprising four RSSI measurements and corresponding 2-D locations of the mobile target. The location estimates obtained from GRNN were further refined by KF and Unscented Kalman Filtering (UKF), leading to significantly improved location estimates compared to GRNN alone.

3. Proposed LSBoost EL Model for Target Localization

LSBoost, or Least Squares Boosting, is a highly capable ensemble learning model in regression tasks. Its strength lies in its ability to effectively capture complex non-linear relationships between input and output variables. By iteratively fitting simple regression models to the residuals of previous models, LSBoost progressively refines predictions, reducing the mean squared error with each iteration. This makes LSBoost particularly well-suited for tasks where the underlying mapping between variables is intricate and non-linear in nature. Its robust performance, coupled with its capacity to handle diverse datasets, has positioned LSBoost as a valuable tool in regression modeling, yielding accurate and reliable predictions even in challenging scenarios.

During the offline training phase, the system accumulates RSSI measurements obtained from anchor nodes (ANs) strategically positioned within the designated operational area. These measurements are combined with their associated target locations to establish a comprehensive training database. Subsequently, in the online location estimation stage, real-time RSSI measurements are input into the proposed pre-trained EL model. The EL model undertakes a search within the training database to identify patterns in the RSSI data that closely resemble the incoming measurements. Once a close match is identified, the proposed EL model returns the corresponding target location, which is deemed to be the closest possible estimation based on the provided RSSI pattern. The visual representation of this proposed EL model can be observed in Figure 1.

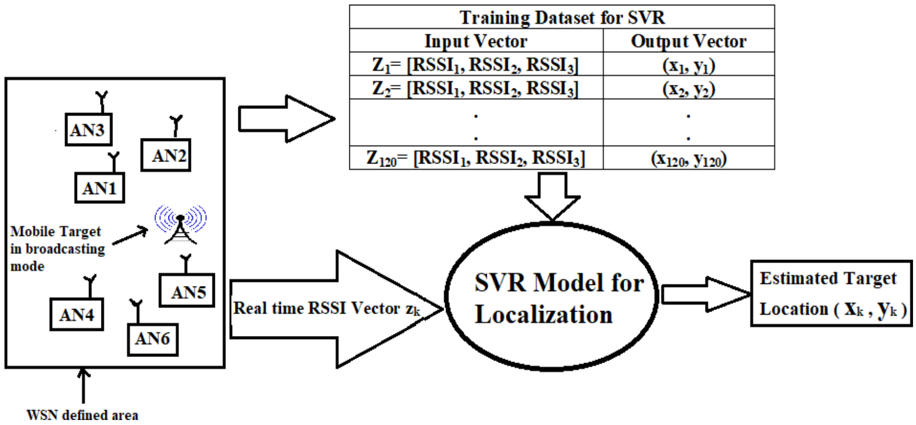


Figure 1. System Block Diagram for proposed EL Based Target Localization Scheme

The RSSI measurements are generated through a logarithmic shadow fading model as described by Equation (1) [30], [31]:

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

Where,

$(z_{\ell j,k})$ - RSSI value received at node N_ℓ having coordinates $(x_{k\ell}, y_k)$ from node N_j with coordinates (x_{jk}, y_{jk}) at k time instance,

$P_r(d_0)$ - RSSI value received at receiver node kept at a distance of d_0 (preferably 1 meter),

X_σ - Normal random variable,

η - Path loss exponent.

The SVR model can be formulated using the concept of structural risk minimization as given by Equation (2) [26]: We used default values of C , γ , and ε , and therefore these are set to 1, 0.01, and 0.001, respectively. However, these parameters can be fine-tuned to get optimum results from SVR model for the underlying application. In this work, we adopted radial basis function (RBF) to create the SVR model because of its ability of fast convergence, simplicity, and optimality in high- dimensional spaces as compared to other types of kernels [16]. The RBF kernel function is given by Equation (5):

4. SYSTEM DESIGN

This research endeavour aims to track the movement of a single target within a 100-meter × 100-meter area, utilizing merely six anchor nodes in both Phase I and Phase II, as illustrated in Figure 2. As previously discussed, Phase I involves a comparison of trilateration, GRNN, and the proposed SVR localization methodologies. In Phase II, we propose the fusion of SVR and Kalman Filtering (KF). In this latter phase, we compare the performance of the proposed SVR and SVR+KF techniques against the conventional trilateration approach concerning localization accuracy. While six anchor nodes are deployed within the operational area of the WSN, it is noteworthy that only three anchor nodes are required to effectively determine the mobile target's position using the proposed SVR and SVR+KF localization techniques. Both Phase I and Phase II consider RSSI measurements from AN1, AN2, and AN3. In contrast, the GRNN-based scheme incorporates RSSI measurements from AN1, AN2, AN3, and AN4. Meanwhile, the trilateration-based scheme utilizes RSSI measurements from all anchor nodes, selecting three RSSI measurements with the highest values, specifically those from the anchor nodes closest to the target at a particular time instance. Consequently, the proposed SVR and SVR+KF localization techniques impose fewer constraints regarding RSSI measurements from anchor nodes for location estimation compared to trilateration and GRNN-based approaches. It is assumed that the mobile target carries a receiving node, which continuously collects RSSI measurements (RF signals) from the six anchor nodes deployed within the WSN area. These RSSI measurements fromthe six anchor nodes are denoted as RSSI1 through RSSI6, respectively. The deployment details of the anchor nodes are provided in Table 1 and depicted in Figure 2. These anchor nodes have been randomly positioned within the designated WSN area and are assumed to remain static.

Table 1. Deployment of Anchor Nodes in the simulations

Anchor Node Number	2-D Location	Anchor Node Number	2-D Location
1	(30, 25)	4	(30, 90)
2	(10, 60)	5	(80, 60)
3	(50, 50)	6	(70, 90)

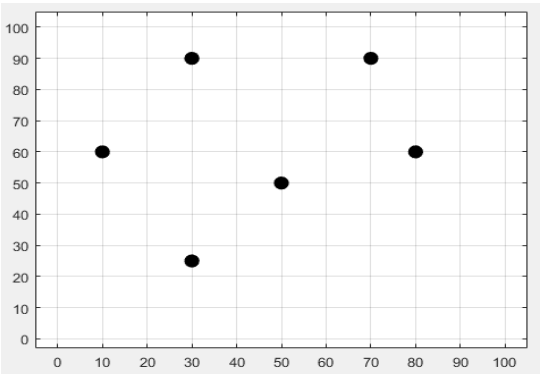


Figure 2. Anchor Node Deployment in the Indoor Environment.

The study assumes that the target traverses a total of 40 positions within the WSN area, and these positions are to be estimated using trilateration as well as the proposed SVR and SVR+KF schemes. In the offline phase, the proposed EL and EL+KF architectures undergo training using 120 sets of RSSI measurements, each associated with a corresponding 2-D location, as depicted in Figure 1. Once the training of the proposed EL-based localization architecture is completed, it becomes ready for use in estimating the mobile target's location during the online localization stage. During the online phase, for each target position within the WSN area during its motion, the input vectors (X_k) for the SVR and the proposed EL architectures at a specific time instance k are defined as follows, as shown in Equation (6) and Equation (7) respectively.

$$X_k = [RSSI_1, RSSI_2, RSSI_3, RSSI_4], \quad k = 1, 2, \dots, 40 \tag{6}$$

$$X_k = [RSSI_1, RSSI_2, RSSI_3], \quad k = 1, 2, ..., 40 \tag{7}$$

The state vector representing the mobile target at a given time instance k is $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$. Within this vector, x_k and y_k correspond to the target's position, while $\dot{x}_k$ and $\dot{y}_k$ indicate the speed in x and y directions respectively at k^{th} time instance. These state vectors can be mathematically expressed using following equations:

$$x_k = x_{k-1} + \dot{x}_k \ dt, \tag{8}$$

$$y_k = y_{k-1} + \dot{y}_k \ dt, \tag{9}$$

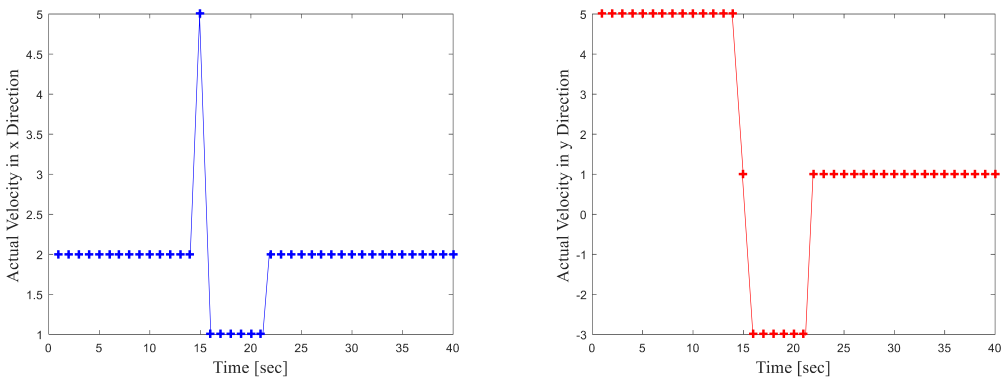
Where, $dt = k - (k-1)$ represents the time interval between two consecutive time instances, and is maintained at 1 second. The sudden variations in the target's velocity throughout the entire duration of the target's motion of T= 40 seconds are characterized by the equations from (10) to (13) as given below.

$$\dot{x}_k = 2, \quad \dot{y}_k = 5, \quad \text{for } 0 < k < 9 \text{ sec}, \tag{10}$$

$$\dot{x}_k = 5, \quad \dot{y}_k = 2, \quad \text{for } 9 \le k \le 15 \text{ sec}, \tag{11}$$

$$\dot{x}_k = 0, \quad \dot{y}_k = 0, \quad \text{for } 16 \le k \le 17 \text{ sec}, \tag{12}$$

$$\dot{x}_k = 2, \quad \dot{y}_k = -3, \quad \text{for } 18 \le k \le 35 \text{ sec}. \tag{13}$$



a) b)

Figure 3. a) Target velocity variation along x direction,
b) Target velocity variation along y direction.

The effectiveness of the trilateration, proposed EL, and EL+KF algorithms in estimating targetlocations is evaluated using three key metrics: average localization error, root mean square error (RMSE), and the coefficient of correlation (R). For each time instance k, we calculate the localization errors with x coordinate as $(\hat{x}_k - x_k)$, and y coordinate estimate as $(\hat{y}_k - y_k)$. The localization error for a k^{th} time instance is obtained by averaging these two error values. Subsequently, the average localization error during a during the total time duration T is determined using Equation (17). Similarly, RMSE values for the x and y coordinate estimates are computed separately, and theaverage RMSE is obtained by averaging these two RMSE values. In pursuit of higher localization accuracy, it is essential for both the localization error and RMSE to be minimized, ideally approachingzero. The value of R quantifies the strength of correlation between the estimated values and the actual values. The R value close to 1 signifies high localization accuracy. The R value can be directly computed using the MATLAB plotregression command.

$$Average\ Localization\ Error = \frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2} \tag{14}$$

Where,

$(\hat{x}_k, \hat{y}_k)$ - Target location estimated for k time instance,

(x_k, y_k) - Actual location of target at k time instance.

$$RMSE_x = \sqrt{\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2}{T}}. \tag{15}$$

$$RMSE_y = \sqrt{\sum_{k=1}^{T}\frac{(\hat{y}_k - y_k)^2}{T}}. \tag{16}$$

$$RMSE_{avg} = \frac{(RMSE_x + RMSE_y)}{2} \tag{17}$$

5. DISCUSSION ON RESULTS

The idea behind conducting simulation experiment is in phase I to explore the target localization capability of the proposed SVR based target localization model as compared against to that of trilateration and GRNN based schemes. As mentioned earlier in Section III and Section IV, the trilateration exploits the advantage of all the six AN's for localization for RSSI measurements, whereas the GRNN and the proposed SVR rely on only four and three AN's respectively. Once it is confirmed that the SVR based scheme outperforms the GRNN based scheme, more focus is given on SVR based localization approach in phase II. The environmental and system setup for phase II is keptsame as that for phase I. The aim of the phase II is to evaluate the SVR+KF based fusion scheme with SVR based scheme and trilateration technique. As the trilateration-based target localization using RSSI measurements is widely used approach by the research community to evaluate the proposed theRSSI based algorithms, we kept localization comparison with traditional trilateration in both the phases.

Phase I: Comparison of SVR with Trilateration and GRNN

The Figure 4 illustrates the actual target track in the WSN defined area and the location estimates obtained with Trilateration, GRNN, and the SVR based localization schemes. The Figure 4 clearly shows that the locations estimated with proposed SVR based scheme are closer to the actual target locations as compared to that with Trilateration and GRNN. Although few location estimates oftarget obtained with SVR are away from the actual target locations, the location estimates obtained for those actual target locations with Trilateration and GRNN are more away than actual target locations as compared to the proposed SVR scheme. Figure 5, and Figure 6 plot the location estimation errors with Trilateration, GRNN, and SVR based localization schemes in x direction, y direction respectively. In order to assess the overall estimation accuracy, the average of estimation errors is plotted for each actual target location in Figure 7. From results it can be observed that location estimates obtained with the proposed SVR are far better than trilateration and GRNN. From Figure 5, Figure 6, and Figure 7, it can be observed that estimation errors with the proposed SVR based scheme are approximately below 15 meters. The estimation errors with trilateration are quite worst for many locations as compared to that with other considered schemes. From Table 2 it is clear that the RMSE and average localization error with trilateration are very high as compared to that withGRNN and SVR based schemes. The average RMSE with GRNN and SVR is decreased by 52% and

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62% respectively as compared to that with trilateration. The average localization error with GRNN and SVR is decreased by 51% and 66% respectively as compared to that with trilateration. In order to clarify the localization performance of the considered three localization schemes, four target locations are selected and estimations obtained with the considered three schemes are compared in Table 3. Forfirst location (16, 25) considered in Table 3, we can see that estimations with GRNN are better than SVR. Whereas, the negative estimated coordinates with trilateration for first location means these are out of WSN defined area considered during simulation. In simple words, the estimations with trilateration for target location (16, 25) are out of WSN defined area, and that's why these are not visible in Figure 4. For other considered locations in Table 3, we can see that for some locations SVR yield very close location estimates, while for other GRNN performs better. From Figure 8, Figure 9, and Table 4, it is clear that R values obtained for SVR based localization scheme is more close to 1 as compared to trilateration and GRNN.

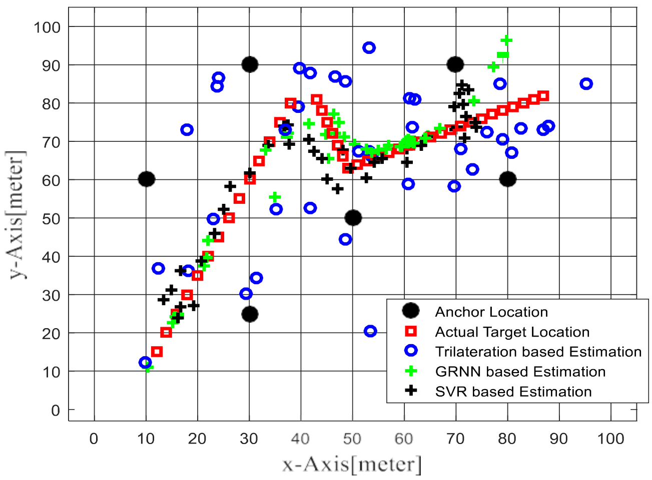

Figure 4. Phase I Result: Location estimation of mobile target with Trilateration, GRNN, and proposed SVR based localization schemes.

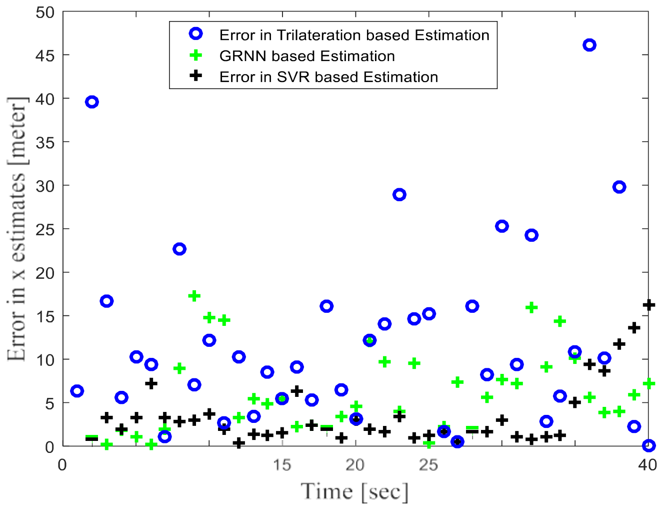

Figure 5. Phase I Result: Location estimation error in x direction with Trilateration, GRNN, and proposed SVR based localization schemes.

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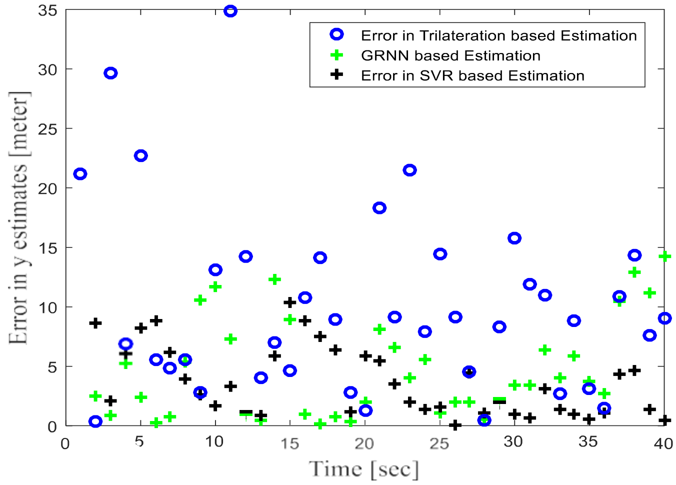

Figure 6. Phase I Result: Location estimation error in y direction with Trilateration, GRNN, and proposed SVR based localization schemes.

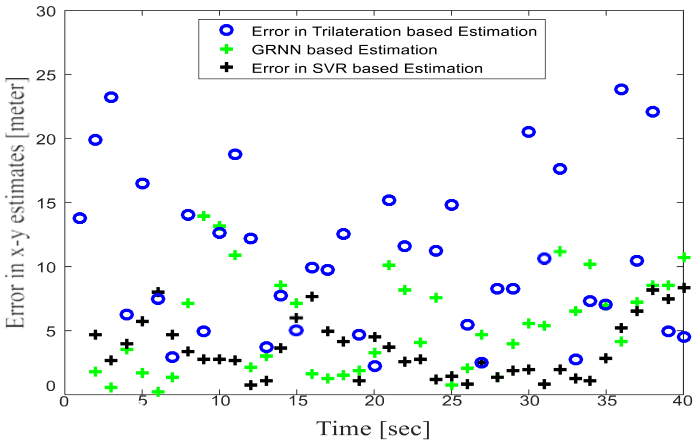

Figure 7. Phase I Result: Location estimation error in x-y direction with Trilateration, GRNN, and proposed SVR based localization schemes

Table 2. RMSE and average localization error obtained in Phase I

Name of Localization Algorithm	RMSE for x Coordinate	RMSE for y Coordinate	Average RMSE for x & y Coordinate	Average Localization Error
Trilateration	15.8403	12.7018	14.2711	11.0682
GRNN	7.6033	6.1926	6.8979	5.3772
SVR (Proposed)	5.0755	5.6407	5.3581	3.7995

Table 3. Location wise estimation results for four target locations for Phase I

Location Number	Actual Coordinate	Coordinates estimated with Trilateration	Coordinates estimated with GRNN	Coordinates estimated with SVR (Proposed)
1	(16, 25)	(-0.70, -4.66)	(15.77, 24.15)	(19.24, (17.12)
2	(32. 65)	(23.74, 84.23)	(37.22, 73.01)	(33.67, 68.80)
27	(55, 66)	(41.76, 52.54)	(56.58, 68.10)	(55.77, 65.37)
35	(85, 81)	(86.99, 73.01)	(79.74, 96.21)	(70.77, 82.51)

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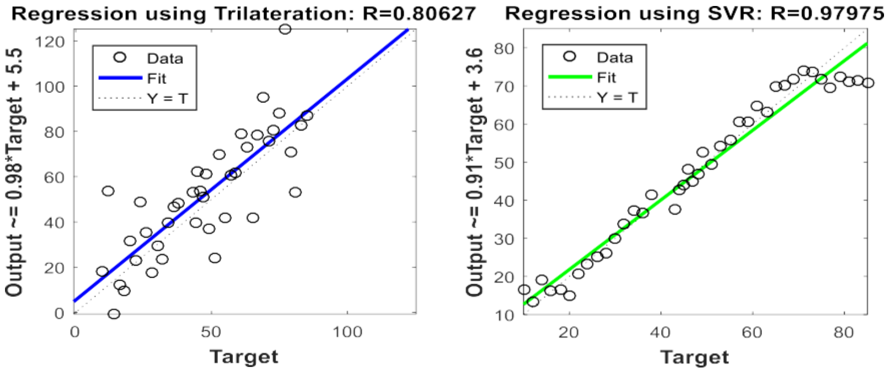

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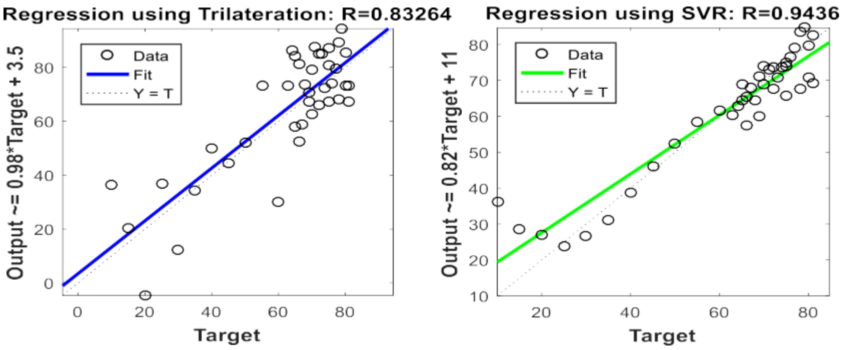
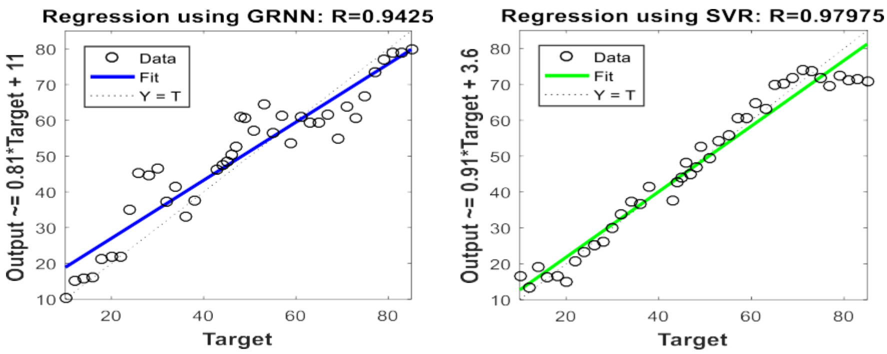


(b)

Figure 8. Phase I Result: a) Regression Coefficient with Trilateration, and proposed SVR for x direction, b) Regression Coefficient with Trilateration, and proposed SVR for y direction



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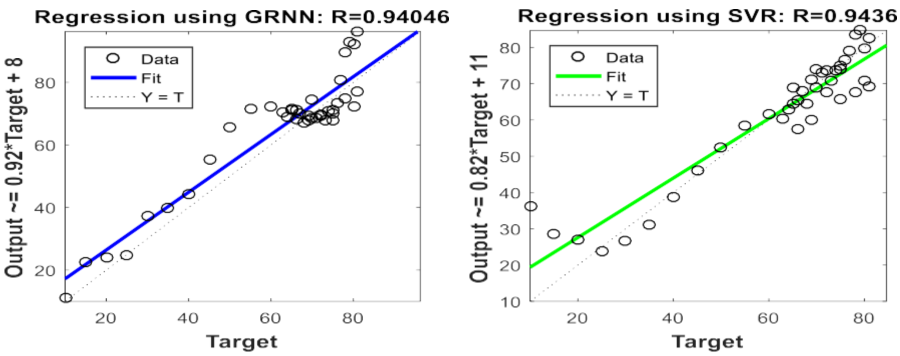


(b)

Figure 9. Phase I Result: a) Regression Coefficient with GRNN, and proposed SVR for x direction, b) Regression Coefficient with GRNN, and proposed SVR for y direction.

Table 4. Comparison of R values for Phase I

Name of Localization Algorithm	R Value for x Coordinate Estimation	R Value for y Coordinate Estimation
Trilateration	0.80627	0.83264
GRNN	0.9425	0.94046
SVR (Proposed)	0.97975	0.9436

Case II: Combination of SVR and Kalman Filter for target localization

In order to focus more upon SVR based scheme, in case II we compared SVR and SVR+KF based schemes with only trilateration. Like Figure 4 in case I, the Figure 10 in case II illustrates the actual target trajectory and the estimates obtained with Trilateration, and both SVR based localization schemes. From Figure 10 it is clear that SVR+KF based estimations are even better than plain SVR based estimations, and are closely following the actual target track. Figure 11, and Figure 12 plot the location estimation errors with Trilateration, and both SVR based localization schemes in x direction,y direction respectively. Figure 13 plots the average of estimation errors for each target location. FromFigure 11 to Figure 13 it can be observed that the location estimation errors with SVR+KF scheme are lowest as compared to trilateration and plain SVR based scheme are well below 2.5 meters. From Figure 13 it is observed that the estimation errors with trilateration are very high and vary between 2 to 26 meters. Table 5 compares RMSE and average localization errors with the three considered localization schemes in case II. The average RMSE and average localization error with SVR+KFscheme is decreased by approximately 95% and 79% respectively as compared to that with plain SVR scheme. From Figure 14 and Table 6, it is seen that the R value with SVR+KF scheme is very close to 1.Thus, by fusing SVR and KF yield very high improvement in the target localization accuracy.

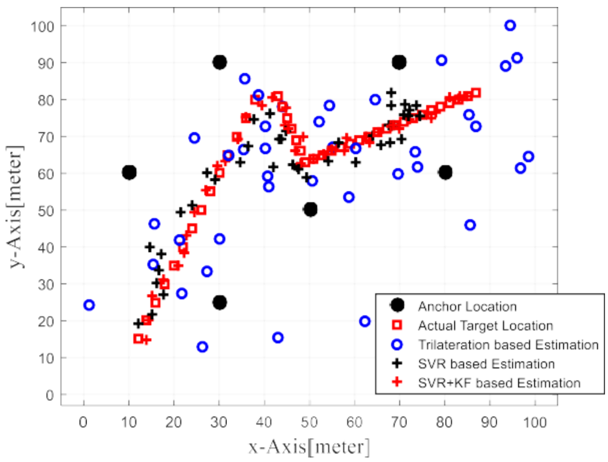


Figure 10. Phase II Result: Location estimation of mobile target with Trilateration, and proposed SVR and SVR+KF based localization schemes

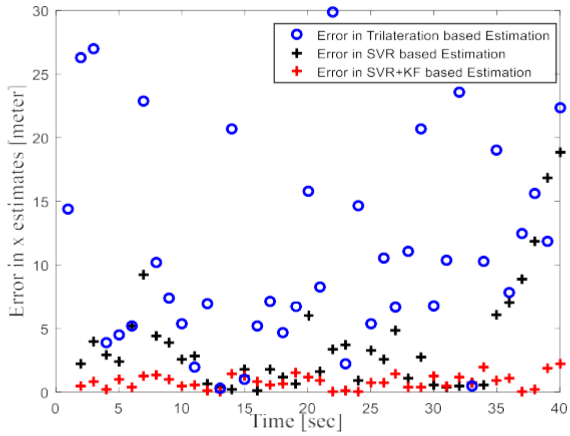


Figure 11. Phase II Result: Location estimation error in x direction with Trilateration, and proposed SVR and SVR+KF based localization schemes

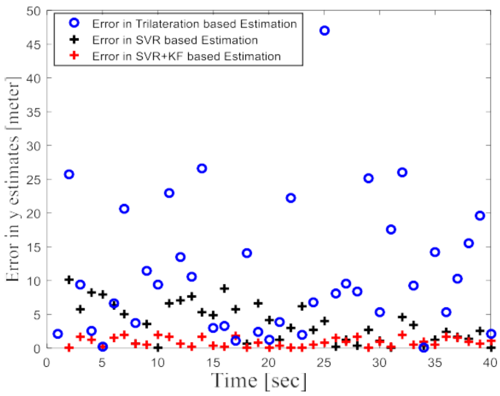


Figure 12. Phase II Result: Location estimation error in y direction with Trilateration, and proposed SVR and SVR+KF based localization schemes.

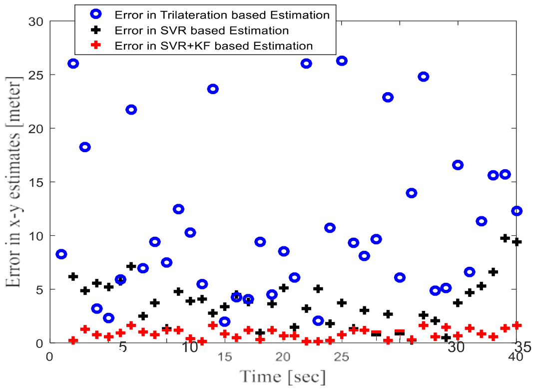


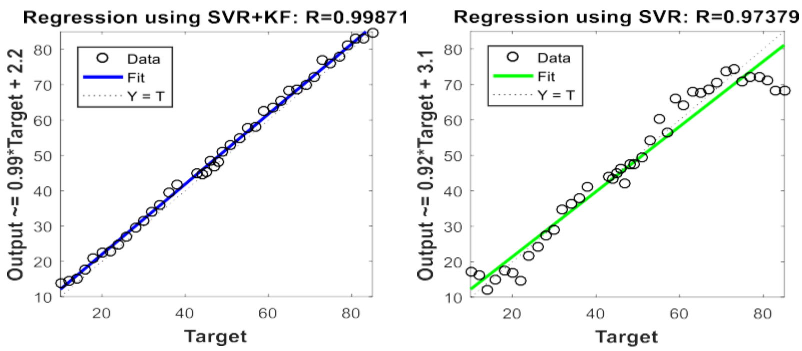
Figure 13. Phase II Result: Location estimation error in x-y direction with Trilateration, and proposed SVR and SVR+KF based localization schemes.

Table 5. RMSE and average localization error obtained in Phase II

Name of Localization Algorithm	RMSE for x Coordinate	RMSE for y Coordinate	Average RMSE for x & y Coordinate	Average Localization Error
Trilateration	13.6668	14.9266	14.2967	11.2034
SVR	5.6929	5.8932	5.7930	4.0430
SVR+KF (Proposed)	0.3497	0.1725	0.2611	0.8528

Table 6. Comparison of R values for Phase II

Name of Localization Algorithm	R Value for x Coordinate Estimation	R Value for y Coordinate Estimation
SVR	0.97379	0.94881
SVR+KF (Proposed)	0.99871	0.99221



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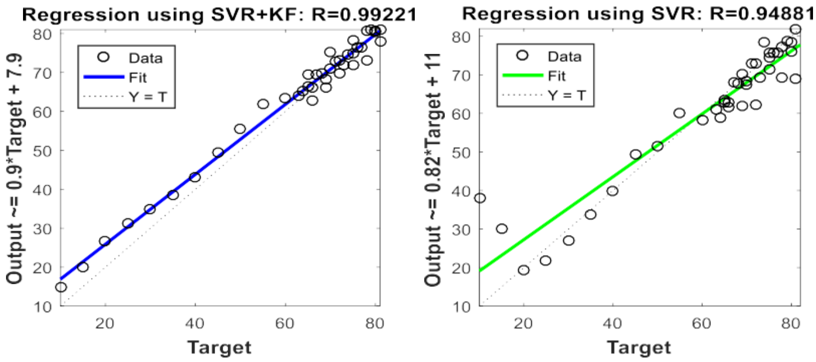

(b)

Figure 14. Phase II Result: a) Regression Coefficient with proposed SVR and SVR+KF for x direction, b) Regression Coefficient with and proposed SVR and SVR+KF for y direction

V. Conclusion And Future Scope

This paper proposes a novel SVR based target localization scheme to track a single target moving in indoor with the help of RSSI field measurements. The proposed SVR based schemeeffectively deal with highly fluctuating field measurements as well as high maneuver in target trajectory. The applications wherein a localization accuracy of 5 to 6 meters is required, the proposed plain SVR based architecture is good lightweight option for the indoor target localization. Whereasthe applications demanding target tracking accuracy below 1 meter, the proposed SVR+KF localization scheme will be a very good option. We believe that the proposed SVR based localization schemes can be extended to solve the problem of multi-target tracking (MTT) in indoor environment.

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