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Tracking Target with Constant Acceleration Motion using Kalman Filtering

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***Abstract*—Maneuvering target tracking is recent hot topic in location based services. In this paper a kalman filtering based approach of mobile target tracking with constant acceleration motion, is presented to deal with uncertainties in measurement noises and abrupt changes in target velocity. Two algorithms namely, RSSI + kalman filter (KF) and RSSI + unscented kalman filter (UKF) are proposed to refine estimates of traditional RSSI based approach to obtain a smoothed target trajectory. The performance of the proposed algorithms are validated over simulated RSSIs and compared with traditional RSSI based approach in the context of tracking accuracy. The simulation results of proposed algorithms show the tracking accuracy of the order of centimeter scale, irrespective of dynamicity in RSSIs due hostile wireless environment.**

Keywords—Kalman Filter (KF), Received Signal Strength Indicators (RSSIs), Target Tracking, Unscented Kalman filter (UKF), Wireless Sensor Networks (WSNs).

I. INTRODUCTION

Dramatic advances in RF and MEMS IC design have made possible the use of wireless sensor network's (WSN's) for a variety of new monitoring and control applications [1]–[3]. The target localization and tracking is one of the fundamental research area of WSN with diverse military and civilian applications. The performance of such applications highly depends on the accuracy in locating the moving target of interest as well as in predicting its future path in WSN area. Although localization can be done with sufficient accuracy by using GPS with the help of satellites. The GPS based localization shows poor performance for non line of sight (NLOS) especially for indoor environments. Consequently, the research trend is to develop WSN based (GPS-less) solutions, aimed to improve the target localization and tracking accuracy especially under constraints of limited resources (energy and bandwidth) of WSNs. GPS-less localization algorithms can be classified as range free and range based algorithms. The Range free technique exploits the connectivity between nodes for estimating locations, whereas the range based technique requires estimation of distance between nodes for localization. Although range free techniques are inexpensive as compared to range based technique, it offers less localization accuracy as well [6]–[8]. *Among all the range based techniques, RSSI based approach is more economical a*s many wireless transceivers have inbuilt RSSI circuitry. However the obstructions such as variations in the indoor layout structure, objects generally lead to reflection, refraction, diffraction, and absorption of radio signals. Due to such a dynamicity of wireless medium, errors in RSSI measurements are unpredictable leading to erroneous tracking results[7]-[8]. Therefore more research efforts are being applied by the research community to cope up with this dynamicity in RSSI measurements since last decade.

In the literature in order to locate the target RSSI measurements are fed to a suitable recursive bayesian framework based filters such as kalman filter (KF) [10], [11],[12], and PF [13]-[17].The choice of KF or PF based system depends primarily on the nature and amount of noise in the process and measurements as well as application requirement [15]. 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 is predominantly higher [16]. A large computational workload in PF is generally not suitable for giving target location estimates in a timely manner so as to suit to real time tracking applications. The unscented kalman filter (UKF) has been proved to be a better alternative to the extended Kalman filter (EKF). In [20], UKF based location and tracking algorithm is proposed which fuses a dynamic model of human walking with a number of low-cost sensor observations to track target position and velocity.

Both the proposed algorithms take into account these real time problems and are evaluated through extensive MATLAB simulations. In this paper a KF and UKF based approach is designed to refine RSSI based position estimates of a moving target with constant acceleration motion, to deal with uncertainty in measurement noise. The structure of the paper is as follows. Section II discusses Localization of Mobile Target. Section III presents the Kalman Filtering For Localization. Performance evaluation of proposed algorithms is presented in Section IV. Finally, conclusions and future work is highlighted in Section V.

II. LOCALIZATION OF MOBILE TARGET

Consider the two-dimensional problem of localization of a mobile target. The vector $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ of positions of the mobile target is estimated given n_r anchors with known coordinates $\{(x_{n+1}, y_{n+1}), (x_{n+2}, y_{n+2}), \ldots, (x_{n+n_r}, y_{n+n_r})\}$ and pair wise measurements $\{z_{ij}\}$, where z_{ij} is a measurement between devices i and j. Generally the locations of anchor nodes are obtained with the help of GPS prior to localization and tracking process. Each anchor node carries a wireless transceiver so as to estimate the distance between target and anchors with the help of RSSI measurements.

A. Motion Model of the Mobile Target

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 [20]. Most of these models are also applicable for mobile nodes localization and tracking. In this paper, we choose a constant velocity model.

The state of moving target at time instant k is defined by the vector $x_k = (x_k, y_k, \dot{x}_k, \dot{y}_k, \ddot{x}_k, \ddot{y}_k)'$, where x_k and y_k specify the position, $\dot{x}_k$ and $\dot{y}_k$ specify the velocity and $\ddot{x}_k$ and $\ddot{y}_k$ in x and y directions respectively. In this research work the target is moving in given WSN area according to constant acceleration model as given below.

$$x_k = x_{k-1} + \dot{x}_k \, dt + \frac{1}{2}\ddot{x}_k dt^2 \quad (1)$$

$$y_k = y_{k-1} + \dot{y}_k \, dt + \frac{1}{2}\ddot{y} dt^2 \quad (2)$$

where dt is discretisation time step between two successive time instants such that $dt = k - (k-1)$.

B. Measurement (Observation) Model

The RSSI measurements are basically an outcome of a particular propagation models. As the log normal shadowing model (LNSM) considers fading effects, it is more widely adopted by the research community. This paper follows LNSM in the research work.

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.

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

where $P_r(d_0)$ is RSSI measured at receiver node located at reference distance d_0 (generally $d_0 = 1\,meter$ meter) from transmitter , and X_σ is normal random variable (a measure of shadowing effect) with a standard deviation of σ . It ranges from 3 to 20 dBm. The n is the path loss exponent, and is selected as per the application environment or empirically determined by field measurement. Larger the value of n, higher would be the amount of obstructions and the rate of decrease of received power as well.

The distance $d_{\ell j,k}$ between nodes N_ℓ and N_j can be computed with the help of equation (4) as given below.

$$d_{\ell j,k} = d_0 10^{(P_r(d_0) - z_{lj,k} + X_\sigma)/10n} \quad (4)$$

III. KALMAN FILTERING FRAMEWORK FOR LOCALIZATION

A. Standard Kalman Filtering

The target motion and measurement models for the standard KF can be written respectively as [10]:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \quad (5)$$

$$z_k = H(x_k) + v_k, \quad (6)$$

where A, B and H are state transition, control input transition and measurement transition matrices respectively as given below. 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 acceleration model the matrices in equation (7) are given as follows.

$$A = \begin{bmatrix} 1 & 0 & dt & 0 & \frac{1}{2}dt^2 & 0 \\ 0 & 1 & 0 & dt & 0 & \frac{1}{2}dt^2 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, B = I_{4\times 3}, H = I_{4\times 4} \quad (7)$$

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 :

$$\overline{x}_k = A\hat{x}_{k-1} + Bu_{k-1} + w_{k-1} \ . (8)$$

$$P_k^- = AP_{k-1}A_k^T + Q_k \ . \ (9)$$

Update **:**

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^- \ . (10)$$

$$\hat{x}_k = \overline{x}_k + K_k(z_k - H_k \overline{x}_k) \ . (11)$$

$$P_k = (I - K_k H_k) P_k^- \ , \qquad (12)$$

where the matrix K is called Kalman's gain matrix and I is identity matrix $(I_{4\times 4})$. The superscript "^" above indicates the estimate of the state vector.

B. *Unscented Kalman Filtering*

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 [20].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.

Like KF, the UKF operation can also be described in two steps: predict and update. 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 (15).

$$\chi_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{x}_{k-1} + \lambda\sqrt{P_{k-1}}] \ . \qquad (13)$$

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 (14)-(19).

Prediction :

$$\chi^*_{k/k-1} = f(x_{k-1}, u_{k-1}) \ \ (16)$$

$$\hat{x}_k = \sum_{i=0}^{2L} w_i^m \chi^*_{k/k-1} \ . \qquad (15)$$

$$P_k = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k] \ [z_{i,k/k-1} - \hat{z}_k]^T + \mathrm{R} \ . \qquad (16)$$

$$\chi_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{x}_{k-1} + \lambda\sqrt{P_{k-1}}] \ . \qquad (17)$$

$$z_{k/k-1} = H\chi^*_{k/k-1} \ . (18)$$

$$\hat{z}_k = \sum_{i=0}^{2L} w_i^m z_{i,k/k-1} \ . (19)$$

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 (20)-(24).

Update:

$$P_{xk,zk} = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k] \ [z_{i,k/k-1} - \hat{z}_k]^T + \mathrm{R} \ . \qquad (20)$$

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

Kalman Gain :

$$K_k = P_{xk,zk} P_{zk,zk}^{-1} \ . \qquad (22)$$

Emendation state estimate:

$$\hat{x} = \hat{x}_{k-1} + K_k(z_k - \hat{z}_k) \ . \qquad (23)$$

Error covariance matrix updates:

$$P_k = P_{k-1} - K_k P_{zk,zk} K_k^T \ , \qquad (24)$$

where w_0^m is weights of mean, w_0^c is weights of covariance, λ is a scaling parameter, as given by equation (25). L is the dimension of augmented state. The general values of $\alpha = 10^{-3}$, $k_i = 0$ and $\beta = 2$.

$$w_0^m = \lambda/(L+\lambda), \ w_0^c = \lambda/(L+\lambda) + (1+\alpha^2+\beta) \ . \quad (25)$$

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

IV. PERFORMANCE EVALUATION

A. *System Design*

The system consists of a set of static anchor nodes at known coordinates, deployed in simulation area of 500 meter by 500 meter, the mobile target, as shown in Figure 3 and a coordinator node (not shown in figure). The anchor nodes are located at [0,0], [250,0], [500,0], [500,250], [500,500], [250,500], [0,500], and [0,250], as shown in Fig. 3. The initial target state vector is [8,10,0,0,0,0]. For $k > 0$, the target moves within the sensor field in accordance with equations (1) and (2).In this research work mobile target is assumed to carry one WSN node, which broadcasts RF signal to anchor nodes for every time step k. Therefore the target itself is assumed to be a transmitter whereas anchor nodes are receivers. This is a case of cooperative localization and tracking. The anchor node are supposed to compute their distances from mobile target based on RSSI's received using equation (33). All the anchors send computed distances along with their coordinates to the coordinator node. The coordinator node is supposed to select lowest three distances out of them and send it to base station along with coordinates of corresponding anchor nodes. The base station attached with a laptop (Core i5, 1.70 GHz, 4 GB RAM) is supposed to run the traditional RSSI and the proposed RSSI+KF, and RSSI+UKF algorithms to estimate the mobile target positions for every sampling interval.

The system is considered to run for a total time period of T, which is divided into several time slots dt.

The target undergoes the variation in acceleration during T seconds as given by equation (26) and illustrated in Figures 1 and 2.

$$\ddot{x}_k = 2, \quad \ddot{y}_k = 1, \quad \text{for } 0 \le k \le 4 \text{ s},$$
$$\ddot{x}_k = 1.2, \quad \ddot{y}_k = 1, \quad \text{for } 5 \le k \le 12 \text{ s}. \quad (26)$$

For the sensor network used in this paper, the communication range is 100 m. The transmitter and receiver antenna gains are set to 1 dB. The transmission power is set to 1 mill watts.

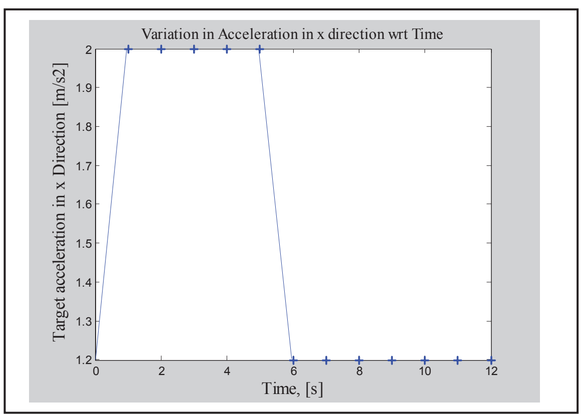

Fig.1. Variation in acceleration in x direction during target motion.

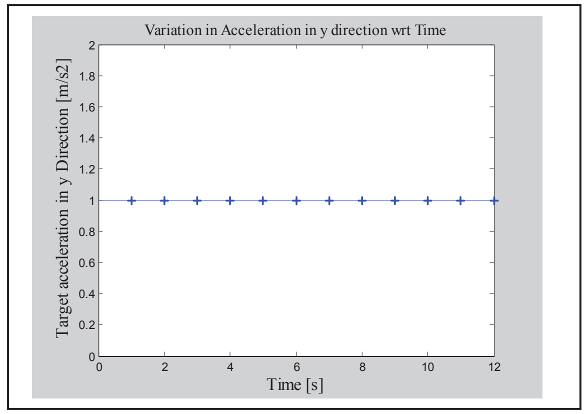

Fig.2. Variation in acceleration in y direction during target motion.

Generally the wireless channels between transmitter and various receivers are distinct due to different amount of obstructions in between, therefore the values of n and $P_r(d_0)$ are to be selected carefully. In order to incorporate these environmental disturbances, average value of n (n_{avg}) and $P_r(d_0)$ are computed empirically during calibration phase (see equations (32)-(37)). For any given three known distances (d_1, d_2 and d_3), three RSSI's (z_3, z_2 and z_3), are noted down and substituted in these equations to get following equations.

$$z_1 = P_r(d_0) - 10 n_1 \log(d_1/d_0) + X_\sigma, \quad (27)$$
$$z_2 = P_r(d_0) - 10 n_2 \log(d_2/d_0) + X_\sigma, \quad (28)$$
$$z_3 = P_r(d_0) - 10 n_3 \log(d_3/d_0) + X_\sigma. \quad (29)$$

where (n_1, n_2 and n_3) are path loss exponents related to three distances (d_1, d_2 and d_3) respectively. By subtracting above three equations with each other, the values of (n_1, n_2 and n_3) can be easily determined. Then average path loss exponent (n_{avg}) can be easily computed by averaging these three as given below.

$$n_{avg} = (n_1 + n_2 + n_3)/3 \quad (30)$$

Therefore equation (2) can be modified as

$$z_{lj,k} = P_r(d_0) - 10 n_{avg} \log(d_{lj,k}/d_0) + X_\sigma \quad (31)$$

The value of $P_r(d_0)$ can now be easily computed using equation (36) by putting the value of RSSI $z_{lj,k}$ for a given distance $d_{\ell j,k}$ and value of n_{avg}.

$$P_r(d_0) = z_{lj,k} + 10 n_{avg} \log(d_{lj,k}/d_0) - X_\sigma \quad . \tag{32}$$

Also the distance equation (6) can be modified as given below.

$$d_{lj,k} = d_0 10^{(P_r(d_0) - z_{lj,k} + X_\sigma)/10 n_{avg}} \quad . \tag{33}$$

The R, P_0 and Q metrices are taken to be,

$$R = \begin{bmatrix} 2.2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \end{bmatrix}, P_0 = \begin{bmatrix} 0.25 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.02 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.02 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.03 \end{bmatrix}, Q = I_{6\times 6} \,. \tag{36}$$

TABLE I
Simulation Parameters for Proposed Algorithms

Symbol	Parameter	Value
X_0	Initial Target State at k=0	[8 10 0 0 0 0]’
dt	Discretisation time step	1 s
T	Total Simulation Period	12 s
f	Frequency of operation	2.4 GHz
X_σ	Normal Random Variable	~N(3,1)
n_{avg}	Average Path Loss Exponent	2.84

B. *Performance Metrics:*

The two metrics that we have used to evaluate the performance of the proposed algorithms are: Localization Error, and Root Mean Square Error (RMSE). The localization error and RMSE represent the average estimation error in target’s $(\hat{x}_k, \hat{y}_k)$ position and the closeness of estimated target trajectory $(\hat{x}_k, \hat{y}_k)$ to given trajectory (x_k, y_k) over T respectively. These two metrics are collectively considered to be a measure target tracking accuracy. Smaller the values of these performance metrics, higher would be the tracking accuracy. The proposed algorithms are run for approximately 20 times. After every sampling instance k, the error in x estimate $(\hat{x}_k - x_k)$, error in y estimate for the traditional RSSI approach, and the proposed RSSI + KF and RSSI + UKF algorithms, are computed. After every simulation run, the Average Localization Error and the RMSE’s are determined by utilizing equations (34) and (35) respectively.

1]Average Localization Error :

$$Average\ Localization\ Error = \frac{1}{T}\sum_{k=1}^{T}(\hat{X}_k - X_k), \tag{34}$$

2] Root Mean Square Error (RMSE) :

$$RMSE = \sqrt{\frac{1}{T}\sum_{k=1}^{T}(\hat{X}_k - X_k)^2} \tag{35}$$

C. *Flow of Proposed Algorithm*

The complete simulation for one time step k consists of three parts. The first part is offline environmental calibration which includes determining n_{avg} (using equations (27)–(30)), and $P_r(d_0)$ (using equations (32)) empirically. The second part of distance estimation is supposed to be executed by anchor nodes using equation (33) whereas the third part is to exploit lowest three distances of anchors from mobile target along with their coordinates as an input to proposed algorithms to be run at the base station. The detailed flow of the proposed algorithms for one time step k is as given in Table II.

TABLE II
RSSI + KF and RSSI + UKF Algorithm Description

I. Environmental calibration
Step 1 : Compute n_{avg} and $P_r(d_0)$

II. For sampling instant k = 0
Step 2 : All anchor node measure RSSI for every k^{th} instance from target to calculate their distances (d_1, d_2,….d_n) from the mobile target.
Step 3 : All anchor nodes sends computed distances along with their coordinates to the coordinator node. The coordinator node after comparison dispatch lowest three distances along with corresponding anchor coordinates to the base station.

III. Computations at Base Station
Step 4 : The base station runs traditional RSSI algorithm to estimate target x-y position using inputs from step 3.
Step 5 : RSSI based target position estimates from step 4 are smoothed with the help of KF and UKF algorithms at the base station. The errors in x and y position estimates are computed as well as recorded.

For sampling instants k = 1,2,…..T
Step 6 : Steps from 1 to 5 are repeated for each next time steps until the completion of total simulation period T.
Step 7 : Compute Average Localization Error and RMSE from the estimated target trajectory at the base station.

D. Discussion of Results

From the figure 3, figure 4 and figure 5 as well as table's 3 and 4, it can be easily concluded that the overall tracking accuracy (average localization error and RMSE) is lowest for RSSI + UKF approach, moderate for RSSI + KF approach and highest for pure RSSI based approach in both the cases. That means the RSSI+UKF based approach outperforms the remaining two approaches in the context of the target tracking accuracy at the cost very small increase in computational complexity and better handles the nonlinearity associated with the motion and the measurement models.

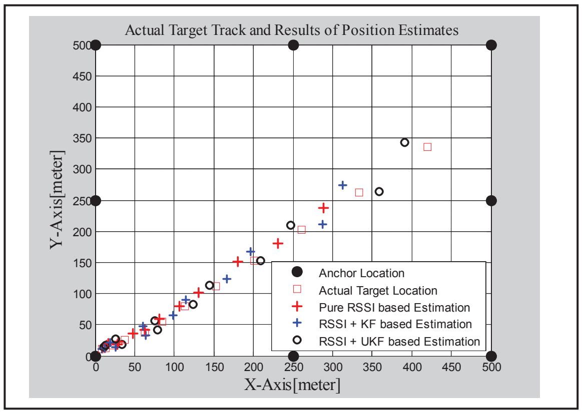

Fig. 3. Actual target trajectory and estimated trajectories by the Traditional RSSI, RSSI+KF and RSSI+UKF algorithms.

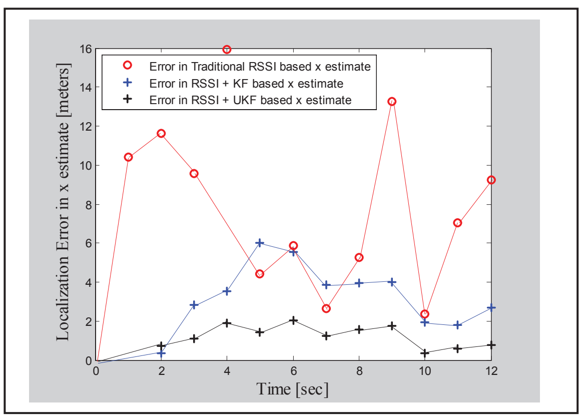

Fig. 4. Comparison of Localization Errors in x coordinate estimate intraditional RSSI, RSSI+KF, and RSSI+UKF algorithms.

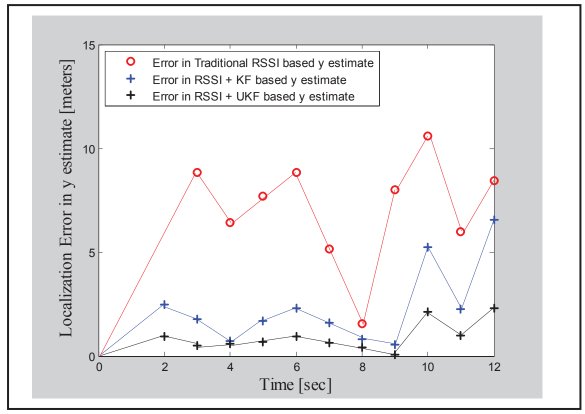

Fig. 5. Comparison of Localization Errors in y coordinate estimate in traditional RSSI, RSSI+KF, and RSSI+UKF algorithms.

TABLE III
Comparison of Average Localization Errors

Number of Anchors used	Avg. Localization Error for Traditional RSSI based Estimation [meter]	Avg. Localization Error for RSSI+KF based Estimation [meter]	Avg. Localization Error for RSSI+UKF based Estimation [meter]
8	7.6350	3.3947	0.4530

TABLE IV
Comparison of RMSE

Number of Anchors used	Avg. Localization Error for Traditional RSSI based Estimation [meter]	Avg. Localization Error for RSSI+KF based Estimation [meter]	Avg. Localization Error for RSSI+UKF based Estimation [meter]
8	14.4858	7.4012	0.9233

V. CONCLUSIONS

This paper contributes to solving the problem of simultaneous localization of constant accelerating mobile node in WSN with uncertain measurement noises. Two bayesian framework based algorithms (RSSI+KF and RSSI+UKF) are proposed for simultaneous localization and tracking of a single moving target in wireless networks. For the estimation, only a few anchor nodes with known locations and received signal strength (RSS) indicator (RSSI) are exploited. The results of extensive simulation experiments carried out demonstrated higher tracking accuracy. The overall tracking performance is assessed in terms of localization error, RMSE, and execution time. The Simulation results show that the RSSI +UKF based approach outperforms the traditional RSSI and RSSI + KF based approaches in the context of the tracking accuracy. The proposed algorithms have the potential to be used in different applications, such as GPS-free position localization of mobile nodes in wireless networks, for localization of moving persons, vehicles and robots in indoor as well as outdoor environment.

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