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Modified Kalman Filtering Framework Based Real Time Target Tracking Against Environmental Dynamicity in Wireless Sensor Networks

SATISH R. JONDHALE* AND RAJKUMAR S. DESHPANDE

E&TC Department, Sanjivani COE, Kopargaon, District: Ahmednagar, Maharashtra, India
(Savitribai Phule Pune University, Pune)
E-mail: raj.deshpande@yahoo.co.in

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One of the most widely used economical approaches to localization and tracking of mobile target with wireless sensor networks (WSNs), is the use of received signal strength indicators (RSSIs). In this paper, a modified kalman filtering based approach of real time tracking of single target moving in 2-D in WSN, 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 the traditional RSSI based approach to obtain a smoothed target trajectory. The performance of the proposed algorithms is investigated against environmental dynamicity such as abrupt variations in target velocity, the limited set of RSSI measurements and the variation in the anchor density. The results confirmed that the proposed algorithms achieve better tracking accuracy and real time performance, irrespective of environmental dynamicity, compared to the traditional RSSI based algorithm.

Keywords: Wireless sensor networks, kalman filter, received signal strength indicator, tracking accuracy, unscented kalman filter

1 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

* Contact author: E-mail: profsatishjondhale@gmail.com

control applications [1–3]. The target localization and tracking is one of the fundamental research area of WSN with diverse military and civilian applications. Originally developed for military applications, today it is being an integral part of plenty of civilian applications such as locating moving objects in building, tracking people inside building, wildlife tracking, environmental monitoring as well as emerging next generation mobile 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 performs well for line of sight (LOS) to several satellites, however maintaining the LOS is generally a rare possibility especially for indoor environments. Target tracking based on data from a low cost WSN is more economical approach as compared to the use of GPS. Consequently, the research trend is to develop WSN based (GPS-less) solutions, aimed to improve the target localization and tracking accuracy especially under the constraints of limited resources (energy, collaborative processing, real time response, security and bandwidth) of WSNs [2, 4]. The use android based Wi-Fi devises can also be exploited to set up Ad Hoc Network for communication [5]. 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, 7, 8].

In WSN domain there are wide variety of technological alternatives to carry out localization and tracking such as radio frequency (RF), infrared (IR), video, acoustic and ultra wideband (UWB). Moreover, RF as compared to rest of the others is widely used because of their ability to penetrate smoke, nonmetallic barriers and walls, making it a better choice for localization and tracking applications [8]. It is basically a range based estimation technique, which utilizes Received Signal Strength Indicator (RSSI) to track moving objects. The RSSI measured is basically a function of the distance between the transmitter and the receiver as described by many propagation models [10]. As many wireless transceivers have inbuilt RSSI circuitry, RSSI based techniques are simple, inexpensive and have a lower power consumption as compared to other range based techniques such as time of arrival (TOA), time difference of arrival (TDOA), and angle of arrival (AOA) [6, 7, 9]. However there are lot of research challenges involved in the RSSI based target tracking approach. Specifically the RSSI based tracking approach has to deal with reflection, refraction, diffraction, and absorption of radio signals due to indoor layout structure, obstacles in between. Other than these, other factors, such as temperature, orientation of antenna, and height to the ground also affect the performance RSSI based tracking. Due to such a dynamicity of wireless medium, errors in RSSI measurements are unpredictable leading to erroneous tracking results [9, 10]. Therefore more research efforts are being applied by the research community to cope up with this dynamicity in RSSI measurements since last decade.

Additionally, it is believed that the RSSI based tracking problem becomes more complex, if the target undergoes the abrupt changes in the velocity during motion. Many times the scenario may become more worst, if the RSSI measurements over some period of time, are not available (due to rigid obstacles) or highly corrupted (due to environmental noise) for the system to estimate current location of target. In order to cope up with this dynamicity of RSSI measurements, wireless environment and the behavior of mobile target, we have designed and analyzed the modified kalman filtering framework based target tracking algorithms for WSN, which utilizes inaccurate target position estimates of the traditional RSSI based tracking algorithm. The structure of the paper is as follows. In section 2, we briefly review the most relevant works that address target localization and tracking techniques for target tracking WSNs. Section 3 presents kalman filtering framework for target localization and tracking. Section 4 describes the target motion model, measurement model, system design and assumptions used in our article. Performance evaluation and detailed investigation of proposed algorithms through extensive simulation experiments are presented in Section 5. Finally, conclusions and future work is highlighted in Section 6.

2 RELATED WORK

The prime objective of localization and tracking is the determination of the possible positions (localization problem) of the moving targets and their trajectories (tracking problem) by exploiting the field measurements at regular intervals of time [8]. That means the tracking problem can be described as the solution of a set of localization problems at successive time intervals. Many research efforts have been reported in target tracking literature to deal with uncertainty in RSSI measurements. Out of those two major approaches are : First, to modify the mathematical model of RF signal propagation through calibration of environmental parameters to suit given tracking application [11, 12] whereas second to fuse RSSI measurements with a suitable recursive bayesian framework based filters such as kalman filter (KF) [13, 14, 15], and PF [16–19].

The reference [20, 21] follows the first approach and describe two indoor location systems. One of them is based on triangulation system and the other is based on neuronal network. More specifically, in the triangulation method the multi-path effect and the wall losses have been introduced whereas in the heuristic method the signal correction based on the received signal variation have been introduced [20]. Although triangulation based method achieves higher accuracy for a specific wireless environment but the neuronal network based system better adapts with dynamicity in the wireless environment with different types of walls. These two algorithms are investigated against the variations in the RF signal due to variety of factors such as receiver mobility, temperature and humidity variations, the effect of opening and closing doors, the changes in the localization of the furniture, and the presence and movement of human beings [21]. Due to less data processing involved, both the presented algorithms achieve optimum localization results and reduced energy consumption, and thereby they are best adapted to wireless sensor networks.

Regarding the second approach of the RSSI and bayesian filter based framework, 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 [17, 18, 19]. In [18, 19], the authors carried out an rigorous survey of various bayesian filter implementations for location estimation. These surveys conclude that though PF in contrast to KF, is superior in handling the nonlinearity in measurements as well it is applicable to non gaussian and multimodal distribution, the computational complexity is predominantly higher than KF. Additionally, the 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 KF and the extended Kalman filter (EKF), especially in the context of system nonlinearity [22–25]. In [25], 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.

The use of Heterogeneous WSN (HWSN) [26] or android devices based mobile ad hoc network (MANET) [27, 28] and collaborative data processing among sensor nodes [29], have also been reported to attain higher security, energy efficiency as well tracking performance in localization and tracking scenario. A distributed protocol Deployment and Tracking Algorithm (DTA) that runs on HWSN is presented in [26]. Two types of sensors: Motion Sensors (MSs) and Camera Sensors (CSs), are employed to detect mobile target. In this research work, MSs deal with the detection phase and activate the CSs which are the most likely to detect the mobile target. The simulation experiments demonstrate higher efficiency of the proposed solution in terms of tracking accuracy, energy consumption. In [27, 28], authors proposed an algorithm on mobile android devices for secure communication of wireless ad hoc networks by employing encryption and decryption keys as well as a suitable middleware. In the wireless sensor networks, the information collected by sensors may be redundant, correlated, and/or inconsistent. Therefore it is desirable to have sensors collaborate on processing the data. The energy efficient Lateration-localizing algorithm presented in [29] demonstrate not only the reduction in the number of packets to be transported and the probability of data collision but also the reduction in the power consumption and prolonged network lifetime. The results confirm that the proposed method can track the target in real-time with reasonable accuracy while achieving improved energy consumption compared to EKF estimation.

Most of the aforementioned works, however, do not take into account the performance of target tracking under conditions such as abrupt changes in target velocity and availability of the limited set of signal measurements. This paper propose two target tracking algorithm based on the second approach of RSSI and bayesian filter framework. Both the proposed algorithms take into account these real time problems and are evaluated through extensive MATLAB simulations. The major contribution of our work is: 1) we designed a novel KF and UKF based approach to refine RSSI based position estimates of a moving target to deal with uncertainty in measurement noise, 2) we critically analyzed the proposed algorithms for abrupt changes in target velocity and anchor density 3) we validated effectiveness of the proposed algorithm with respect to tracking accuracy even under the limited RSSI measurements over the certain period of time.

3 KALMAN FILTERING FRAMEWORK FOR TARGET LOCALIZATION AND TRACKING

In the bayesian filter based implementations, the discrete-time target motion model and observation model can be generalized to the forms:

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

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

where X_k is the target state vector and z_k is the observation vector at the current time step k, u_{k-1} is the vector containing any control inputs, while w_{k-1} and v_k are white noise, mutually independent from each other. These parameters are defined in detail in the section 3.1. In general f and h are non-linear functions.

3.1 Standard Kalman Filtering

The KF can be applied as an estimator of the state of a dynamic system. The KF provides the optimal bayesian estimator when the underlying system applied is, linear and noises in system dynamics are gaussian with zero mean [13]. The target motion and measurement models for the standard KF can be written respectively as:

$$X_k = AX_{k-1} + B\,u_{k-1} + w_{k-1}, \tag{3}$$

where,

- X_k is the state vector containing the terms of interest for the system (e.g., position, velocity, acceleration) at time k.
- u_{k-1} is the vector containing any control inputs (steering angle, throttle setting, etc.)
- A is the state transition matrix which applies the effect of each system state parameter at time $k-1$ on the system state at time
- B is the control input matrix which applies the effect of each control input parameter in the vector u_{k-1} on the state vector.
- w_{k-1} is the vector containing the process noise terms for each parameter in the state vector. The process noise is assumed to be drawn from a zero mean multivariate normal distribution with covariance given by the covariance matrix $Q_k(w_k \sim N(0, Q_k))$

$$z_k = H(X_k) + v_k, \tag{4}$$

where,

- z_k is the vector of measurements (e.g. position, velocity, acceleration, etc).
- H is the transformation matrix that maps the state vector parameters into the measurement domain
- v_k is the vector containing the measurement noise terms for each observation in the measurement vector. It assumed to be normally distributed zero mean white gaussian with covariance $R_k(v_k \sim N(0, R_k))$

These two noise terms w_{k-1} and v_k are assumed to be independent of each other or in other words they are uncorrelated. For the constant velocity model the matrices in equations (3) and (4) are given as follows.

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \; B = \begin{bmatrix} \frac{1}{2}dt^2 & 0 \\ 0 & \frac{1}{2}dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}, \; H = I_{4\times 4} \tag{5}$$

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. The mathematical equations associated with the predict and update steps are as follows.

Prediction:

$$\overline{X}_k = A\hat{X}_{k-1} + Bu_{k-1} + w_{k-1}. \tag{6}$$

$$P_k^- = AP_{k-1}A_k^T + Q_k. \tag{7}$$

Update:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^-. \tag{8}$$

$$\hat{X}_k = \overline{X}_k + K_k(z_k - \ H_k \overline{X}_k). \tag{9}$$

$$P_k = (I - K_k H_k)P_k^-, \tag{10}$$

where the matrix K is called Kalman's gain matrix and I is identity matrix ($I_{4\times4}$). The superscript " $\wedge$ " above indicates the estimate of the state vector. Notice in equations (6) and (7), given the initial state variable X_{k-1} and its process covariance matrix P_{k-1}, the state variable and its process covariance matrix of next time step k can be predicted. These estimates can be further refined (updated) with the help of measurement at time step k using equations (8)-(10).

3.2 Unscented Kalman Filtering Framework

Generally in practice motion model and measurement models are nonlinear. The EKF and the UKF are techniques aimed at relaxation of the linearity requirement in contrast to KF [22–24]. The EKF is based on model linearization and is highly sensitive to significant nonlinearities. Whereas the UKF effectively copes with the nonlinearities and performs approximations on the target mean and covariance instead.

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).

$$\chi_{k-1} = [\hat{X}_{k-1} \quad \hat{X}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{X}_{k-1} + \lambda\sqrt{P_{k-1}}] \, . \tag{11}$$

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 (12)-(17).

Prediction:

$$\overset{*}{\chi}_{k/k-1} = f(X_{k-1}, u_{k-1}) \tag{12}$$

$$\hat{X}_k = \sum\nolimits_{i=0}^{2L} w_i^m \, \overset{*}{\chi}_{k/k-1} \, . \tag{13}$$

$$P_k = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k \,]\,]\, z_{i,k/k-1} - \hat{z}_k]^T + \text{ R} \, . \tag{14}$$

$$\chi_{k-1} = [\hat{X}_{k-1} \quad \hat{X}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{X}_{k-1} + \lambda\sqrt{P_{k-1}}] \, . \tag{15}$$

$$z_{k/k-1} = H \overset{*}{\chi}_{k/k-1}. \tag{16}$$

$$\hat{z}_k = \sum\nolimits_{i=0}^{2L} w_i^m \, z_{i,k/k-1}. \tag{17}$$

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 (18)-(22).

Update:

$$P_{xk,zk} = \sum_{i=0}^{2L} w_i^c [z_{i,k/k-1} - \hat{z}_k \,]\,]\, z_{i,k/k-1} - \hat{z}_k]^T + \text{R} \, . \tag{18}$$

$$P_{xk,zk} = \sum_{i=0}^{2L} w_i^c \left[X_{i,k/k-1} - \hat{X}_k\right] \left[z_{i,k/k-1} - \hat{z}_k\right]^T + R. \tag{19}$$

Kalman Gain:

$$K_k = P_{xk,zk} \; P_{zk,zk}^{-1}. \tag{20}$$

Emendation state estimate:

$$\hat{X} = \hat{X}_{k-1} + K_k(z_k - \hat{z}_k). \tag{21}$$

Error covariance matrix updates:

$$P_k = P_{k-1} - K_k P_{zk,zk} K_k^T, \tag{22}$$

where w_0^m is weights of mean, w_0^c is weights of covariance, λ is a scaling parameter, as given by equation (23). L is the dimension of augmented state.

$$w_0^m = \lambda/(L+\lambda),\ \ w_0^c = \lambda/(L+\lambda) + (1+\alpha^2+\beta), \tag{23}$$

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 [15]. For gaussian distributions, its optimal value is 2. k_i is a secondary scaling parameter.

4 SYSTEM MODEL AND ASSUMPTION

4.1 Target Motion Model

Variety of state mobility models are previously described in the literature such as random walk, constant-velocity, constant-acceleration, Random way point, Column mobility, Graph based mobility models, singer acceleration model, mean-adaptive acceleration model [30, 31]. Although some advanced soft computing techniques such as fuzzy logic have also been successfully adopted in the mobility model in MANET [32]. This Fuzzy based model performs better to control the overall system. In [33], the authors have integrated MANET and cloud together and formed a new mobility model named Cloud-MANET. They have implemented a middleware in Cloud-MANET mobility model for communication on internet of smart devices. Most of these models are also applicable for mobile nodes localization and tracking. In this paper, for the sake of simplicity, we choose a constant velocity model.

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

$$x_k = x_{k-1} + \dot{x}\ dt, \tag{24}$$

$$y_k = y_{k-1} + \dot{y}\ dt. \tag{25}$$

where dt is discretisation time step between two successive time instants during tracking process.

4.2 Sensor Measurement (Observation) Model

The RSSI measurements are basically an outcome of a particular propagation models. Currently the major popular propagation models are free space model, two-ray ground reflection model, and the log normal shadowing model (LNSM) [10]. The free space model and the two ray model predict the received power function of distance deterministically. They both consider the distance between transmitter and receiver as an ideal circle. But practically the received power at certain distance is a random variable due to multipath fading effects. As the 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 [8, 9, 16]:

$$z_{\ell j,k} = P_r(d_0) - 10n\log(d_{lj,k}/d_0) + X_\sigma, \tag{26}$$

where

- $P_r(d_0)$ is RSSI measured at receiver node located at some reference distance d_0 (generally $d_0 = 1\ meter$ meter) from transmitter,
- X_σ is normal random variable (a measure of shadowing effect) with a standard deviation of σ. It ranges from 3 to 20 dBm,
- 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 Table 1 shows typical values of n for indoor and outdoor environments [34].

The distance $d_{\ell j,k}$ between nodes N_ℓ and N_j can be computed with the help of equation (25) as given below.

$$d_{\ell j,k} = d_0 10^{(P_r(d_0) - z_{lj,k} + X_\sigma)/10n} \tag{27}$$

Environment		**n**
Outdoor	Free space	2
	Shadowed urban area	2.7 to 5
Indoor	Line-of-sight	1.6 to 1.8
	Obstructed	4 to 6

TABLE 1
Typical Values of Path Loss Exponent (n)

In order to locate the mobile target using the traditional RSSI based technique at any given time instance and thereby track it for successive time instances, minimum three (in case of trilateration) or four (in case multilateration) distances of target from reference nodes along with their location coordinates, are required to compute the location of target [9].

4.3 System Assumption and Design

The system consists of a set of static anchor nodes at known coordinates, deployed in simulation area of 100 meter by 100 meter, the single mobile target, as shown in Figure's 3, 5, 7, and 9, and a coordinator node (not shown in figure). 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 (25). 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. In this paper, the traditional and pure words hold the same meaning. The RSSI + KF algorithm is equivalent to the traditional RSSI algorithm + KF algorithm whereas the RSSI + UKF algorithm is equivalent to the traditional RSSI algorithm + UKF algorithm.

Practically the variation in RSSI values for a given known distance due to different transmitter antenna orientation is not significant as the average signal strength remains within few dB. In this research work it is assumed that transmitter antenna is perfectly isotropic. For simplicity, we limit this work to estimation of a single target. The base station is assumed to be located outside the WSN area. 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 abrupt variations in the velocity during T seconds as given by equations (26)-(31) and illustrated in Figure 1 and 2. Here negative velocity value indicates that target is moving to a location with smaller coordinate value as compared to that at previous time instance.

$$\dot{x}_k = 2, \quad \dot{y}_k = 5, \quad \text{for } 0 < k < 9 \ s, \tag{28}$$

$$\dot{x}_k = 5, \quad \dot{y}_k = 2, \quad \text{for } 9 \le k \le 15 \ s, \tag{29}$$

$$\dot{x}_k = 0, \quad \dot{y}_k = 0, \quad \text{for } 16 \le k \le 17 \ s, \tag{30}$$

$$\dot{x}_k = 2, \quad \dot{y}_k = -3, \quad \text{for } 18 \le k \le 35 \ s. \tag{31}$$

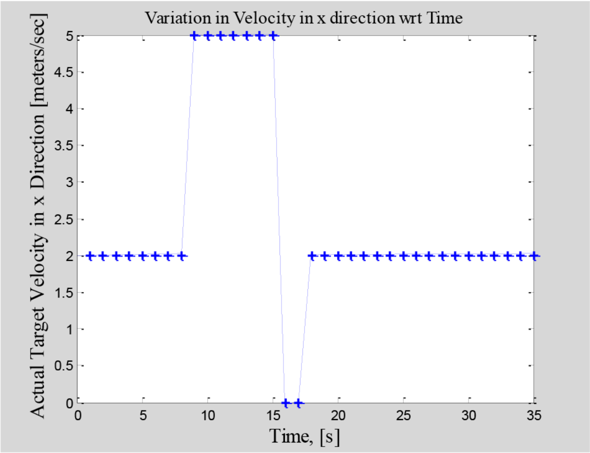

FIGURE 1
Actual Speed of target. This figure shows abrupt variation in velocity in x direction during motion.

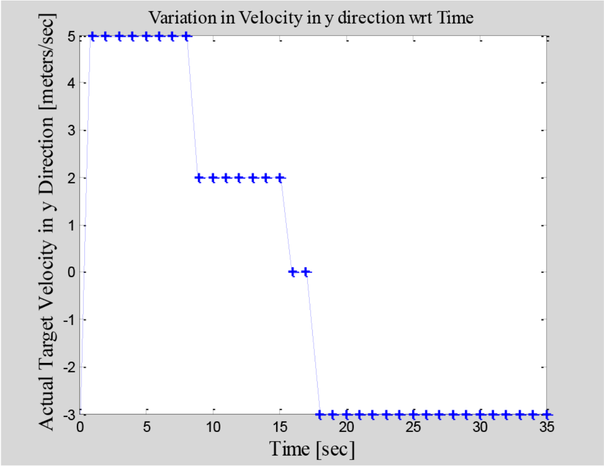

FIGURE 2
Actual Speed of target. This figure shows abrupt variation in velocity in y direction during motion.

There are many methods of estimating speed of a moving object. In this research, velocities of target are estimated using the time the target takes to travel between two successive positions and the distance travelled. 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 milli-watts.

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.

$$z_1 = P_r(d_0) - 10n_1 \log(d_1/d_0) + X_\sigma, \tag{32}$$

$$z_2 = P_r(d_0) - 10n_2 \log(d_2/d_0) + X_\sigma, \tag{33}$$

$$z_3 = P_r(d_0) - 10n_3 \log(d_3/d_0) + X_\sigma. \tag{34}$$

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 rearranging and 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.

$$n_{avg} = (n_1 + n_2 + n_3)/3 \tag{35}$$

Therefore equation (2) can be modified as

$$z_{lj,k} = P_r(d_0) - 10n_{avg} \log(d_{lj,k}/d_0) + X_\sigma. \tag{36}$$

The value of P $_r$ (d $_0$) can now be easily computed using equation (36) by putting the value of RSSI for a given distance $d_{\ell j,k}$ and value of n_{avg}.

$$P_r(d_0) = z_{lj,k} + 10n_{avg} \log(d_{lj,k}/d_0) - X_\sigma\ . \tag{37}$$

Also the distance equation (25) can be modified as given below.

$$d_{lj,k} = d_0 10^{(P_r(d_0)\ -\ z_{lj,k}\ +\ X_\sigma)/10n_{avg}}. \tag{38}$$

In the carried out research work, two cases have been investigated:

- ***Case I : Availability of All the RSSI Measurements***

  To test the efficiency of proposed algorithms with availability of all RSSI measurements at all instances k (for 4, 6, and 8 anchors).

- ***Case II : Availability of the Limited RSSI Measurements***

  To analyze proposed algorithms with availability of the limited set of RSSI measurements (no measurements beyond $k = 18\,s$).

Symbol	Parameter	Value
X_0	Initial Target State at k=0	[12 15 0 0]
dt	Discretization time step	1 s
T	Total Simulation Period	35 s
f	Frequency of operation	867 MHz
X_σ	Normal Random Variable	$\sim$ N(3, 1)
n_{avg}	Average Path Loss Exponent	2.84

TABLE 2
Simulation Parameters for Proposed Algorithms

In both the cases target undergoes through the abrupt changes in velocity as given by equation (26)–(31). The initial values of R, P *and* Q metrices are taken to be,

$$R = \begin{bmatrix} 2.2 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}, P = \begin{bmatrix} 0.25 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix}, \ Q = I_{4\times4}. \tag{39}$$

4.4 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 (32)–(35)), and $P_r(d_0)$ (using equations (37)) empirically. The second part of distance estimation is supposed to be executed by anchor nodes using equation (36) 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. More than 50 trials of the proposed algorithm are taken. Values of performance metrics for both simulation cases in Table 2 to Table 5 are average values of 50 simulation trials. The detailed flow of the proposed algorithms for one time step k is as given in Table 3.

5 PERFORMANCE EVALUATION

5.1 Performance Metrics

The two metrics that we have used to evaluate the performance of the proposed algorithms are: average localization error, and root mean square error (RMSE). The average localization error and RMSE represent the average estimation error in target's $(\hat{x}_k, \hat{y}_k)$ position and the closeness of the estimated target trajectory $(\hat{x}_k, \hat{y}_k)$ with the actual target trajectory (x_k, y_k) over

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 the Base Station

Step 4: The base station runs the 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.

TABLE 3
RSSI + KF and RSSI + UKF Algorithm Description

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 50 times. After every sampling instance k, the error in x estimate $(\hat{x}_k - x_k)$, error in y estimate $(\hat{y}_k - y_k)$, and the execution time (using MATLAB tic-toc commands) for the traditional RSSI approach, and the proposed RSSI + KF and RSSI + UKF algorithms, are computed for both cases I and II. The investigation of case II and the execution time for these three approaches is carried out only for 8 anchor. After every simulation run, the average localization error and the RMSE's are determined by utilizing equations (40) and (41) respectively.

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

$$Average\ Localization\ Error = \frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2}, \qquad (40)$$

2] Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2}{2}}. \qquad (41)$$

5.2 Discussion of Results

In each of the two cases mentioned earlier, the target start from position (12,15) and stops at (97,10) as shown in Figure 3, 5, 7, and 9. These figures depict the actual and the estimated target trajectories by the traditional RSSI, RSSI+KF and RSSI+UKF algorithms. The black filled squares represent anchor nodes, whereas red unfilled squares, red plus symbols, green plus symbols and unfilled red circles represent actual target position, RSSI based estimated position, RSSI + KF based estimated position and RSSI + UKF based estimated position respectively at a specific time instance k in these figures. The Figure 4, 6, 8 and 10 illustrate the comparison of average localization errors for these three algorithms for each time instance k. The red line (joining unfilled circle symbols), the blue line (joining plus symbols) and the black line (joining plus symbols) represent average localization errors in pure (traditional) RSSI, RSSI + KF, and RSSI + UKF based estimation approaches for the total simulation period T respectively. The different line styles are used in these figure to differentiate tracking results of three approaches.

In this research work, the anchor nodes are located at [0,0], [100,0], [0,100], and [100,100] in an experiment with 4 anchors, at [0,0], [50,20], [100,0], [100,100], [50,80], and [0,100] in an experiment with 6 anchors, and at [0,0], [50,0], [100,0], [100,50], [100,100], [50,100], [0,100], and [0,50] in an experiment with 8 anchors, as shown in Figure 3, 5, 7, and 9 respectively. In the first case the anchor nodes at any location within the sensor field is able

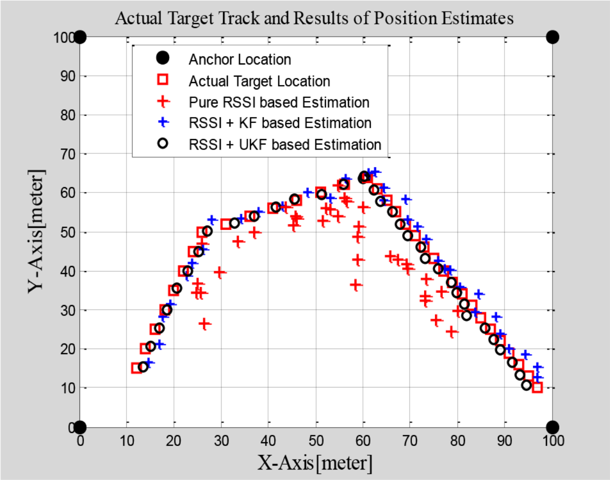

FIGURE 3
Actual target trajectory and estimated trajectories by the pure RSSI, RSSI+KF and RSSI+UKF algorithms. (Case I, Number of Anchors = 4).

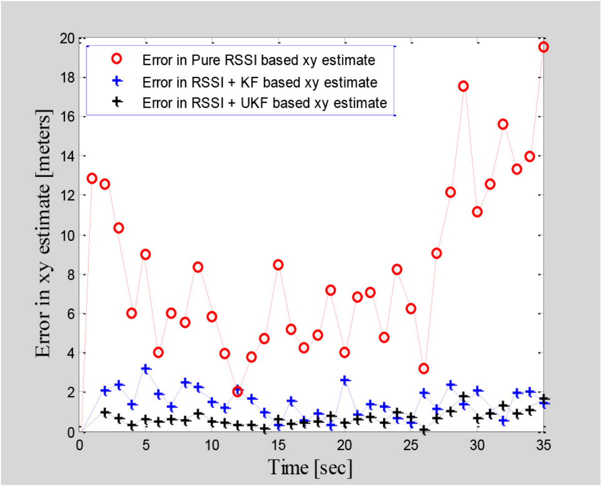

FIGURE 4
Comparison of Average Localization Errors in pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case I, Number of Anchors = 4).

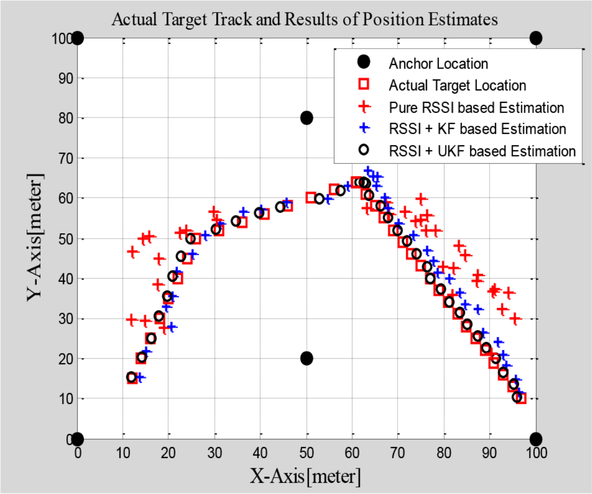

FIGURE 5
Actual target trajectory and estimated trajectories by the pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case I, Number of Anchors = 6).

to measure the RSSI from the mobile target, whereas in the second case due to obstructions RSSI's are available only for few instances. The initial target state vector is [12, 15, 0, 0]. For $k > 0$, the target moves within the sensor field in accordance with equations (3) and (4).

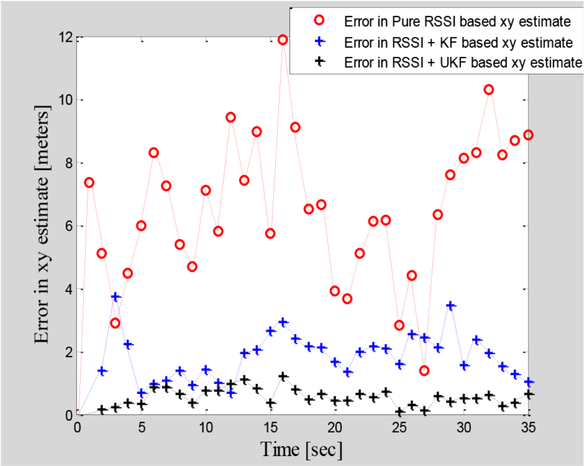

FIGURE 6
Comparison of Average Localization Errors in pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case I, Number of Anchors = 6).

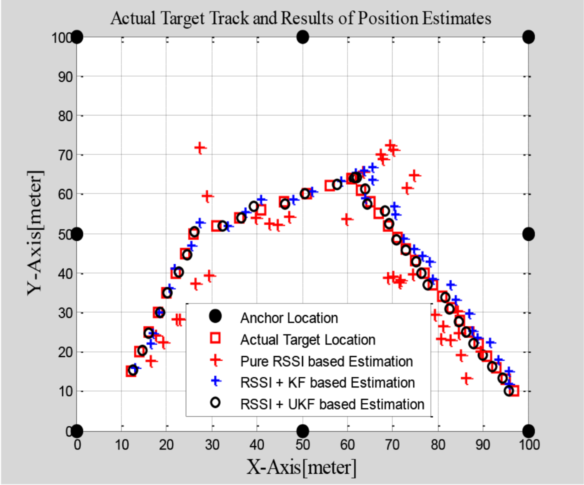

FIGURE 7
Actual target trajectory and estimated trajectories by the pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case I, Number of Anchors = 8).

All the simulation results of case I show that the tracking performance improves by raising the density of anchor nodes. The highest improvement in the tracking performance is observed to be for 8 anchor case. It can be easily noted that the reduction in RMSE for 8 anchor case is approximately

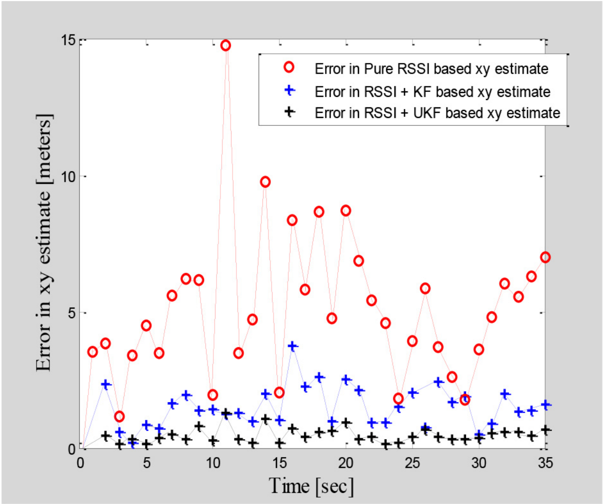

FIGURE 8
Comparison of Average Localization Errors in pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case I, Number of Anchors = 8).

70% and 90% in RSSI + KF and RSSI + UKF algorithms respectively as compared to the traditional RSSI based approach (see Table 5).

That means higher the number of anchors, higher would be the tracking accuracy. However more the density of anchors, more would be the additional cost of hardware and maintenance. Although the choice of optimum anchor

Number of Anchors used	Avg. Localization Error for Pure RSSI based Estimation [meter]	Avg. Localization Error for RSSI+KF based Estimation [meter]	Avg. Localization Error for RSSI+UKF based Estimation [meter]
4	8.2803	1.5173	0.7107
6	6.5721	1.8233	0.5458
8	5.1626	1.5070	0.4765

TABLE 4
Comparison of Average Localization Errors for Case I

Number of Anchors used	RMSE of Pure RSSI Based Estimation [meter]	RMSE of RSSI+ KF Based Estimation [meter]	RMSE of RSSI+UKF Based Estimation [meter]
4	14.0459	2.5396	1.3314
6	11.5814	2.9594	1.0486
8	8.8024	2.5285	0.8105

TABLE 5
Comparison of RMSE for proposed algorithms for Case I

Number of Anchors used	Avg. Localization Error for Pure RSSI based Estimation [meter]	Avg. Localization Error for RSSI+KF based Estimation [meter]	Avg. Localization Error for RSSI+UKF based Estimation [meter]
8 (Case I)	5.1626	1.5070	0.4765
8 (Case II)	12.8510	2.1280	0.8369

TABLE 6
Comparison of Average Localization Errors for Case I and Case II

density is dependant on the transmission power level (communication range) and application in hand, increasing the transmission power will surely consume more energy. That means there is a trade-off between tracking performance, economical budget and transmission power level. Therefore, to adjust the anchor density and the transmission power to achieve different tracking accuracies adaptive to the application requirements, can be a very important research direction.

In the case II, the anchor nodes are assumed that they doesn't receive any RSSI measurements beyond $k = 18\,s$ from the mobile target due to obstructions in the surrounding environment. Therefore average localization error sharply increases in the traditional RSSI based estimates as compared to the proposed algorithms (see Figure 10). The impact of absence of measurements on the RSSI + UKF based algorithm is observed to be lowest as compared to other two. Although average localization error and RMSE for the proposed algorithms are increased as compared to that for case I, it can still be

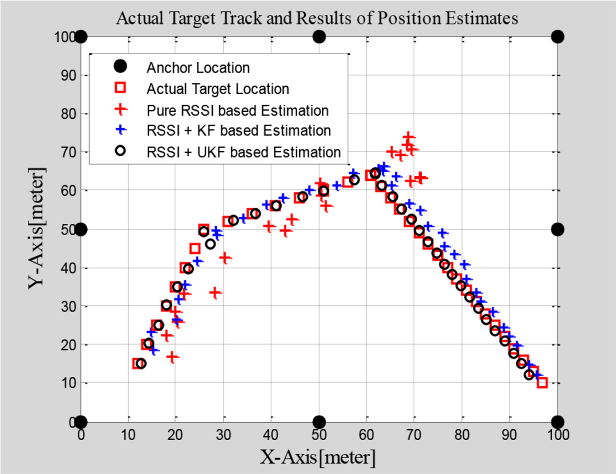

FIGURE 9
Actual target trajectory and estimated trajectories by the pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case II, Number of Anchors = 8).

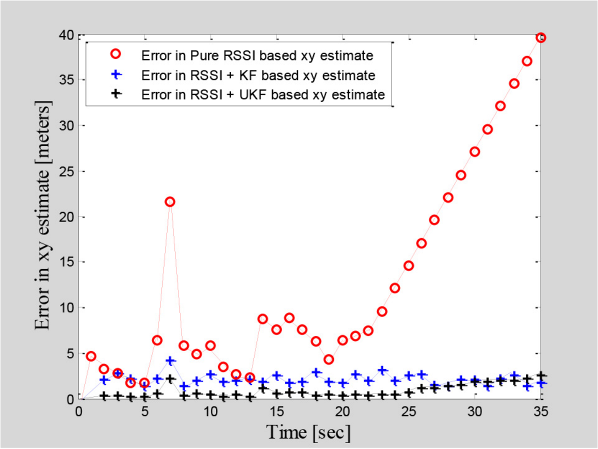

FIGURE 10
Comparison of Average Localization Errors in pure RSSI, RSSI+KF, and RSSI+UKF algorithms. (Case II, Number of Anchors = 8).

considered to be a better estimate of the track of the given mobile target. The case II results shows that the RSSI + UKF algorithm outperforms the rest of the two approaches (see Figure 9 and 10). The RMSE is reduced approximately by 87% and 94% in the RSSI + KF and the RSSI + UKF algorithms as compared to the traditional RSSI based and the KF + RSSI based approaches respectively (see Table 7).

The computational complexity is another important issue in the context of real time target tracking that we investigated. The execution time for the traditional RSSI based approach and the proposed RSSI + KF and RSSI + UKF algorithms is found to be 0.21 milliseconds, 2.4 milliseconds, and 2.7 milliseconds respectively for the case I. Whereas for the case II, the execution time for the traditional RSSI approach and the proposed RSSI + KF and RSSI + UKF algorithms is found to be 2 microseconds, 2 milliseconds, and 2.3 milliseconds respectively. It is noted that the computational complexity is lowest, moderate and highest for the traditional RSSI, the RSSI + KF and the RSSI + UKF based approaches respectively.

Number of Anchors used	RMSE of Pure RSSI Based Estimation [meter]	RMSE of RSSI+ KF Based Estimation [meter]	RMSE of RSSI+UKF Based Estimation [meter]
8 (Case I)	8.8024	2.5285	0.8105
8 (Case II)	26.0044	3.3513	1.5808

TABLE 7
Comparison of RMSE for proposed algorithms for Case I and Case II

Therefore 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 as well as it better handles the nonlinearity associated with the motion and the measurement models for both the cases.

6 CONCLUSIONS AND FUTURE WORK

This paper contributes to solving the problem of simultaneous localization of mobile nodes in wireless networks 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 (in the scale of few centimeters) irrespective of the abrupt changes in the target velocity, unpredictable measurement noise as well as the limited set measurements available.

There are many parameters that affect the performance of RSSI based tracking algorithm namely, the density of anchors, variations in target velocity, algorithmic complexity, intensity of measurement noise,..etc. Higher the density of anchors, higher would be the tracking accuracy as well as system cost. To study this effect, the anchor density is varied from 4 to 8 in steps of 2. To study the effect of variations in target velocity, it is varied within the range of -3 to 5 (m/s) abruptly at specific time instances during simulation. In order to test the impact of algorithmic complexity on the performance of proposed tracking algorithm, the execution time for the all three approaches is compared. The overall tracking performance is assessed in terms of the localization error, RMSE, and the 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. Future work will be focused on localization and tracking of mobile target using real RSSIs. The simulation results also revealed that higher the anchor node density, more improved the target tracking performance is, which is quite logical. In order to deal with this trade off, one can extend our solution to handle more sophisticated network configuration and fulfill diverse application requirements.

There are several avenues for the further research such as tracking of multiple moving targets, investigation of various other motion models and observation models, testing the performance of tracking algorithm for varying measurement noises and measurement time interval. It is believed that mobile sensor network may track mobile target more effectively than static sensor network. This research can also be extended by assigning mobility to few anchor nodes.

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