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Application of Extended Kalman Filter for Tracking of Mobile Target

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Abstract
Knowledge of continuous location updates is very important aspect in many location based services (LBS). Therefore, localization and tracking a mobile target using RSSI measurements with wireless sensor network (WSN), is one of the widely research topic. The trilateration based localization using received signal strength indicators (RSSIs) is simple and widely used approach in the literature. However, high localization accuracy may not be obtained with the trilateration due to dynamicity (highly fluctuating nature) of RSSI measurements. Therefore, the location estimates of trilateration must be refined further with the help of some more advanced state estimation technique to guarantee high localization accuracy. In this paper a novel fusion of trilateration and extended kalman filter (EKF) to address the issue of uncertainties in measurement noise in the received signal strength indicators (RSSIs) is proposed named as Trilateration+EKF. The localization performance of the proposed Trilateration+EKF algorithm is compared with traditional trilateration technique in this paper. The simulation results demonstrate the efficacy of the proposed Trilateration+EKF algorithm with respect to trailateration technique in the context of dynamicity in RSSIs.
Index Terms— Location Based Services (LBS), Extended Kalman Filter (EKF), Received Signal Strength Indicators (RSSI's), Target Tracking, Wireless Sensor Networks (WSNs).

I. INTRODUCTION

In WSN domain there are wide variety of technological alternatives to carry out localization and tracking such as radio frequency (RF), infrared, 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 [1]–[4]. 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 [5]–[8]. 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) [9]. However, there are many challenges in applying these models especially in indoor environment as compared to outdoor environment, due to variations in the indoor layout structure, objects, and humans. Such obstructions generally lead to reflection, refraction, diffraction, and absorption of radio signals. Moreover, many other factors also influence the RSSI, such as temperature, orientation of antenna, and height to the ground. Due to such a dynamicity of wireless medium, errors in RSSI measurements are unpredictable leading to erroneous tracking results [8], [10], [11]. Therefore more research efforts are being applied by the research community to cope up with this dynamicity in RSSI measurements since last decade.

Many research efforts have been reported in target tracking literature to deal with uncertainty in RSSI measurements. A recursive method capable of maintaining a position estimate must be used to guarantee state estimates even when no RSSI measurements are available or they are highly corrupted by noise. 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 [12]–[14]. Depending on the application in hand, the requirement of localization accuracy may change. For example, if it is a marketing/advertisement case then roughly a 5 to10 meters should serve the purpose [7], [15]. On the other hand for industrial applications, localization accuracy below 1 meter may be required. The proposed Trilateration+EKF algorithm is designed keeping in mind the indoor environment such as shopping mall wherein the localization accuracy of the order of 2 meter is sufficient. The main contributions of this research work are listed below.

1) We formulated a novel fusion framework of trilateration, and EKF for the problem of RSSI based localization of single target moving in indoor environment. With this fusion framework, we proposed a robust localization algorithm namely, Trilateration+EKF. This novel fusion proved to produce the localization accuracy to the scale of 2 meter.
2) The proposed Trilateration+EKF algorithm is tested and verified against dynamicity in the surrounding environment as well as target motion through MATLAB simulations. In order to realize dynamicity in the RSSI measurements, we set measurement noise in RSS to be 3 dBm. The simulation and numerical results demonstrate that the proposed Trilateration+EKF localization algorithm better deals with the high measurement noise in RSS and time variations in the target velocity as compared to trilateration based localization system.

The structure of the paper is as follows. Section II discusses Localization of Mobile Target. Section III presents the Extended Kalman Filter For Localization. Performance evaluation of proposed algorithm is presented in Section IV. Finally, conclusion is highlighted in Section V.

II. LOCALIZATION OF MOBILE TARGET

The localization problem means finding out target location at specific time instance using field measurements. Whereas, the tracking problem means locating the moving target continuously throughout the target motion using field measurements. Thus the localization problem is a subset of the tracking problem.

A. Motion Model of the Mobile Target

The state of mobile target considered in this research work at time instant k is given by the state vector $x_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)'$ [16]–[18].

Where,

x_k - x coordinate of the target at time k,

y_k - y coordinate of the target at time k,

$\dot{x}_k$ – Target velocity along x direction at time k,

$\dot{y}_k$ – Target velocity along x direction at time k,

dt - time step between two consecutive time instants such that $dt = k - (k-1)$.

B. Measurement (Observation) Model

The RSSI $(z_{\ell j,k})$ received at the node N_ℓ with coordinates $(x_{\ell k}, y_{\ell k})$ at time k, after being transmitted from the node N_j with coordinates (x_{jk}, y_{jk}), propagates as follows [16]–[18]:

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

Where,

$P_r(d_0)$ - RSSI value at receiver node located at reference distance d_0 from transmitter

X_σ - Normal random variable (a measure of measurement noise in RSSI),

η - Path loss exponent. Larger the value of n, higher would be the amount of obstructions and the rate of decrease of received power as well.

The RSSI values are highly dynamic in nature as shown in Fig. 1. The Fig. 2 depicts that how the RSSI measurements vary at a distance of 10 meter with respect to time for the same transmitter, receiver, and the wireless channel.

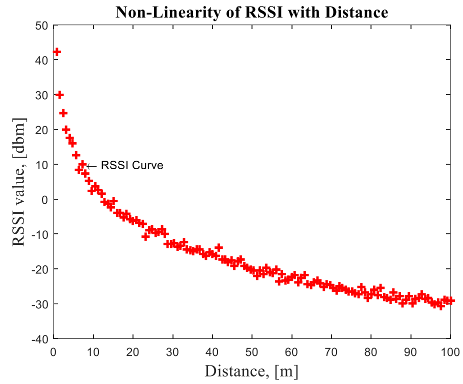

Fig. 1 Dynamicity in RSSI measurements

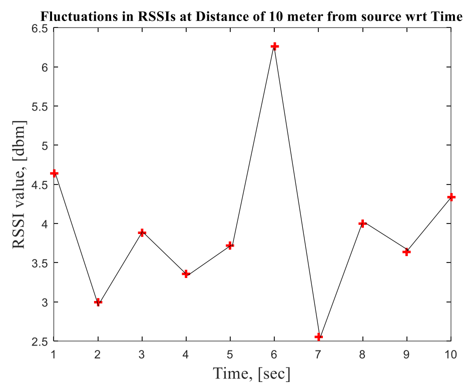

Fig. 2 Fluctuations in RSSI measurements at a distance of 10 meter from an RF Source.

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 [10].

III. EXTENDED KALMAN FILTERING FRAMEWORK FOR LOCALIZATION

KF is an bayesian estimator which can provide optimal estimation when the underlying system is linear and the associated measurement noise is gaussian [16]–[18]. The target motion and measurement models for the standard KF can be described using equation (2), and equation (3) respectively as:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \qquad (2)$$

$$z_k = H(x_k) + v_k, \qquad (3)$$

where A, B and H are state transition matrix, control input transition matrix, and measurement transition matrix respectively as given below. In this work, we selected a constant velocity (CV) model. The values of these matrics for the CV model are taken as given below [16]–[18].

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

Where,

w_{k-1} - Process noise with $Q_k\,(w_k \sim N(0,Q_k))$,

v_k - Observation noise with

In case of KF the measurement noise in the system is assumed to be Gaussian. Whereas if the process noise and the measurement noise in the system are non-linear, then extended kalman filter (EKF) and unscented kalman filter (UKF) are preferred over the standard KF [19]–[21]. However, the UKF is computationally complex as compared to the EKF. Basically the EKF is an extension of the standard KF applicable for the non-linear systems. The non-linearity in the system dynamics is approximated using the first or second order derivative in the EKF. The detailed mathematical fundamentals of EKF can be found in [19]–[21].

IV. PERFORMANCE EVALUATION

A. System Design

The proposed localization and tracking system consists of a set of static anchor nodes deployed in area of 100 meter by 100 meter as shown in Fig. 3. These anchor nodes are deployed at known locations and the target is supposed to be moving in the WSN defined area. The moving target carries 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. All the anchors send computed distances along with their coordinates to the coordinator node.

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. For three distances $(d_1, d_2 \text{ and } d_3)$, three RSSI's $(z_3, z_2 \text{ and } z_3)$, can be given by equation (5) to equation (7).

$$z_1 = P_r(d_0) - 10n_1\log(d_1/d_0) + X_\sigma \,, \quad (5)$$
$$z_2 = P_r(d_0) - 10n_2\log(d_2/d_0) + X_\sigma \,, \quad (6)$$
$$z_3 = P_r(d_0) - 10n_3\log(d_3/d_0) + X_\sigma \,. \quad (7)$$

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

$$n_{avg} = (n_1 + n_2 + n_3)/3 \quad (8)$$

Therefore equation (1) can be modified as

$$z_{lj,k} = P_r(d_0) - 10n_{avg}\log(d_{lj,k}/d_0) + X_\sigma \quad (9)$$

The value of $P_r(d_0)$ can now be easily computed using equation (15) by putting the value of RSSI $z_{lj,k}$ for a given distance $d_{\ell j,k}$ and value of n_{avg}.

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

Also the distance equation (2) can be modified as given below.

$$d_{lj,k} = d_0 10^{(P_r(d_0) - z_{lj,k} + X_\sigma)/10n_{avg}} \ . \qquad (11)$$

The values of R, P and Q metrics considered for this research are given below in equation (18).

$$R = \begin{bmatrix} 2.2 & 0 & 0 & 0 \\ 0 & 1.2 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}, P = \begin{bmatrix} 0.25 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix}, Q = I_{4\times 4} \ . \qquad (12)$$

B. Performance Metrics:

The two metrics that we have used to evaluate the performance of the proposed algorithm 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 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 algorithm are run for approximately 10 times. After every sampling instance k, the error in x estimate $(\hat{x}_k - x_k)$, error in y estimate $(\hat{y}_k - y_k)$, After every simulation run, the average localization error and the RMSE's are determined by utilizing equations (19) and (20) respectively.

$$\text{Average Localization Error} = \frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k) + (\hat{y}_k - y_k)}{2}, \quad (13)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{k=1}^{T}\frac{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2}{2}} \ . \qquad (14)$$

C. Discussion on Results

The proposed Trilateration+EKF and trilateration alone are given input of a vector consisting of three real time RSSI measurements obtained during real time target motion. The trilateration as well as the proposed Trilateration+EKF algorithm does not need any prior training for location estimation. The target is assumed to start from (8, 10) and stop at (87, 55). Numeric values of RMSE and average localization error are by taking average of 30 simulation trials (See Table 1).

The Fig. 3 depicts comparison of localization estimation with Trilateration, and the proposed Trilateration+EKF algorithm. From this result it is quite clear that the proposed Trilateration+EKF algorithm location estimations are almost coincide with the actual target locations as compared location estimates of trilateration alone. The Fig. 4, Fig. 5 and Fig. 6 illustrate the time variation of estimate error with Trilateration, and the proposed Trilateration+EKF based Localization in the context of x coordinate estimation, y coordinate estimation, and x-y coordinate estimation respectively. Thus, from The Fig. 4, Fig. 5 and Fig. 6, Table 1 we can conclude that target localization accuracy is high, and low with Trilateration, and the proposed Trilateration+EKF algorithm respectively. Speaking more clearly, from Table 1 it

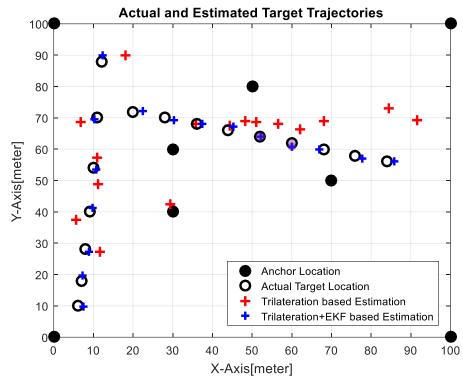

Fig. 3 This figure shows the deployment of anchor nodes, actual target locations during motion, and location estimates obtained with trilateration and the proposed Trilateration+EKF algorithm.

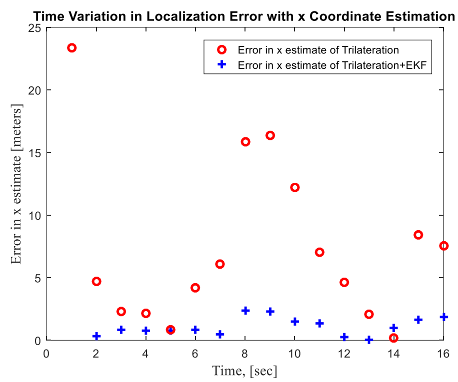

Fig. 4 Comparison of localization error in x estimate with trilateration and Trilateration+EKF.

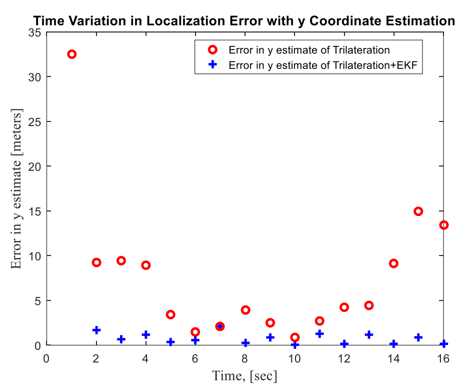

Fig. 5 Comparison of localization error in y estimate with trilateration and Trilateration+EKF.

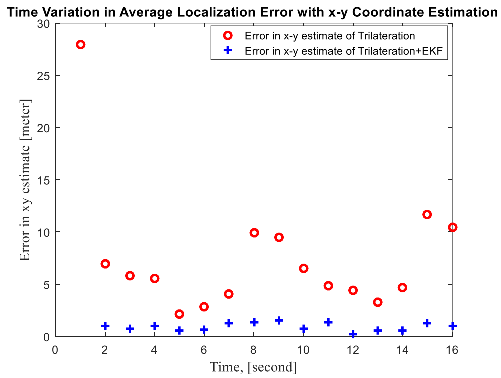

Fig. 6 Comparison of localization error in x-y estimate with trilateration and Trilateration+EKF.

is clear that the RMSE of the proposed Trilateration+EKF is reduced by approximately 89% as compared that of trilateration. From Table 1, it is evident that the Average Localization Error of the proposed Trilateration+EKF is reduced by approximately 87% as compared that of trilateration. The highest localization error in x-y estimation with the proposed Trilateration+EKF is 1.8793, which is far less than that with the trilateration technique.

Table 1 Comparison Numeric Results of RMSE, Average Localization Error, Highest Localization error, and Lowest Localization error with Trilateration, and proposed Trilateration+EKF architecture.

Algorithm	RMSE (meter)	Average Localization Error (meter)	Highest Localization error in x-y estimation (meter)	Lowest Localization error in x-y estimation (meter)
Trilateration	14.5362	7.5283	28.5623	2.5643
Trilateration+EKF	1.6136	0.9224	1.8793	0.2014

V. CONCLUSIONS

This paper presents robust range-based RSSI based target localization algorithm namely, Trilateration+EKF, obtained by the fusion of trilateration, and EKF. The extensive simulation results indicate that the proposed algorithms demonstrate superior localization performance as compared to the other state of art algorithms. The proposed algorithms efficiently deal with the issues of dynamic RF channel and non-linear system dynamics to solve the problem of indoor L&T of a mobile target. In order to realize uncertainty in the noise in RSSI measurements, the normal random variable parameter in LNSM path loss model is kept high to 3 dBm during simulations. The extensive simulation results prove that the proposed Trilateration+EKF algorithm demonstrate superior localization performance as compared to trilateration based localization algorithm. We believe that the proposed localization algorithms are useful in localization applications wherein the demand of high localization accuracy is to the scale of 1-2 meters. The proposed research work may be extended in many ways. For instance, the proposed Trilateration+EKF algorithm can be applied to multi-target tracking scenario in indoor environment.

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