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Performance Enhancement of a Wi-Fi based Indoor Localization system through a Cooperative Sigma Point Kalman Filter approach

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ABSTRACT

Present work investigates one solution to indoor localization problem. Due to quality degradation of GPS signals in indoor premises, Extended Kalman filter based processing of preinstalled Wi-Fi access points signals are popularly used for this purpose, which suffer due to underestimation of error covariance of true system dynamics. A Sigma Point Kalman Filter outperforms Extended Kalman Filter by achieving higher order accuracy in its computation. Present work implements and demonstrates one innovative Cooperative Sigma Point Kalman Filter approach which uses two nearest access points' measurements to compute the scaling factor during generation of the deterministic sigma points. Received signal strength-based trilateration algorithm is applied to measure the proximity of the access points based on which the two nearest Wi-Fi access points are selected. This adaptation of scaling factor incorporates two best measurements in the computation which makes the filter capable of estimating the system dynamics more accurately. Performance of this proposed scheme is evaluated with 100 Monte Carlo runs in which less than 1 meter of accuracy is found which is comparable with other state of the art algorithms. Moreover, the proposed scheme exhibited similar performance in fast gait speed as well, in which case, extended Kalman filter based approach did not succeed.

Keywords: *Indoor Localization; Received Signal Strength; Trilateration; Sigma Point Kalman Filter; Scaling factor adaptation*

1. INTRODUCTION

Location based services (LBS) for smartphone device require optimal estimation of navigation states (position, velocity, acceleration) of a smartphone [1]. Indoors, quality of GPS signal suffers attenuation problem [2], [3]. In such situations, preinstalled Wi-Fi signals are fed into trilateration-based algorithm to estimate the proximity between the mobile smartphone and the access points (APs), which, in turn, yields the estimation of the smartphone's navigation information [4]–[7].

A Kalman filter employs linear system equations to capture the dynamics of the moving object [8], [9]. However, presence of interference in terms of various obstacles of indoor environment make the moving object system dynamics nonlinear which does not fit into Kalman filter paradigm [10], [11].

As an alternative, Extended Kalman Filter (EKF) has been used successfully [3], [12], [13]. In EKF approach, the nonlinear system dynamics is approximated as a linear one using Taylor series expansion up to first order terms [14]. This type of linear approximation of nonlinear dynamics suffers due to inaccurate initialization of system states and scattered measurements [15]–[17].

In real-time implementation of Wi-Fi signaling based trilateration algorithm, a person carrying a smartphone is free to move at her own choice of gait speed. This will lead to non-uniform arrival of measurements which is the input to the filter. The EKF in this situation will fail to capture the system dynamics correctly. To overcome this problem one Sigma Point Kalman Filter (SPKF) may be used [18], [19]. Contrary to EKF, SPKF uses unscented transformation using deterministically chosen sigma points for better linear approximation of the nonlinear system dynamics.

In a recent work presented in [20], the scaling factor of sigma point filter has been determined by combining measurements of multiple such filters. This cooperative multi model approach in scaling factor computation has been proven effective in better capturing of the nonlinear system dynamics.

The present work discusses one cooperative SPKF (CSPKF) based indoor localization scheme. In this work, a subject is asked to traverse a pre-planned path with a smartphone tightly attached to her body. Six different mobile phones are kept in six different places on or around the path which will act as the APs. While moving through the path, the objects' RSS information is obtained and recorded online in a smartphone application. This recorded information is then processed offline to serve the following two objectives.

- Optimal estimation of location information of the smartphone through adaptive CSPKF based approach. The CSPKF uses two nearest APs signals to deterministically generate sigma points, which is a novel approach.

- Testing and validation of the proposed approach with different gait speed of the moving object

Organization of this article is as follows. After this brief introduction, the description of the work is presented in Section II. Results and analysis of simulations are described in Section III which is followed by a concluding remark in Section IV

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2. MATERIALS AND METHODS

For execution of the proposed work, one trajectory is planned which will be followed by the subjects carrying smartphones tightly attached to the waist. Six other smartphone devices are placed at six different positions surrounding the preplanned trajectory, which will work as the access points (APs) by turning the Wi-Fi hotspot option on. The trajectory and placements of the APs are shown in Fig. 1.

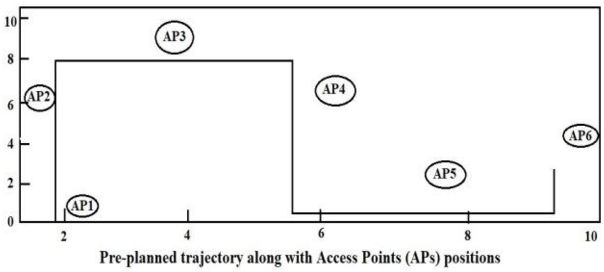

Fig. 1. Trajectory and placement of Aps

The carriers' smartphone will capture and record the

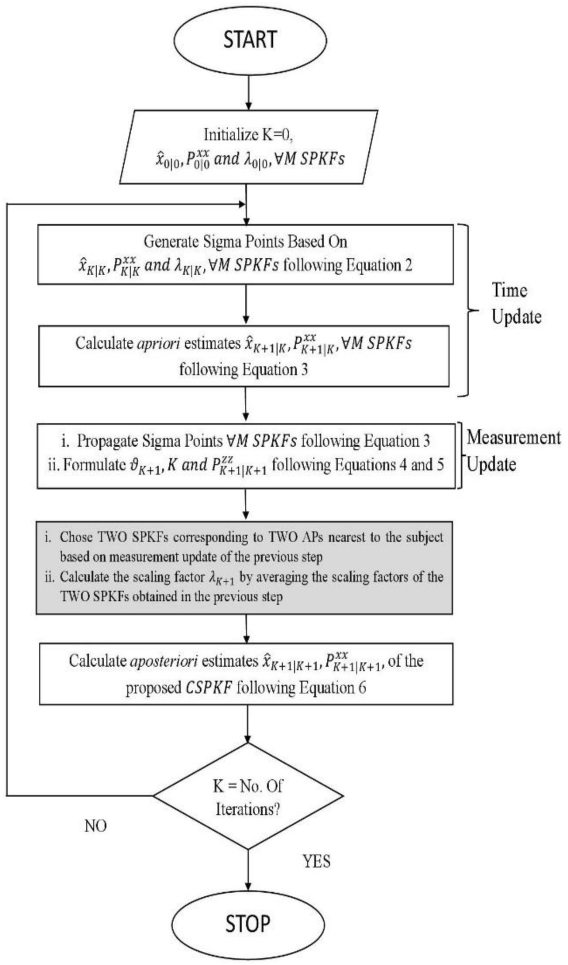

Fig. 2. The proposed CSPKF algorithm

Received Signal Strength (RSS) values during every traversal of the trajectory on online mode.

After this online data collection, all the collected data are taken into a computer. Then the proposed CSPKF approach will be applied to the collected data as depicted in Figure 2 and Explained in Section II.

Discussion on CSPKF

To formulate the CSPKF, the conventional nonlinear Bayesian estimation model is assumed [16]. The system and measurement models of the said estimation process is given as follows:

$$x_{k+1} = f_k(x_k, v_k)$$

$$z_k = h_k(x_k, n_k) \tag{1}$$

Here, $x_k = [x\ y\ v_x\ v_y]$ and $z_k = [x, y]$ are the state and measurement vectors respectively. f_k and h_k are the state transition matrix and measurement sensitivity matrix. v_k and n_k are the Gaussian system and measurement noises driving the model.

In the SPKF, the state distribution is approximated by a set of weighted points known as sigma points which are generated using the mean and covariance of the system states and are chosen in such a way that they capture the mean and covariance of the distribution accurately. Sigma Points X are generated as follows:

$$x_0 = \hat{x}$$

$$x_i = \hat{x} + \sqrt{(x+\lambda)P_i} \tag{2}$$

$$x_{i+n} = \hat{x} - \sqrt{(x+\lambda)P_i}$$

Here, $\hat{x}$ is the state estimate, x_i is the sigma points vector, P is the state covariance and λ is the scaling factor that affect the spreading and accuracy of the sigma points.

Determination of scaling factor

There are two choices of determining the scaling factor.

•Fixed value - In this scheme, one fixed value for the scaling factor is determined through offline experimentation in a range [0, 3] and will remain constant through to all iterations.

•Adaptive value - The scaling factor is determined online, during each iteration of the filter. This makes the SPKF scheme adaptive to the changing situation which helps in capturing the nonlinear system dynamics better.

In present work, the selection of scaling factor has been made adaptive. The highlighted block of Fig. 2 describes the process of selection of scaling factor in the present work. At the end of the measurement update phase of filter, two APs nearest to the subject smartphone are chosen. The resultant scaling factor is computed by averaging the scaling factors of the corresponding SPKFs of the associated filters. This approach is a new one which makes the proposed system adaptive to capture the nonlinear system dynamics at any gait speed.

Mean Propagation

The predicted mean and covariance after nonlinear transformation f is given by the following equations:

$$\hat{x}_{k+1|k} = f\left(x_{k|k}^{i}\right) \qquad i = 0,1,2,\dots,2n$$

$$\hat{x}_{k+1|k} = \sum_{i=0}^{2n} W_i^s \; x_{k+1|k}^{i}$$

$$P_{k+1|k}^{xx} = \sum_{i=0}^{2n} W_i^c \left[x_{k+1|k}^{i} - \hat{x}_{k+1|k}^{i}\right]\left[x_{k+1|k}^{i} - \hat{x}_{k+1|k}^{i}\right]^T + Q_k \qquad (3)$$

In above mentioned equations, W^s & W^c are taken to be the weights of system states and covariance [21] which are calculated following equations below:

$$W_s^0 = \frac{\lambda}{(L+\lambda)}$$

$$W_c^0 = \frac{\lambda}{(L+\lambda)}\left(1-\alpha^2+\beta\right)$$

$$W_s^i = W_c^i = \frac{\lambda}{2(L+\lambda)}$$

$$\lambda = \alpha^2(L+\kappa) - L$$

Values of κ = 0, α = 10−3 and β = 2 are typically considered for this work while L = 4 is the number of system states.

Prediction and Update

The state and covariance are predicted using the propagated sigma points, updating for the measurement z as given below.

$$\hat{z} = \sum_{i=0}^{2n} W_i^m \, h(x_i)$$

$$v_{k+1} = z_{k+1} - \hat{z}_{k+1|k}$$

$$P_{k+1|\,k+1}^{zz} = \sum_{i=0}^{2n} W_i^c \left(h(x_i) - \hat{z}\right)\left(h(x_i) - \hat{z}\right)^T + R$$

$$P_{k+1\,|\,k+1}^{xz} = \sum_{i=0}^{2n} W_i^c \left(x_i - \hat{x}_{k|k-1}\right)\left(h(x_i) - \hat{z}\right)^T \qquad (4)$$

Updating the state estimates and covariance:

$$K = P^{xz}\left(P^{zz}\right)^{-1}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K\,(z - \hat{z}) \qquad (5)$$

$$P_{k|k} = P_{k|k-1} - K\,P^{zz}\,K^T \qquad (6)$$

3. RESULTS AND DISCUSSIONS

To fulfil the requirement of 100 Monte-Carlo simulations, five different persons were asked to participate in the data collection process voluntarily. These subjects were asked to cover the pre-planned path as depicted in Figure 1 with different walking speed. At the end of this data collection phase, participants gait speeds were classified as follows:

a. No. of steps for slow speed of walk -> 75 - 85 steps

b. No. of steps for moderate speed of walk -> 95 - 105 steps

c. No. of steps for fast speed of walk -> 115 - 125 steps

This classification of gait speed commensurate with human gait speed described by [22, 23]. Subjects are chosen with different statures which is an important support towards the reliability and completeness of the collected data.

Five subjects walked through the pre-planned path 20 times each with fast, moderate and slow speed of walks as per their convenience. At the end of data collection phase, 100 sample files were collected for each of three different paces of walks. Therefore, 3 × 100 = 300 data files were collected for Monte-Carlo simulation in the next phase.

In Fig. 3, typical tracking plots of CSPKF algorithm are shown for slow, moderate and high speed of walks. It could be seen that, CSPKF is well capable of tracking the subject optimally in each of these paces of walk.

Functioning of a mobile object tracking filter can be better understood though their acceleration tracking performance. An optimal motion tracking filter is expected to track the acceleration accurately. Typical estimation of acceleration of CSPKF in X and Y directions for all three paces of walk are plotted in Fig. 4 to 6. Acceleration estimation accuracy has been found quite satisfactory in all the three cases. As may be seen in Fig. 4 and Fig. 5, CSPKF is exhibiting *< 0.1 meter/s*^{2} acceleration tracking accuracy in slow and moderate paces of walks which is optimal. More significantly, the proposed filter shows *<0.3 meter/s*^{2} accuracy in case of fast pace of walk as presented in Fig. 6. Fast pace of walk may incorporate some unmodeled system dynamics which complicates the estimation process. However, the proposed filter could manage such intricacy by using the innovative approach.

During analysis of slow and moderate speed of walks, both of the EKF and CSPKF based indoor localization schemes were considered and found performing at par.

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Their typical position tracking performances are plotted in Fig. 7.

During similar experimentation with fast pace of walk, EKF based algorithm did not converge. However, due to adaptive scaling factor determination, CSPKF converged in the said situation and its' performance was found satisfactory. One typical estimation of position error of CSPKF algorithm during fast speed of walk has been shown in Fig. 8. In this case, the proposed algorithm exhibited < 1 meter accuracy which is well within acceptable limit.

For better realization of the performance, 100 Monte Carlo simulations were conducted for each pace of walk. Performance of both algorithms on those simulations are summarized as Root Mean Squared Error (RMSE) of the final position error and is tabulated in Tab. 1. It may be observed that, during slow and moderate speed of walk,

EKF and CSPKF algorithms performed at par exhibiting < 1 meter accuracy which is within acceptable limit. Notably, proposed CSPKF algorithm performed similar even during fast speed of walk when EKF failed.

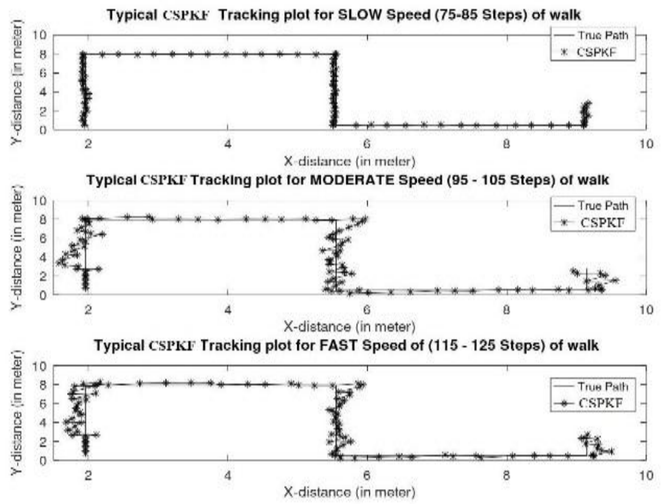

Fig. 3: Typical CSPKF Position Tracking performance

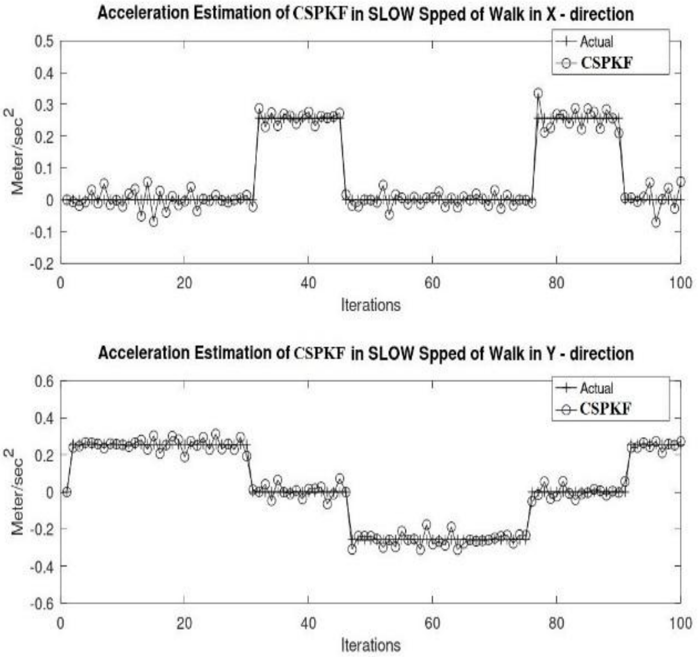

Fig. 4: Typical CSPKF Acceleration Tracking performance for SLOW Speed of Walk

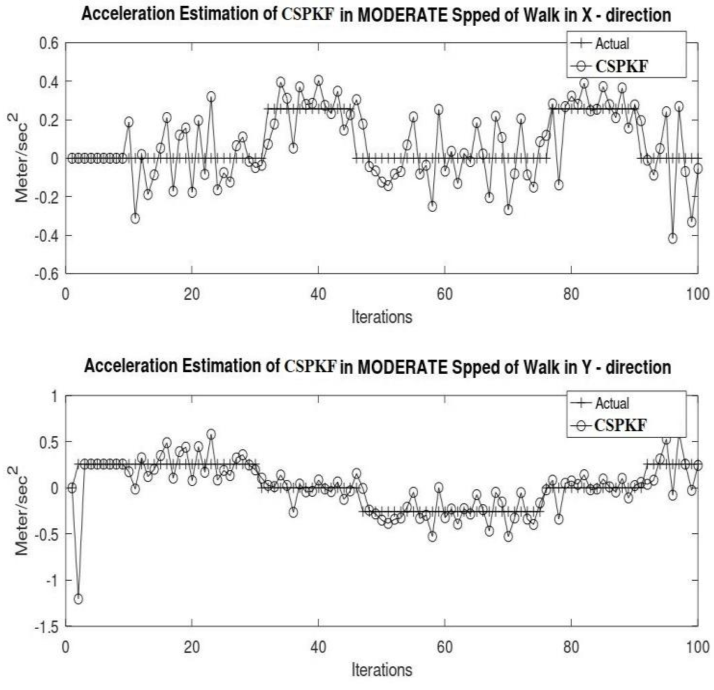

Fig. 5: Typical CSPKF Acceleration Tracking performance for Moderate Speed of Walk

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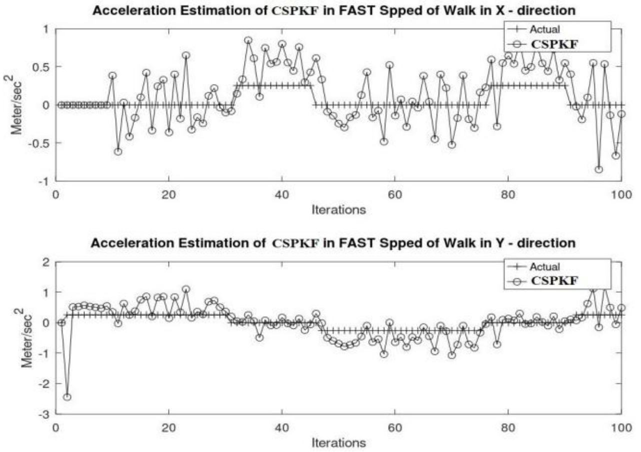

Fig. 6: Typical CSPKF Acceleration Tracking performance for Fast Speed of Walk

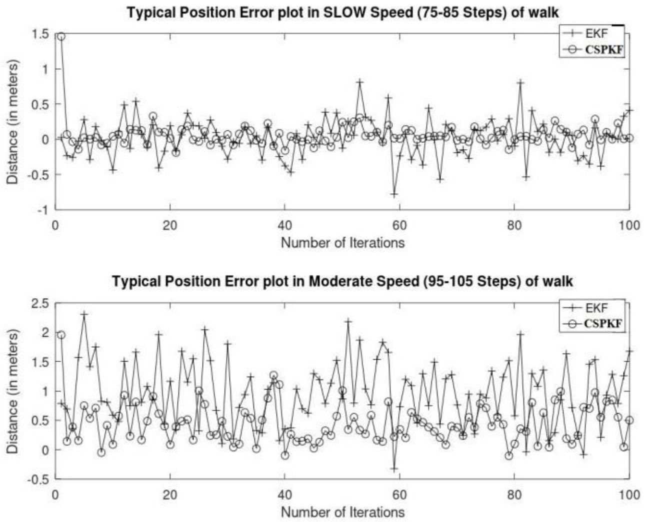

Fig. 7: Typical EKF and CSPKF Position Tracking performance for Slow and Moderate Speed of walk

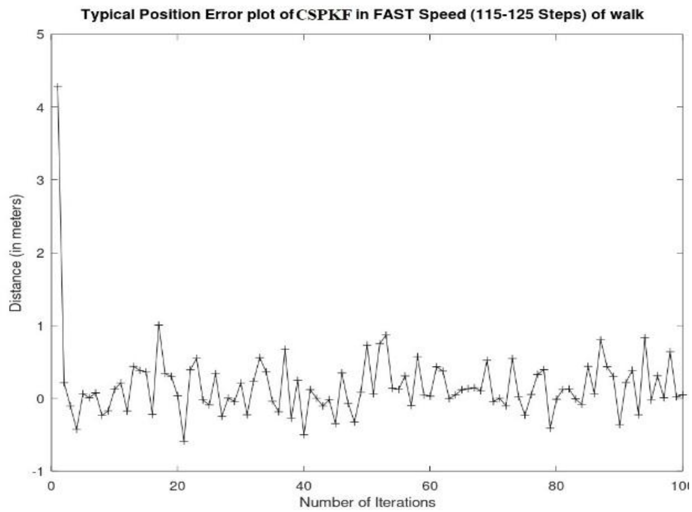

Fig. 8: Typical CSPKF Position Error plot for Fast pace of walk

Table 1: RMSE of Position Errors in 100 Monte-Carlo Simulations

	RMSE of Position estimation error (in Meter)		
	Slow Speed Walk	Moderate Speed Walk	Fast Speed Walk
EKF	0.8751	0.7103	Did Not Converge
CSPKF	0.7352	0.6676	0.8732

4. CONCLUSION

This work presents one cooperative sigma point Kalman filter (CSPKF) based solution to indoor localization problem. A new cooperative scaling factor determination process for sigma point generation has been introduced. For this purpose, measurements of two best performing SPKFs are considered making the filter capable of capturing the true mean and variances of the system states accurately even in situations where an EKF fails. Performance of this new CSPKF approach is evaluated and compared with that of EKF using Monte-Carlo simulations for slow, moderate and fast pace of walks. Simulation results show that the proposed CSPKF approach exhibit < 1 meter accuracy which is at par with EKF as well as other state of the art approaches. Moreover, the proposed CSPKF approach could perform analogously during fast pace of walk when the EKF presented diverging performance.

This work is subject to limitations. During data collection phase, all the measurements were taken with due consideration without any missing or corrupted data. But in real time situation, the problem of having missing data is very common. Furthermore, presence of other types of wireless signals with similar frequency may cause interference in the measurements which in turn may affect the performance of the overall system. Managing such technical issues are challenging which may open some scopes of further research.

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