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IMPROVING INDOOR LOCALIZATION ACCURACY BY LINEAR INTERPOLATION OF WIFI RSS AND SMARTPHONE SENSOR DATA

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Abstract

Multilateration is a popular geometrical algorithm to determine the location of a mobile smartphone in an indoor environment. In this method, the distance of the smartphone from three or more WiFi access sites is calculated based on the strengths of radio signals. Intermittent measurements of radio signals due to the presence of obstacles in the indoor environment affect the overall localization accuracy. The present work addresses this problem and manages the intermittent measurements issue with an innovative Kalman filter-based approach. The linear interpolation method is applied to obtain uninterrupted coordinate information from WiFi RSS measurements. A Kalman filter is designed that uses these interpolated measurements along with its own sensor data to obtain an optimal localization estimate. Less than 2 meters of final position estimation accuracy is attained in Monte-Carlo simulations, which is better than other state-of-the-art techniques in this domain. Additionally, the performance of this intended approach has been found indistinguishable during frequent loss of measurements, in case of which the conventional trilateration approach could not succeed.

Keywords: Linear Interpolation, Indoor navigation, Wi-Fi Access Points, Intermittent measurement, Kalman filter

I. Introduction

With the advent of sensor technologies, indoor localization has become an on-demand research topic to facilitate location-based services [IV]. The need for indoor localization is essential in modern applications ranging from navigation to emergency detection or context-aware services [VI]. Due to the absence of satellite signals in the indoor environment, localization of a mobile object mainly depends on smartphone sensor data. Smartphones' built-in sensors, such as gyroscope and accelerometer is widely used to obtain reliable positioning information [XIV, XVII]. Smartphone-based indoor localization often depends on external radio signals, which heavily depend on preinstalled WiFi access points [I, II, VII]. However, it is more likely to be prone to noise or sometimes get intermittent, leading to inaccuracy in positioning [III, X].

To handle these intricacies of irregular or intermittent signals, the concept of linear interpolation can be utilized [V, XVI]. One of the primary objectives of the linear interpolation concept is to handle the intermittent data, which can be used to improve localization accuracy [X]. Robust positioning information could be achieved by supplementing the irregular data that are lost due to some technical or environmental glitch, and are handled by prioritizing the concept of linear interpolation of position coordinates. The possibility of reducing the impact of abrupt variations and improving the continuity of movement tracking within an indoor environment can be observed while utilizing the concept of linear interpolation [IX]. Advantages of the linear interpolation technique are its simplicity, low computational demand, and effectiveness in estimating intermediate values between sampled sensor data points [XI].

This study investigates the applicability of linear interpolation to improve performance and accuracy in indoor position estimation. For this, a linear interpolation algorithm has been combined with a smartphone sensor-based Kalman Filter method to achieve enhanced position estimation [XII, XII]. This study aims to bridge the gap in position coordinates and produce more precise location estimates. Application of this type of integration is a novel approach. Simulation results show the potential of this proposed novel approach to build trustworthy, infrastructure-free indoor positioning systems that can perform well even with intermittent WiFi measurements.

This paper is organized into sections. Following this introduction, the actual problem addressed in this work is stated in Section II. Methods to solve the stated problem and the design of the proposed system have been demonstrated in Section III. The simulation results and their analysis are presented in Section IV, and the concluding remarks are made in Section V.

II. Problem Statement

In a WiFi signal-based indoor localization method, the strengths of received signals emitted from preinstalled WiFi access points (APs) are processed to find the location of the smartphone. The correctness of this technique, however, relies on the quality of the received signal. The existence of diverse obstacles within indoor scenarios, as well as the fast movement of a smartphone user, generates breaks in the signal measurements, affecting localization performance significantly. While occasional, transient accelerometer and gyroscope data from the smartphone could validate these erratic readings, they can also be interrupted as well. The linear interpolation method may be used to interpolate the position coordinates obtained from RSS measurements during intermittent periods. In this work, a Kalman filter method is introduced to work on interpolated WiFi RSS data, which complements the intermittent measurement phases by a linear interpolation method.

III. Proposed Solution

The proposed approach implements a Kalman filter, which interpolates the interrupted position coordinates and thus is named as $KF_{WiFi+Interpolation}$ throughout this work. The block diagram depicting the operation of the proposed KFWiFi+Interpolation approach is provided in Figure 1.

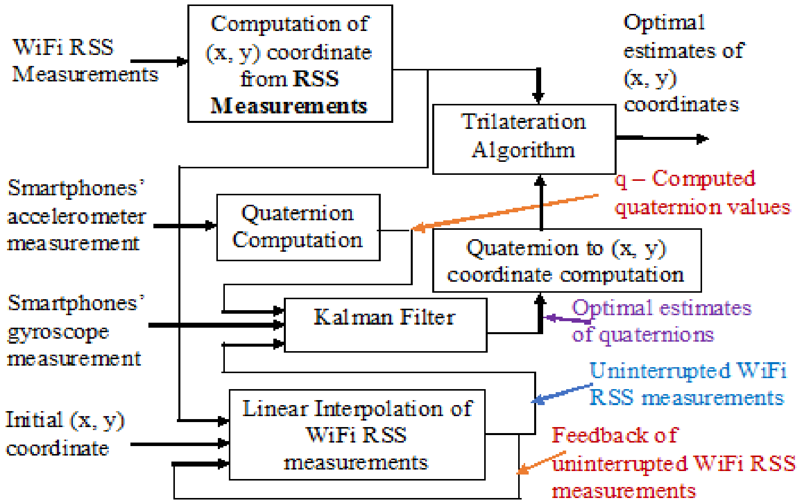

Fig 1. Structure of the proposed method

Received Signal Strength (RSS) readings from the user's smartphone are compared to find the three nearest WiFi APs. With these, the current position of the smartphone in (x, y) coordinates is calculated by the trilateration algorithm. The log-normal shadowing formula used to convert RSS values to (x, y) coordinates is given as :

$$d = 10^{(p(d_0) - p(d))/10\eta} * d_0 \qquad (1)$$

Here, 'd' is the distance to be estimated, 'd_0' is the reference distance taken as 1 meter for this work, p(d) and $p(d_0)$ are measured RSS values in dBm. The path loss exponent is taken as $\eta = 2$, considering the data collection setup is a computer lab, which is heavily loaded with furniture.

Readings from the device's inertial navigation sensors and WiFi RSS values are processed in order to get a constant stream of measurements. In case of discontinuity in obtaining WiFi RSS measurements, linear interpolation is used to interpolate missing (x, y) coordinates and fed to the proposed Kalman filter.

The linear interpolation formula used to interpolate position coordinates in this work may be described as follows:

$$y = y_0 + (x - x_0)\,[(y_b - y_a) / (x_b - x_a)] \qquad (2)$$

Here, (x, y) is the point whose x-coordinate is known, but whose y-coordinate needs to be interpolated. (x_0, y_0) is the initial point whose coordinates are known, and (x_a, y_a) and (x_b, y_b) are two other known data points. Linear interpolation is very fast and thus used in this work for interpolation purposes.

Input to the linear interpolation module of the proposed system is the initial position (x_0, y_0) and coordinates of previous time steps (x_b, y_b), (x_b, y_b). The output of this module is the continuous (x, y) values. These continuous position coordinates and smartphones' own sensor measurements are fed to the Kalman filter as input. The filter, in turn, uses interpolated Cartesian coordinates and its own sensor data to compute the orientation (roll, pitch, and yaw) information, which is processed to provide an optimal estimate of the smartphone's optimal orientation in terms of quaternion values.

The yield of the Kalman filter is the quaternion values corresponding to the smartphone's Cartesian coordinates. These quaternion values are then passed through an inverse transformation to produce the optimal Cartesian coordinates of the smartphone. These optimal estimates are further processed using a trilateration algorithm to provide smartphones' current (x, y) coordinates. When RSS measurement is available, position coordinates obtained from both the RSS module and the Kalman filter are used in trilateration. However, in the case of discontinuous RSS measurement, the position estimate is obtained from the filter module only, which yields optimal position estimates because of interpolated and uninterrupted position coordinate input.

The Kalman filter implemented in this work employs a state vector $x = [q_0\, q_1\, q_2\, q_3]^T$ [VI, VIII, XII] where $q_0\, q_1\, q_2\, and\, q_3$ are accelerometer-derived quaternion measurements obtained using Equation 3.

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} = \begin{bmatrix} cos(\emptyset/2)\,cos(\theta/2)\,cos(\psi/2) + \, sin(\emptyset/2)\,sin(\theta/2)\,sin(\psi/2) \\ sin(\emptyset/2)\,cos(\theta/2)\,cos(\psi/2) - \, cos(\emptyset/2)\,sin(\theta/2)\,sin(\psi/2) \\ cos(\emptyset/2)\,sin(\theta/2)\,cos(\psi/2) + \, sin(\emptyset/2)\,cos(\theta/2)\,sin(\psi/2) \\ cos(\emptyset/2)\,cos(\theta/2)\,sin(\phi/2) - \, sin(\emptyset/2)\,sin(\theta/2)\,sin(\phi/2) \end{bmatrix} \tag{3}$$

Roll, pitch, and yaw of the moving smartphone are indicated by $[\phi, \theta, \psi]$ angles. Values of these angles are obtained from smartphones' INS and WiFi RSS values. Here $[w_x\, w_y\, w_z]$ is the roll rate which can be obtained from aerial platforms by using smartphone's gyroscope sensors, the state transition matrix (F) based on the proposed Kalman Filter is given by Equation 4.

$$F = \frac{1}{2}\begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix} \tag{4}$$

The measurement to be employed in the proposed Kalman filter is the quaternion representation of gyroscope data. Then the tensor of measurement sensitivity matrix is given by Equation 5.

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

The system and measurement noise covariance for this work has been assumed to be Q (μ = 0.01, σ = 0.002) and R (μ = 0.001, σ = 0.0002). In order to capture the fast pace of walking, the sampling rates of $KF_{WiFi+Interpolation}$ have been assumed to be 5 Hz, i.e., capturing and feeding 5 measurements per second to all the implemented filters.

IV. Result Analysis

Performance of the proposed $KF_{WiFi+Interpolation}$ approach is compared with two other state-of-the-art approaches in this domain. The first one of these is the conventional Kalman filter, which works with only WiFi signals and does not use any external aiding. This filter is implemented and termed as KF_{WiFi} [I, II] in this work. Another state-of-the-art and widely used technique fuses WiFi signals with smartphone inertial sensors (INS) data in order to achieve better performance. This filter is implemented in this work and named as $KF_{WiFi+INS}$ [III, XII]. Other variants of Kalman filters, like the Extended Kalman filter (EKF) or Particle filter (PF), have not been tried in this work, as these filters fit well with non-linear systems, which are not exercised in this work.

In this section, simulation results of abovementioned three approaches are presented. In KF_{WiFi} approach, only RSS measurements are used. The intermittent measurement issue has not been remedied by any means. The $KF_{WiFi+INS}$ approach fuses smartphone INS measurements with WiFi sensors RSS values without any special consideration to interpolated RSS values. On the contrary, the $KF_{WiFi+Interpolation}$ uses the interpolated RSS measurements and smartphone sensor measurements to complement the intermittent measurement.

A typical example comparing the three tracking methods is demonstrated in Figure 2. It shows that the KF_{WiFi} and $KF_{WiFi+INS}$ deviate significantly and end up more than 2 meters away from the actual moving trace, while $KF_{WiFi+Interpolation}$ can track the real path much closer (less than 1 meter from the true terminal point).

The position error (drift) plot for the same trial is presented in Figure 3. It is shown that in KF_{WiFi} and $KF_{WiFi+INS,}$ there are large position errors compared to the $KF_{WiFi+Interpolation}$, across all iterations. The cause of this proper management of large drift in the position estimation of $KF_{WiFi+Interpolation}$ may be attributed to its ability to interpolate the RSS measurement during intermittent transmission, which is not taken care of by the other two approaches.

For a clear understanding of positional errors in two dimensions, the CDF for all the methods is plotted along the X and Y axes individually, which are depicted in Figure 4. $KF_{WiFi+Interpolation}$ shows considerable accuracy, over 80 % of the points are less than 0.2 on the X-axis, and a maximum deviation of 1 metre along the Y-axis. In contrast, KF_{WiFi} and $KF_{WiFi+INS}$ algorithms achieve significantly lower accuracy: in over 80% of the test cases its errors are over 1.5 meters on the X-axis and above 2 meters along the

Y-axis. These large drifts across all iterations along the Y-axis cause substantial error in the final position estimation of both conventional approaches.

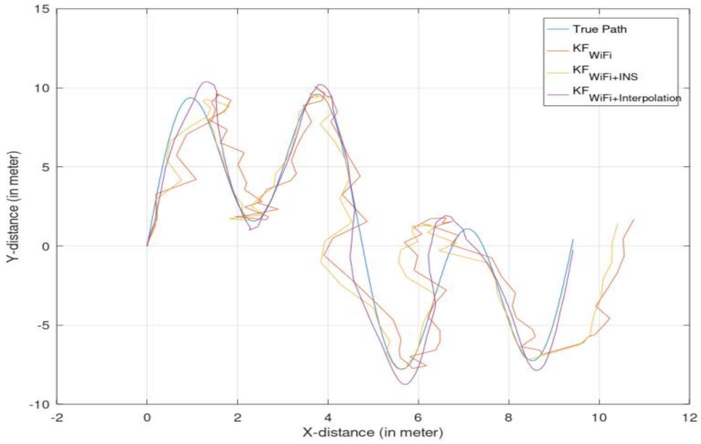

Fig 2. Typical tracking result of the filters

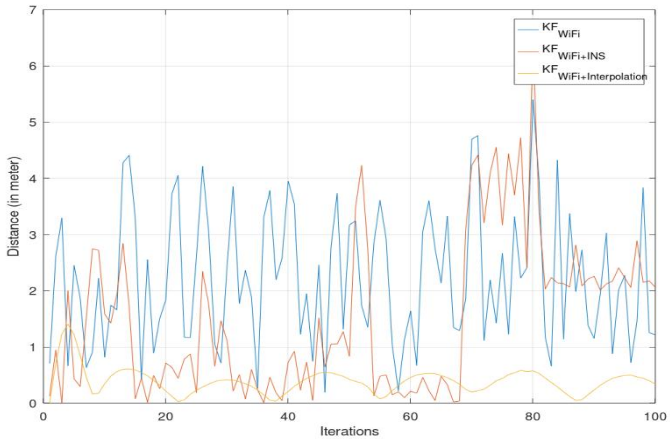

Fig 3. Position error plot of three filters

How well a localization technique performs is highly related to its ability to accurately track the smartphone's acceleration, particularly while traveling at high speed. The present work simulates fast moving object situation when the possibility of having intermittent measurements is much higher. Acceleration tracking plots for both approaches along the X & Y axes have been presented in Figures 5 and 6. In this regard, the performance of the $KF_{WiFi+Interpolation}$ approach has been found optimal as the proposed approach could track the acceleration correctly, even being affected by intermittent measurements. However, the other two conventional approaches, KF_{WiFi} and $KF_{WiFi+INS}$, failed to track the acceleration badly, as can be noticed in Figures 5 and 6.

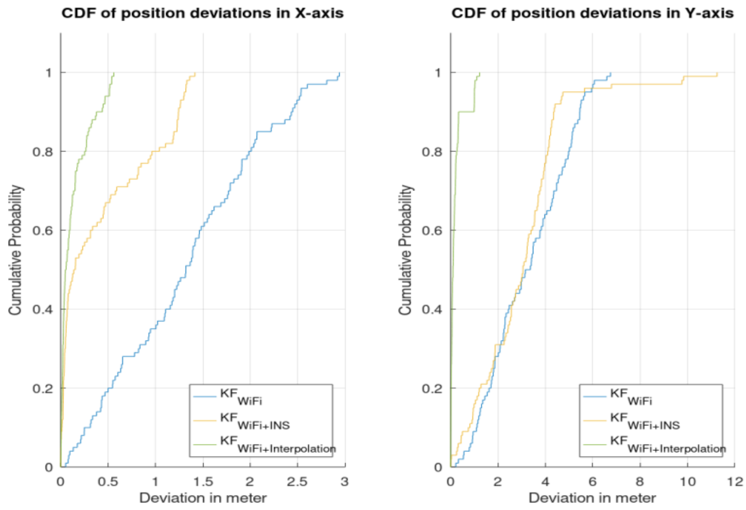

Fig 4. Cumulative distribution of probability plot of position errors

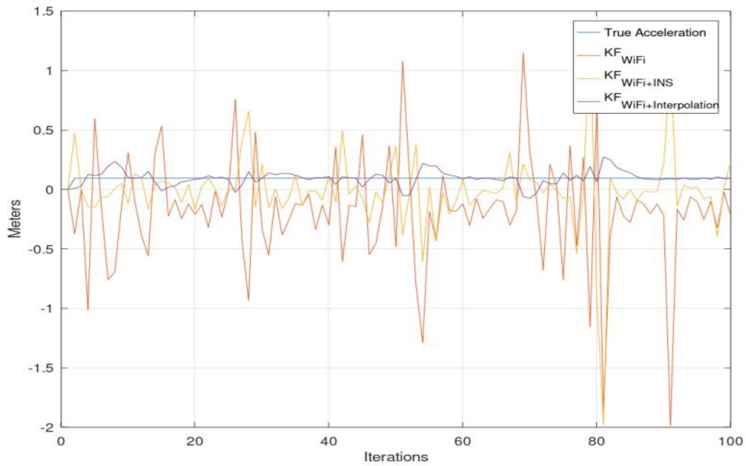

Fig 5. Acceleration tracking along the X direction

For in depth analysis of the performance of $KF_{WiFi+Interpolation}$, 100 Monte-Carlo experiments were performed on all three methods in simulation settings under different system and measurement noise levels. However, to make the performances of all approaches comparable, noise covariance Q_i and R_i for the i^{th} run are indistinguishably used for all methods. Table 1 gives the average root mean square error (RMSE) and mean absolute error (MAE) of velocity estimation of these Monte-Carlo simulations. The findings demonstrate that the $KF_{WiFi+Interpolation}$ method obtains much less velocity errors - both RMSE and MAE - than conventional approaches.

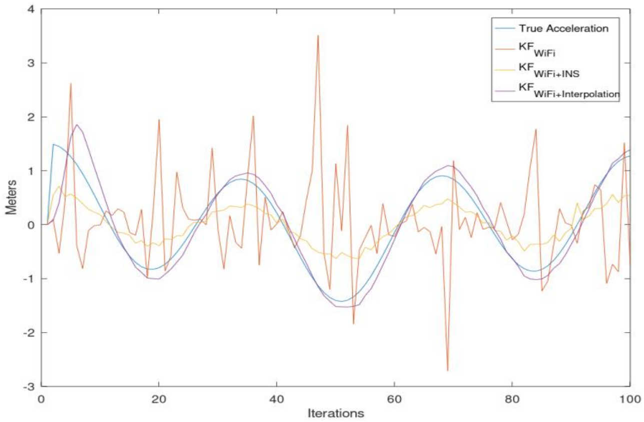

Fig 6. Acceleration tracking along the Y direction

Table 1: Mean of velocity errors for three approaches

Velocity error (ms^{-1})	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
KF_{WiFi}	3.24361	2.16543
$KF_{WiFi+INS}$	2.43568	1.11507
$KF_{WiFi+Interpolation}$	0.24683	0.22315

Table 2: Mean and STD of final position error of three filters

Final position error	Mean (m)	Max value (m)	STD (σ)
KF_{WiFi}	3.37392	5.75	2.32201
$KF_{WiFi+INS}$	3.20237	4.78	1.19601
$KF_{WiFi+Interpolation}$	2.20237	2.76	0.13601

Mean of final position errors as obtained during 100 Monte Carlo runs is tabulated in Table 2. $KF_{WiFi+Interpolation}$ limits the mean of final position error to 2.20237 meters with standard deviation (σ) = 0.13601. The maximum value obtained for this final position error is 2.76 meter which is not far apart from the mean value. This performance of the proposed approach is comparable to other indoor localization approaches reported in the literature, but not exercised in this work. On the contrary, conventional approaches, KF_{WiFi}, and $KF_{WiFi+INS}$ exhibit a mean value of final position error of 3.37392 meters and 3.20237 meters with σ = 2.32201 and 1.19601, respectively, signifying a high variability of the final position errors from the mean. The maximum value obtained in any final position error is 5.75 meters and 4.78 meters, respectively, with conventional approaches, which support the notion of large variability and poor performance.

As an interpretation of this Monte-Carlo simulation performance, it may be inferred that the proposed approach could outperform conventional approaches because of incorporating more number of measurements in its computation. Moreover, the intermittent measurements of accelerometers were complemented by a linear interpolation method, which in turn helped the system to sustain during intermittent measurement.

In general, the time complexity of the Kalman filter can be expressed as $O(n^3)$, where 'n' is the size of the state vector. For this current execution, the size of the state vector is assumed to be four (due to quaternion representation) and thus, does not affect computational complexity much. However, the actual execution times of the three filters are found to be different during simulation, which is tabulated in Table 3. Mean of Execution time of $KF_{WiFi+INS}$ has been found to be 1.33 seconds, which is considerably more than that of 0.779 seconds and 0.473 seconds for KF_{WiFi} and $KF_{WiFi+Interpolation}$, respectively. Integration of INS measurements with WiFi signals is a time-consuming process, which is the main cause of $KF_{WiFi+INS}$ execution delay. Standard deviations are found well within acceptable limits.

Table 3: Mean and STD of execution times of three filters

Filter Execution Time	Mean (s)	Max value (s)	STD (σ)
KF_{WiFi}	0.779	1.25	0.2101
$KF_{WiFi+INS}$	1.33	2.18	0.1054
$KF_{WiFi+Interpolation}$	0.473	0.637	0.0012

V. Conclusion

Intermittent or a lack of measurements causes severe deterioration in the accuracy of indoor localization systems. In this paper, a new KF-based WiFi RSS data interpolation method is proposed to address this problem. Often in real time situation, WiFi signals become sporadic, which adversely affects indoor tracking filters' performance. One remedy to this problem is to use sensor fusion techniques to supplement intermittent WiFi measurements. However, this introduces extra computational load in the system and often fails to survive in real time situation. To address this problem, the linear interpolation method is used in the proposed filter to produce uninterrupted sensors' input to facilitate persistent tracking. Simulation results comparing the proposed method with two conventional approaches in this domain are presented to demonstrate the efficiency of the proposed method. Around 2 meters of accuracy has been obtained for this proposed approach in final position error estimates during Monte-Carlo simulations with intermittent measurements, in case of which conventional approaches suffered.

This work is subject to limitations. The work assumes indoor navigation as a linear system perturbed with white, Gaussian noise. In real time situation, multipath propagation of WiFi signals or the presence of other signals in the same environment may cause nonlinearity in the system. For such cases, nonlinear variants of Kalman filters along with other types of interpolation techniques should be used, which may open up scopes for some other research.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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