The Indoor Localization Method Based on the Integration of RSSI and Inertial Sensor

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Abstract—The research of localization has become a more and more important topic with the popularity of ubiquitous mobile computing. In indoor environments, since the global positioning system (GPS) is disabled, many miniaturized wireless and sensing technologies have shown giant potential in positioning applications such as Inertial Navigation.

In this context, this paper presents a methodology to locate and track pedestrians accurately in indoor scenarios, the proposed method employs the extended Kalman filter (EKF) to integration Received Signal Strength Indication (RSSI) measurements with the Inertial Navigation technology. Aiming at the cumulative errors existed in Pedestrian Dead Reckoning (PDR) algorithm, this method uses RSSI information as measurement vector of EKF to correct the cumulative errors. Experimental results show that the proposed fusion method can present more reliable positioning estimations.

Keywords—indoor localization; RSSI; dead reckoning; inertial navigation; Kalman filter

I. INTRODUCTION

As one major component of ubiquitous computing, the locations of wireless devices become a critical input to many context-aware networking services and applications, such as healthcare monitoring, personal asset tracking, emergency rescue, and military operations, etc. In indoor environments, since the limitation of Global positioning system (GPS), several extensive research are carried out during the last years, depending on various types of sensors and communication technology, there are many approaches being discovered for indoor localization systems [1].

Among all these approaches, the methods based on inertial sensor or inertial measurement unit (IMU), plays a significant role in the indoor positioning and tracking systems. These approaches do not depend on the preinstalled infrastructure, and provides the information of implicit pose, which could be utilized to compute body’s movement parameters, then these movement data are used to estimate and track people’s instantaneous position by dead reckoning solutions. However, the inertial system suffers from the error drifts quickly with time, commonly the drifting errors are called cumulative errors. Therefore, more and more people devote to improve and develop these methods through many other means, for instance, Zigbee, Wi-Fi or RFID units are usually taken as additional positioning references, which are fused with the inertial navigation. Considering of the performance and cost, the Zigbee units with RSSI measurements could be important artifices to improve the positioning accuracy.

In this paper we study the localization and tracking method in indoor positioning system. Differs from previous studies, the extended Kalman filter (EKF) is employed to fuse both RSSI and inertial data, then the pedestrian dead reckoning (PDR) with step detection is considered to update the system state of EKF, finally, RSSI values are utilized as the measurement vector to correct the cumulative error of inertial navigation. Moreover, we evaluate the performance of the proposed fusion method by indoor experiments.

The remainder of this paper is organized as follows. Section II gives a brief overview of related works to the indoor localization. After that the system model is discussed in Section III, including the RSSI model and IMU-based PDR. We introduce our proposed approach in Section IV, which consists of the thorough analysis of the integration of the RSSI and inertial data through an extended Kalman filter. The implementation of our proposed fusion algorithm is also presented in Section IV. Simulation results for the performance evaluation of our proposed approach are presented and discussed in Section V. Then Section VI summarizes and concludes the paper.

II. RELATED WORK

Despite the difficulties of indoor localization, numerous recent works have focused on this issue. Some localization approaches have been proposed to use angle, distance even connectivity information [2]-[5]. In order to take advantage of the inertial measurements on many wireless platforms, inertial navigation using inertial sensing has also been presented. Pedestrian Dead Reckoning (PDR), as one of the most important techniques of inertial navigation systems, can estimate pedestrian’s position by utilizing a detected step procedure, including calculating the step length and person’s direction [6], C. Clift and H. Muller proposed a method which is suitable for using by pedestrians, and compared a number of sensors that can be used to achieve a robust and accurate dead reckoning systems [7].

Many practical indoor navigation technologies, however, make use of additional sensors and measurements as a complementary to the inertial navigation systems, to mitigate the effect of cumulative errors in long time duration and further improve the positioning performance. Wending Xia et al. combined Wi-Fi fingerprinting approach with inertial information by using a stochastic system model [8]. Johannes Schmid et al. fuse the location estimates from an organic Wi-Fi localization system with PDR from inertial sensors, outline a possible design and analyze its behavior [9]. Manh Kha Hoang...
et al. gathered relative RSSI information by inertial smartphone, and estimated positions based on map tile and database [10]. Benjamin R et al. proposed an algorithm to combine inertial sensor measurements with RSSI readings to achieve accurate localization, they apply a distributed extended Kalman filter based on the two measurements and a kinematic movement model, simulation shows the network could self-localize despite large inaccuracy [11], some similar studies were also made by Veerachai Malyavej et al. and Johannes Schmid et al [12][13].

III. SYSTEM MODEL

The localization system contains two kinds of sensors: the IMU sensors to provide inertial data, and the Zigbee sensors to transmit data. During the positioning process, users can use Zigbee modular to gather RSSI information from the fixed anchor nodes, which have known location information.

A. RSSI Measurement Model

RSSI measurements, which are detected by the wireless receivers, should be a significant input in most of the localization techniques. It is well known that transmitted power loss is related to propagation distance, and in order to directly verify this claim, we carry out a practical experiment under the typical indoor environment in our laboratory building. The transmitter and receiver both employ the Zigbee module of CC2530, the transmitter is fixed at a certain point and receiver samples uniformly around it, the measured distance varies from 0 to 3 meters. At each measurement 50 RSS values are obtained by sampling, the average of the 50 values is then set as the received signal strength result. The results draw a contour map of signal strength as shown in Fig. 1.

![Fig. 1. The contour map of signal strength distribution at the receiver using Zigbee modular CC2530.](image)

The contour map indicates that function relation seems to be existed between RSSI and distance. Usually to facilitate the modeling, assumptions are held for systematical analysis that there is a relationship between RSSI and distance. A logarithmic signal attenuation model is employed by many researchers to describe this relationship, let \( d \) represents the distance between the receiver and the transmitter, the RSSI can be written as

\[
\mu(d, \beta) = -10\beta_1 \log d + \beta_2
\]  

where \( \beta_1 \) is a coefficient related to the surrounding environment, and \( \beta_2 \) is the power detected by the receiver at which the distance from the transmitter is 1m. Generally, it is not easy to obtain these parameters via theoretical analysis, as the variability of surroundings leads to different values in different localization environment. Therefore, they usually could be determined by real experiments, for example, in our system we obtain the parameters by fitting sampled data in the least-squares sense, with the 95% confidence interval. The fitting curve and RSS distribution are shown in Fig. 2.

![Fig. 2. RSS values vs. distance between transmitter and receiver in a typical indoor environment. Red curve is the least squares fit on RSS measurements, the fitting function is listed on the top of the figure.](image)

B. IMU-based Pedestrian Dead Reckoning

The PDR algorithm is one of the major inertial navigation techniques for IMU sensors. It is a process of calculating one's current position by advancing a previously determined position using the output information of IMU. Based on the characteristics of athletic physiology, PDR utilizes the periodic feature and statistical value of acceleration wave to confirm the step length and user’s direction, by adopting step detection. Then pedestrian's current position could be simply calculated by using the previously position.

Dead Reckoning was first used in sailing, and the specific procedure of the technology is shown in Fig. 3. Assuming the previous position is \( (E(t_{k-1}), N(t_{k-1})) \), and the corresponding current position is \( (E(t_k), N(t_k)) \), we can describe the relationship between the two positions as follow:

\[
\begin{align*}
E(t_k) &= E(t_{k-1}) + S(t_{k-1}) \cdot \sin(a(t_{k-1})) + N(t_{k-1}) \cdot \cos(a(t_{k-1})) \\
N(t_k) &= N(t_{k-1}) + S(t_{k-1}) \cdot \cos(a(t_{k-1})) + S(t_{k-1}) \cdot \sin(a(t_{k-1}))
\end{align*}
\]  

where \( a(t_{k-1}) \) represents the azimuth during this period, \( S(t_{k-1}) \) represents the pedestrian’s velocity.

When starting an inertial navigation, first and foremost the measurement error of both the accelerometer and digital compass should be compensated. Then the attitude angles from carrier coordinates to geographical coordinates (ENU coordinates) are employed to compute the transfer matrix \( H_p^{ENU} \), and the acceleration under ENU coordinates is obtained as follow:
\[ a_{ENU}(t_k) = R^E_N(t_k) \cdot a_b(t_k) \]  

where \( a_b(t_k) \) and \( a_{ENU}(t_k) \) denote the acceleration under carrier coordinates and ENU coordinates respectively. Then the velocity which related to ENU coordinates could be expressed as:

\[ S(t_k) = S(t_0) + \int_{t_0}^{t_k} [a_{ENU}(t) - g] \, dt \]  

where \( g \) is the local acceleration of gravity, \( S(t_0) \) represents the initial velocity. Therefore, the location coordinates in (2) could be rewritten as:

\[
\begin{align*}
E(t_k) &= E(t_0) + \int_{t_0}^{t_k} S(t) \cdot \sin(a(t)) \, dt \\
N(t_k) &= N(t_0) + \int_{t_0}^{t_k} S(t) \cdot \cos(a(t)) \, dt
\end{align*}
\]

where \( a(t) \) denotes the horizontal angle obtained from digital compass.

\[ \text{Fig. 3. The flow chart of PDR algorithm.} \]

Meanwhile, if the step detection technology is adopted, according to the periodic feature and statistical value of acceleration wave, the algorithm could expediently convert the information of accelerometer into step frequency and length using step model, and through the similar process with (5), the pedestrian’s location could be calculated by associate the step information with horizontal angle.

PDR algorithm usually gives available position results, but it is subject to the cumulative errors badly, due to many factors as both speed and direction must be accurately known, each estimation is relative to the previous one, thus the errors are cumulative.

IV. PROPOSED INDOOR LOCALIZATION METHOD

Since inertial navigation cannot deal with the accumulative error, we consider correcting the error by other methods, such as using RSSI information as an assistant. In our localization system as mentioned in Section III, inertial sensors are carried by person and generate inertial information. Meanwhile, pedestrian could receive RSSI measurements from several anchor nodes which have prior known positions. Then through the models illustrated in section III.A, the obtained RSSI values could be translated to the distance information between user and anchor nodes. To combined with these two kinds of measurements that acquired by our system, both the RSSI and inertial data can be put into an EKF that iteratively produce the estimation, and Fig. 4 shows the structure of our proposed fusion method. Note that different from other EKF positioning algorithm, we employ the measurements of IMU-based PDR, including step length and the change of heading angle, to update the state function of Kalman filter, rather than the kinematic model which is used commonly but inaccurately. Meanwhile, we select 2 of the strongest RSSI values as the inputs of measurement function.

\[ \text{Fig. 4. Structure of the proposed localization method based on integrating the RSSI and Inertial Sensor information with the EKF filter.} \]

The EKF is a well-known and widely used version of the Kalman filter for nonlinear systems [14][15]. Here we consider the general system state equation and measurement equation at \((k+1)\)th time as:

\[ X(k+1) = \Gamma_k[X(k), U(k), k] + W_k \]  

\[ Z(k) = \Pi_k[X(k), k] + V_k \]  

where \( X(k) = [x_k, y_k, \theta_k]^T \) represent the system state at \( k \)th step, \( (x_k, y_k) \) denote the position vector from (5) under ENU coordinates, and \( \theta_k \) is the horizontal heading angle obtained from compass. Additionally, \( W_k \) and \( V_k \) are the system process and measurement noise, which are assumed to be white Gaussian noise with covariance as \( E(W_k \cdot W_k^T) = Q_k \) and \( E(V_k \cdot V_k^T) = R_k \), in which \( E(\cdot) \) represents the mathematic expectation.

All of the inertial information are put into the EKF as the input of system state that continuously does the estimation. The dynamics of pedestrian adopted in our algorithm could be modeled as the following nonlinear equation:

\[ X(k+1) = \begin{bmatrix} x_k + D_k \cos(\theta_k) \\ y_k + D_k \sin(\theta_k) \\ \theta_k + \Delta \theta_k \end{bmatrix} + W_k \]  

where \( D_k \) and \( \Delta \theta_k \) denote the step length and heading change. To decrease the impact of accumulative error in inertial navigation, we introduce the step detection technology is adopted, which is the input of measurement equation, then the measurement equation can be modeled by:
\[
Z(k) = \begin{bmatrix}
-10\beta_1 \log \sqrt{(x_k - x_a)^2 + (y_k - y_a)^2} + \beta_2 \\
-10\beta_1 \log \sqrt{(x_k - x_b)^2 + (y_k - y_b)^2} + \beta_2 \\
\end{bmatrix} + V_k
\]

(9)

where \(\beta_1\) and \(\beta_2\) are the environment coefficients which have been calculated in Section III. In the proposed algorithm, two of the biggest measurements are taken from the set of RSSI values collected from all anchors, \((x_a, y_a)\) and \((x_b, y_b)\) denote the coordinates of corresponding anchors.

Then the EFK recursively executes the coordinate updating process. The estimation process using the method of state’s feedback control, time update equations are adopted for calculating the current state variable and the value of error covariance estimation, in order to construct the priori estimation for the next time step. The filter employs the posteriori estimation of last time step as the priori estimation of current time step, and the iterative process could be executed repeatedly. To estimate the system state in EKF, first a Gaussian probability density representing this state is assumed, and similar with Taylor series, due to the nonlinear relationship of the state and measurement, we can find and measure the partial derivative to linearization and calculate the current estimation. Then the EKF process could be summed up as follow:

\[
X(k+1|k) = \Gamma_k(X(k), k)
\]

(10)

\[
Z(k+1) = \Pi_{k+1}(X(k+1|k))
\]

(11)

\[
P(k+1|k) = A_k \cdot P(k|k) \cdot A_k^T + Q_k
\]

(12)

\[
K_{k+1} = P(k+1|k)H_{k+1}^T/(H_{k+1}P(k+1|k)H_{k+1}^T + R_k)
\]

(13)

\[
X(k+1|k+1) = X(k+1|k) + K_{k+1}(Z(k+1) - Z_{RSSI})
\]

(14)

\[
P(k+1|k+1) = (I - K_{k+1} \cdot H_{k+1})P(k+1|k)
\]

(15)

both \(Q_k\) and \(R_k\) obey the Gaussian distribution, and the prior statistical information about the noises of the system process and measurement should be estimated by preliminary experiments. \(K_k\) represents the Kalman gain and \(Z_{RSSI}\) is the values of RSSI measurements. \(A_k\) and \(H_k\) are the Jacobian matrices of the system state equation and the measuring equation respectively, where

\[
A_k = \frac{\partial X}{\partial x} \bigg|_{x=X(k+1|k)}
\]

(16)

\[
H_k = \frac{\partial Z}{\partial x} \bigg|_{x=X(k+1|k)}
\]

(17)

V. EXPERIMENTAL RESULTS

In order to analyze the performance of the proposed fusion localization methodology, we carry out a practical indoor test in a large meeting room of our laboratory building. The room’s sizes is 10m×15m, with no obstacles, one pedestrian walks according to a predetermined path with even pace, and the localization system estimates and tracks his trajectory. We adopt a common IMU chip: MPU6050, which has three accelerometers and three gyroscopes. The velocity is then calculated by microcontroller from the IMU raw data with equations suggested in the product manual. When positioning, user uses the IMU mounted to the waist and Zigbee modular CC2530 also attached to waist, which communicates with each other by 2.4GHz carrier frequency, then user can receive RSSI values periodically from four anchor nodes fixed to the corners of the room. All Zigbee nodes are organized as a wireless sensor network, the RSSI and IMU data are dynamically transmitted to a sink node and then sent to computer through serial port.

Fig. 5 shows the environment layout and an example of trajectories for several exemplary runs. In the experiment, pedestrian walks two times along a predetermined route, and we estimate the trajectory using two different methods respectively, one is only IMU-based PDR algorithm and the other is our proposed fusion method. By comparing to the real path, obviously we find that the proposed method effectively modifies the cumulative error of inertial navigation, and with the increase of walking time, the positioning accuracy is improved for a certain degree.

![Fig. 5. Comparison of the localization trajectories using two methods.](Image 311x422 to 555x580)

Fig. 6 shows the cumulative distribution functions (CDF) of the localization estimation error of both the PDR methods and the proposed fusion method using EKF, which are obtained by calculating the errors of the localization estimations. The experimental results demonstrate one fact that our proposed method could present a more reliable positioning estimation, effectively decrease the impact of cumulative errors in PDR, especially for a long time interval.

![Fig. 6. CDFs of the localization estimation error of two methods.](Image 314x149 to 552x304)
VI. CONCLUSION

In this paper we proposed a fusion indoor localization methodology based on the integration of RSSI and inertial navigation. We employ EKF fusing both RSSI and inertial information, the PDR algorithm with step detection is considered to update the system state of EKF, and Meanwhile, RSSI values are utilized as measurement vector to correct the cumulative error of inertial navigation. Then the proposed fusion method could position and track user’s trajectory with small cumulative error. In experiments we verified the performance of our fusion method, and experimental results show that the proposed method can present more accurate positioning estimations, effectively reduce the cumulative errors in PDR algorithm.

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