Multi-Sensor Wireless Location System with Extended Kalman Filter

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Abstract

The ability to determine the position of a device has fundamental importance in context-aware and location dependent mobile computing. Most previously proposed location systems may not be appropriate for nomadic applications such as home service robots due to low update rate and insufficient accuracy. In this paper, we propose a multi-sensor wireless location system that provides accurate location for nomadic applications. We employ advanced algorithms like an extended Kalman filter (EKF) to achieve high accuracy and fast update rate. The performance of the proposed location system is confirmed by experimental results.

1. Introduction

Determining the location of a device is a fundamental problem in mobile computing. Especially, tracking of the locations of the moving objects including users is basic context which makes it possible to derive other useful information. The importance and promise of location-aware applications has led to the design and implementation of systems for providing location information, particularly in indoor and urban environments where the Global Positioning System (GPS) does not work well [1]. Examples of indoor location systems include the Active Badge [2], Active Bat [3], Ubisense [4] systems, and Cricket system [5]. In general, these systems provide more accurate location information when a moving device is at rest than when it is in motion. In other words, the accuracy of indoor location systems is degraded in nomadic environment. For example, the pre-existing Cricket system provides 30cm positioning accuracy to support location-dependent computing services within building. The BAT system is designed to offer 15cm positioning accuracy with active manner. However, the accurate positioning estimation is one of the important keys for nomadic applications.

In this paper, we propose and implement the multi-sensor wireless location system focusing on high accuracy of indoor location system. Also, we use statistical median methods, outlier rejection method, and an extended Kalman filter to obtain better performance than existing systems.

The organization of this paper is as follows. Section 2 describes our proposed multi-sensor wireless location system in detail. In section 3, we present location estimation algorithms for high precision including extended Kalman filter model, statistical methods, and outlier rejection method. Then in section 4, we present experimental setups and discuss the experiment results. Finally, the following section summarizes our work.

2. System Configuration

Figure 1. (a) Ultrasonic waveform of PLL Detection and (b) Ultrasonic waveform of envelop detention

The multi-sensor wireless location system which we implemented in this paper is based on the Cricket system. However, both hardware and software is modified to get better performance. First, we change the detection method of received ultrasonic signal from beacons to reduce processing time delay. In existing Cricket system, the listener used a phase locked loop (PLL) ultrasonic detector. As shown in Figure 1(a), while listener detects the
ultrasonic signal from each beacon in location system, a PLL detector has highly variable detection characteristics, leading to distance measurement errors as high as 30cm. Hence, we replaced the PLL-based detector with the envelop detection method using OP-AMP comparator in our system. This method improved the detection accuracy substantially, to about 1.5cm, and also reduced the sensitivity of the detector circuit as shown in Figure 1(b). Secondly, we use multiple receiver sensors. We attached 8 ultrasonic receiving sensors instead of one receiver sensor of existing Cricket system for various experiments including orientation of an object. Using multiple sensors guarantee both simultaneity of distance samples and the improvement higher accuracy. And, in this paper, we only used three receiving sensors having triangle form to get high precise position. This sensor array is represented in Figure 2.

3. Used Some Algorithms

To get high performance, we use statistical methods and signal processing algorithm. This section introduces statistical methods used in this experiment. The flow chart showing the used overall algorithms is shown in Figure 3. There are three procedures to estimate the position of moving object: a median method, an outlier rejection method (ORM), and an extended Kalman filter (EKF).

3.1 Median Method

We used three receiving sensors in our location system, so that listener gets three distance data from a beacon at the same time. With multiple data, statistical process improves the performance of location system.

We take the median to deal with these received three data from beacons to be sure of picking up more accurate distance.

3.2 Outlier Rejection Method (ORM)

In this section, a simple algorithm called outlier rejection method is described. We propose this method to remove the reflected data which can affect the precision of location system. Also, this method is used in canceling unreliable readings from system. We use average values in sliding window for comparing the new measured distance data to know whether the data is reflected or not. The average value in window size is

\[ d_{\text{avg}_n} = \frac{1}{N} \sum_{i=0}^{N} d_{n-i}, \]

where \(d_{\text{avg}_n}\) is average value in \(N\) window size.

After acquiring the average value, we compute the residual between average value and new measured distance data as

\[ |d_{\text{avg}_n} - d_n| = \epsilon, \]

where \(\epsilon\) is residual between average value and new measured distance. In this method, if the residual between average and new measured value is bigger than the predefined threshold value, new measured value can be considered as a reflected distance or unreliable readings from system counter. If the residual is less than the threshold value, new measured distance can be accepted and average value is updated with new measured one. The flow chart of ORM is described in Figure 4.

3.3 Extended Kalman Filter (EKF) Algorithm

The EKF algorithm approach applies the linear Kalman filter to nonlinear systems with additive white noise by continually updating a linearization around the previous state estimate, starting with an initial guess. In other words, we only consider a linear Taylor approximation of the system function at the previous state estimate and that of
Figure 4. Flow chart of outlier rejection method

the observation function at the corresponding predicted position. This approach gives a simple and efficient algorithm to handle a nonlinear model. The recursive updating procedure of EKF is shown as follow:

- **Initialization.** The EKF is initialized with the posterior state estimate $\hat{x}^+_0$ and uncertainty $\hat{P}^+_0$ at time step 0.

- **Prediction Step.** At every time step, the EKF propagates the state and uncertainty of the system at the previous time step to the current using the prediction equations

$$\dot{x}^- = f(\hat{x}^+_{k-1}),$$

$$\hat{P}^- = \hat{A}_k \hat{P}_k A_k^T + Q_k,$$

where $\hat{P}^-$ is the a priori estimate error covariance and the Jacobian matrix $A_k$ contains the partial derivatives of system function $f(\cdot)$ with respect to state $x$, evaluated at the posterior state estimate $\hat{x}^+_{k-1}$ of the last time step,

$$A_k = \left[\frac{\partial f(x)}{\partial x}\right]_{x=\hat{x}^+_{k-1}}.$$  

- **Correction Step.** The EKF corrects the prior state estimate with a full measurement $z_k$ by means of the correction equations,

$$K_k = P^-_k H_k^T (H_k P^-_k H_k^T + R_k)^{-1},$$

$$\dot{x}_k^- = \dot{x}_k^+ + K_k (z_k - h(\dot{x}_k^-)),$$

$$P^-_k = (I - K_k H_k) P^-_k,$$

where $\hat{P}^+$ is the a posteriori estimate error covariance, $K$ is the Kalman gain, and the Jacobian matrix $H_k$ contains the partial derivatives of the measurement function $h(\cdot)$ with respect to the state $x$, evaluated at the prior state estimate $\hat{x}^+_k$,

$$H_k = \left[\frac{\partial h(x)}{\partial x}\right]_{x=\hat{x}^+_k}.$$  

With above EKF procedures, we design an EKF using a state vector with four components, two position components $(x, y)$ and two velocity components $(v_x, v_y)$.

We express the position-velocity model, which assumes that the device moves at constant velocity between time-steps. In other words, we assume that acceleration and higher order derivatives are zero in position-velocity model:

$$x_k = A_k x_{k-1} + B_k w_k.$$  

and the components of each vector is

$$\begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & \Delta t & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ v_{x,k-1} \\ v_{y,k-1} \end{bmatrix} + \begin{bmatrix} \Delta t \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} w_{1,k} \\ w_{2,k} \end{bmatrix},$$

where we assume that a random noise vector $W$ is zero-mean independent Gaussian distributed. Also we define the measurement model as:

$$z_k = H_k x_{k-1} + G_k N_k.$$  

and the each component of Eq.12 is

$$\begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ v_{x,k-1} \\ v_{y,k-1} \end{bmatrix} + \begin{bmatrix} 0 & \Delta t \\ 0 & 0 \end{bmatrix} \begin{bmatrix} n_{w1,k} \\ n_{w2,k} \end{bmatrix},$$

where we assume that a random noise vector $N$ is zero-mean independent Gaussian distributed.

4. Experimental Result

In this section, we present experimental setups with
moving device and several beacons, and we characterize the performance of the implemented multi-sensor wireless location system in various velocities. We also conduct the simulation with EKF to estimate location in off-line. We then discuss and analyze the results from various experiments.

4.1 Experimental Setup

In this experiment, we use a LEGO train set, equipped with location system to investigate performance of proposed location system in nomadic environment. The speed of LEGO train can be controlled by a regulator box. The location system attached to the Lego train is shown in Figure 5, and the trajectory of the train is shown in Figure 6. The length of the train rail is 7.87 m and the Lego train has four different speeds: 0.35 m/s, 0.51 m/s, 0.70 m/s, and 0.91 m/s. To conduct our nomadic tracking experiment, we attached our multi-sensor wireless location system to the train and beacons on the ceiling. We utilized four beacons to cover the whole areas in which a Lego train can move. The coordinate of each beacon was calculated by manual measurements.

![Figure 5. The LEGO train attached multi-sensor listener](image)

Figure 5. The LEGO train attached multi-sensor listener

![Figure 6: Schematic representation of the LEGO train's trajectory](image)

Figure 6: Schematic representation of the LEGO train's trajectory

Besides, we connected the RS232 cable between location system and notebook computer to collect raw data samples.

4.2 Location Tracking Experiment in Rectangular Path

We now investigate the tracking performance at various velocities. We assumed that velocity of Lego train is constant. Figure 7 shows the observed position with respect to estimated position using extended Kalman filter at each velocity. Here, the Observed means the positions applied to median method and ORM and the ‘With EKF’ means the positions applied three algorithms including EKF. A listener gets relatively precise position in slow velocity with most samples as shown in Figure 7(a). However, as the velocity becomes faster, a listener cannot receive samples very well from beacons which is shown in Figure 7.

![Figure 7. Estimated trajectory with EKF at each velocity](image)

Figure 7. Estimated trajectory with EKF at each velocity

Also, we investigate the position error CDF based on the estimated location trajectory. In this experiment, we define the position error as RMSE (root mean square error) of the only one axis in x-y coordinate because of measurement limitation about exercise axis. For example, while the train is moving along x-axis, we only calculate the RMSE of y-axis as position error. The Figure 8 shows the error CDF of observed positions at four specific velocities.

![Figure 8. Error CDF of the different velocities without EKF](image)

Figure 8. Error CDF of the different velocities without EKF

In this Figure 8, the tracking performance is degraded as velocity of train increases in nomadic environment. The
bottom curve tells that the maximum error is more than 50cm in 0.91 m/s. However, we improve the location system by applying EKF algorithm. The error CDF of EKF is shown in Figure 9. Although the tracking performance is proportional to the velocity of a train, maximum error is reduced by 20cm with EKF. The accuracy has less than 10cm with the measurements of 90 % confidences even in 0.91 m/s. The average error and maximum error at each velocity are described in the Table 1.

![Figure 9. Error CDF of the different velocity with EKF](image)

<table>
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<tr>
<th>Velocity (m/s)</th>
<th>Raw Data Average (cm)</th>
<th>Raw Data Maximum (cm)</th>
<th>EKF Average (cm)</th>
<th>EKF Maximum (cm)</th>
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<td>19.21</td>
</tr>
</tbody>
</table>

In above Table 1, we sure that an extended Kalman filter reduce the position error.

5. Conclusion

We focus on high precision of indoor location system in nomadic application. In point of view of hardware, we use multiple sensors and envelop detection method. By doing so, we guarantee simultaneity of distance samples and reduce processing delay. Furthermore, we applied advanced algorithms including an extended Kalman filter to proposed location system. Finally, we confirm that position precision is improved in nomadic environment from experimental results.

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7. Reference