Motion Restricted Information Filter for Indoor Bluetooth Positioning

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ABSTRACT
This paper studies wireless positioning using a network of Bluetooth signals. Fingerprints of received signal strength indicators (RSSI) are used for localization. Due to the relatively long interval between the available consecutive Bluetooth signal strength measurements, we propose a method of information filtering with speed detection, which combines the estimation information from the RSSI measurements with the prior information from the motion model. Speed detection is further assisted to correct the outliers of position estimation. The field tests show that the new algorithm proposed applying information filter with speed detection improves the horizontal positioning accuracy of indoor navigation with about 17% compared to the static fingerprinting positioning method, achieving a 4.2 m positioning accuracy on the average, and about 16% improvement compared to the point Kalman filter.

Keywords: Bluetooth, Kalman filter, information fusion, fingerprints, received signal strength (RSS)

INTRODUCTION

Navigation and the related location based services are increasingly incorporated into mobile devices. The built-in GPS (Global Positioning System) on the handset is capable of providing location information in open signal environments. However, for indoor positioning, GPS is unable to provide the desired level of accuracy or even unavailable. One alternative to GPS is to utilize the signals of opportunity (SoOP), which are intended for purposes other than navigation.

Bluetooth is a technology for short-range wireless data and voice communication with low power consumption. It has been utilized in the communication and proximity market for a long time. As widely supported by mobile devices, Bluetooth is a potential technology to become an alternative for indoor positioning. However, indoor positioning using Bluetooth signals has not been widely studied so far. Bandara et al. [1] developed a multi-antenna Bluetooth Access Point (AP) for location estimation based on received signal strength indicators (RSSI). The test obtained 2 meters of error in a 4.5 m×5.5 m area with four antennas. Sheng and Pollard [2] modified the Bluetooth standard to estimate the distance between a reference transmitter and a mobile receiver, using RSSI measurements and a line-of-sight radio propagation model within a single cell. A high-density Bluetooth infrastructure is necessary to achieve an accurate position in the above two approaches. In order to minimize the Bluetooth infrastructure, Damian et al. [3] used only one class 1 Bluetooth AP for a home localization system, which combined the
measurements of the link quality, RSSI, and cellular signal quality to obtain room-level accuracy. Pei et al. [4] present a Bluetooth locating solution in a reduced Bluetooth infrastructure area by using RSSI probability distributions. Other topics related to Bluetooth positioning can be found in [5]-[9].

New specifications and products have been developed for a relatively longer range of transmission. Compared with the class 2 device (e.g. the Bluetooth module in a smart phone), which has only the range of about 20-30 meters [10], a class 1 Bluetooth device (e.g. the Bluegiga AP 3201) has an effective range up to 200 meters and the newly developed Bluegiga AP 3241 can even achieve an effective range of 800 m in an open area without obstructions [11].

In this study, we investigate the indoor positioning in a Bluetooth network. 13 long range APs (Bluegiga 3201 and 3241) have been deployed in the area of interest. Utilizing the RSSI from Bluetooth APs, we consider a fingerprinting method for position estimation, which is based on database matching to particular fingerprints in the area at hand. We propose a method of information filtering with speed detection. The position is sequentially estimated by combining the information from the measurements and the prior motion model. Speed detection is further assisted to correct for the outliers of position estimation.

The paper is organized as follows: the system model and the problem of indoor positioning are formulated in the Section of system description. Section 3 considers the information filtering with speed detection as assistance. In Section 4, the experimental platform is described in detail and Section 5 shows the numerical results and a performance comparison is presented and discussed. In Section 6, conclusions are drawn as well as future improvements discussed.

SYSTEM DESCRIPTION

In this work, we focus on the fingerprint positioning method in a Bluetooth network. Fingerprinting is a feasible technique for positioning using RSSI measurements. It works in two phases: the training phase and the online positioning phase. In the training phase, the radio map is constructed based on the calibration point within the area of interest. The radio map implicitly characterizes the RSSI position relationship through training measurements at the calibration points with known coordinates. In the online positioning phase, the mobile device measures the RSSI observations and the positioning system uses the radio map to provide position estimation.

The fingerprinting method has been widely discussed for indoor positioning. To name a few, [12] gives a thorough summary and analysis for different steps and factors that affect fingerprints. In [13], different positioning algorithms are compared using wireless local network (WLAN) fingerprints.

The basic fingerprinting method only compares the current RSSI measurements with the radio map to estimate the position. The positioning accuracy can be improved by exploiting the measurements collected in time series and the information from a pedestrian motion model. In this work, we consider sequential estimation of the pedestrian movements indoors.
State Model

A mobile device carried by a pedestrian is assumed to move on a two-dimensional Cartesian plane. The state at time instant $t_k$ is defined as the vector $\mathbf{x}_k = [x_k \ y_k \ \dot{x}_k \ \dot{y}_k]^T$, where $[x_k \ y_k]^T$ corresponds to the East and North coordinates of the mobile position; $[\dot{x}_k \ \dot{y}_k]^T$ are the corresponding velocities. The mobile state can be modeled as [14, p. 267]:

$$\mathbf{x}_{k+1} = F_k \mathbf{x}_k + \mathbf{w}_k \quad (1)$$

where the state transition matrix $F = \begin{bmatrix} I_2 & \Delta t I_2 \\ 0 & I_2 \end{bmatrix}$, with $I_2$ being the $2 \times 2$ identity matrix and $\Delta t$ the sampling period. The random process $\mathbf{w}_k$ is a white zero mean Gaussian noise, with covariance matrix

$$Q = \begin{bmatrix} \frac{\Delta t^4}{4} \Omega & \frac{\Delta t^3}{2} \Omega \\ \frac{\Delta t^3}{2} \Omega & \Delta t^2 \Omega \end{bmatrix} \quad (2)$$

where $\Omega = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix}$.

Measurements

1) measurements to build a radio map: In the training phase, the RSS values of the radio signals transmitted by Bluetooth APs are collected in the calibration points for a certain period of time and stored into the radio map. Denote the $i$th fingerprint as $\mathbf{R}_i$ with the form:

$$\mathbf{R}_i = (\mathbf{c}_i, \{\mathbf{a}_{i,j}\}), \ j \in \{1, \ldots, N\}$$

where $\mathbf{c}_i$ is the coordinate of the $i$th calibration point and $\mathbf{a}_{i,j}$ holds the $l$ RSSI samples from the access point $\text{AP}_j$, i.e. $\mathbf{a}_{i,j} = \{a_{i,j}^1, a_{i,j}^2, \ldots, a_{i,j}^l\}$, $N$ is the total number of Bluetooth APs. The set of all fingerprints is denoted as $\mathbf{R} = \{\mathbf{R}_1, \ldots, \mathbf{R}_M\}$, where $M$ is the total calibration points.

2) measurements for position estimation: In the positioning phase, denote $\mathbf{z}_k$ as RSS values measured from the different Bluetooth APs at time $t_k$. Then, the measurement sequence is

$$\mathbf{z}_{1:k} = \{\mathbf{z}_1, \ldots, \mathbf{z}_k\}.$$

Problem Formulation

The problem of tracking the pedestrian indoors is to infer the mobile state $\mathbf{x}_k$ from the measurement sequence $\mathbf{z}_{1:k}$ and the constructed radio map $\mathbf{R}$. Within the Bayesian estimation

framework, solving this problem corresponds to computing the posterior \( p(x_k \mid z_{1:k}, R) \). By applying the Bayes’ Rule, the posterior can be calculated as:

\[
p(x_k \mid z_{1:k}, R) = \frac{p(z_k \mid x_k, R) p(x_k \mid z_{1:k-1}, R)}{p(z_k \mid z_{1:k-1}, R)}
\]

Due to the complex electromagnetic environment indoors, it is not easy to give an explicit measurement function \( z_k = h_k(x_k) \) within the whole positioning area. Thus, the likelihood \( p(z_k \mid x_k, R) \) could not be exactly calculated.

An alternative approximation is to compute \( p(z_k \mid R) \), which is based on the assumption that the whole area of interest is divided into \( M \) small cells and the RSSI distribution on the \( i \)th calibration point represents the distribution of all the points within the corresponding cell. However, \( p(z_k \mid R) \) is the discrete probability distribution on the \( M \) coordinates of calibration points, based on which the mean and covariance of the position can be estimated, while \( p(x_k \mid z_{1:k-1}, R) \) predicts of the position and velocity. Therefore, the posterior \( p(x_k \mid z_{1:k}, R) \) relates to fusing two state estimations with different dimensions, which is not straightforward to update.

**INFORMATION FILTERING WITH VELOCITY DETECTION**

Decompose the mobile state \( x_k \) into position \( u_k = [x_k, y_k]^T \) and velocity \( v_k = [\dot{x}_k, \dot{y}_k]^T \). The state model (1) can be written as:

\[
\begin{align*}
\dot{v}_k &= v_{k-1} + \xi_{k-1} \\
\dot{u}_k &= u_{k-1} + H\nu_{k-1} + v_{k-1}
\end{align*}
\]

where \( H = \Delta t \mathbf{I}_2 \), \( \xi_{k-1} \sim \mathcal{N}(0, Q_\xi) \), \( \nu_{k-1} \sim \mathcal{N}(0, Q_\nu) \). According to (2), \( Q_\nu = \frac{\Delta t^4}{4} \Omega \), \( Q_\xi = \Delta t^2 \Omega \).

In addition, the process noise \( \xi_k, \nu_k \) are correlated, \( C = \mathbf{E}[\xi_k \nu_k^T] = \frac{\Delta t^3}{2} \Omega \). The posterior of mobile state \( p(x_k \mid z_{1:k}, R) \) can be factorized as

\[
p(x_k \mid z_{1:k}, R) = p(u_k, v_k \mid z_{1:k}, R) = p(v_k \mid u_k, z_{1:k}, R) p(u_k \mid z_{1:k}, R)
\]

According to the Bayes rule, \( p(u_k \mid z_{1:k}, R) \) can be computed as

\[
p(u_k \mid z_{1:k}, R) = \eta p(z_k \mid u_k, R) p(u_k \mid z_{1:k-1}, R) \approx \eta p(z_k \mid R) p(u_k \mid z_{1:k-1}, R)
\]

where \( \eta = 1 / p(z_k \mid z_{1:k-1}, R) \) is the normalization factor.

**Position Prediction by Motion Model**
Suppose at time $t_{k-1}$, the estimated mean and covariance of $u_{k-1}$ are $\{u_{k-1|k-1}, P_{k-1|k-1}\}$, and the estimated mean and covariance of $v_{k-1}$ are $\{v_{k-1|k-1}, P_{v_{k-1|k-1}}\}$. Then, according to the linear model (3) the predicted mean $u_{k|k-1}$ and covariance $P_{u_{k|k-1}}$ of the position are

$$
u_{k|k-1} = u_{k-1|k-1} + H_k v_{k-1|k-1}$$

$$P_{u_{k|k-1}} = E[u_{k|k-1}^T u_{k|k-1}^T] = H(P_{v_{k-1|k-1}} + Q_v)H^T + Q_u + H^T C + HC^T$$

$P_{u_{k|k-1}}$ is calculated by considering the correlated process noise $\epsilon_t$ and $\nu_t$

**Position Estimation from Measurements**

To compute $p(z_k | R)$, we use the statistical information from the radio map. From the $i$ th fingerprints $R_i$, the mean $\bar{a}_{i,j}$ and the variance $\sigma_{i,j}^2$ can be obtained from the measurements $a_{i,j}$. In the positioning phase, based on the RSS measurement $z_{k,j}$ and the Gaussian approximation to the histogram of $a_{i,j}$, the weight $w_{i,j}$ can be computed as

$$w_{i,j} = N(z_{k,j}; \bar{a}_{i,j}, \sigma_{i,j}^2), j \in \{1, \cdots, N\}$$

(7)

When the measurement $z_{k,j}$ does not exit, which means the device did not hear the AP $j$ at time $t_k$, set $w_{i,j} = w_0$, where $w_0$ is a very low value. Assume the measurements $z_k$ from different AP $j$ are independent, then

$$p(z_k | R) = \prod_{j=1}^{N} w_{i,j}$$

(8)

and the normalized weight $w_i$ equal to

$$w_i = \frac{\prod_{j=1}^{N} w_{i,j}}{\sum_{i=1}^{M} \prod_{j=1}^{N} w_{i,j}}$$

(9)

Thus, from (7-9), $p(z_k | R)$ is the discrete probability distribution with the weight $w_i$ on the $i$ th coordinate of the calibration point $c_i$. Accordingly, the first two moments are

$$u^r_k = \sum_{i=1}^{M} w_i c_i$$

$$P^r_k = \sum_{i=1}^{M} w_i \left( (u^r_k - c_i)(u^r_k - c_i)^T \right)$$

(10)

**Position Update by Information Filtering**

When fusing the measurement estimation (10) and the model prediction (6), the estimated mean $u_{k|k}$ and covariance $P_{u_{k|k}}$ of the position $u_k$ can be updated as
$$\begin{align*}
(P^n_{k|k})^{-1} &= (P^n_{k|k-1})^{-1} + (P^r_k)^{-1} u_{k|k} = (P^n_{k|k}) \left[ (P^n_{k|k-1})^{-1} u_{k|k-1} + (P^r_k)^{-1} u^r_k \right]^{-1} \\
u_{k|k} &= (P^n_{k|k}) \left[ (P^n_{k|k-1})^{-1} u_{k|k-1} + (P^r_k)^{-1} u^r_k \right]^{-1}
\end{align*}$$

(11)

**Velocity Update by Kalman Filter with Correlated Noise**

Based on state model (3) and the position estimation (11), update the estimation of velocity $v_k$ by Kalman filter with correlated noise:

$$\begin{align*}
v_{k|k} &= v_{k|k-1} + P^v_{k|k-1} \left( P^n_{k|k-1} \right)^{-1} (u_k - u_{k-1} - H v_{k|k-1}) \\
P^n_{k|k} &= P^n_{k|k-1} - P^v_{k|k-1} \left( P^v_{k|k-1} \right)^T
\end{align*}$$

where

$$\begin{align*}
v_{k|k-1} &= v_{k-1|k-1} \\
P^v_{k|k-1} &= P^v_{k-1|k-1} + Q_e \\
P^v_{k|k-1} &= \mathbb{E}[u_{k|k-1} v_{k|k-1}^T] = (P^v_{k-1|k-1} + Q_e) H^T + C
\end{align*}$$

$P^n_{k|k-1}$ is given in (6). $P^v_{k|k-1}$ is also calculated by considering the process noise $e_\tau$ and $v_\tau$ are correlated.

**Velocity Detection and Position Correction**

Exploiting the fact that the indoor pedestrian has a limited walking speed, we set the constraint that if $\|v_{k|k}\| > V_{\text{max}}$, then

$$\begin{align*}
\alpha &= \arctan \left( \frac{\hat{y}_k}{\hat{x}_k} \right) \\
v_{k|k} &= [V_{\text{max}} \cos \alpha, V_{\text{max}} \sin \alpha]^T \\
P^v_{k|k} &= P^v_{k|k} \left( V_{\text{max}} / \|v_{k|k}\| \right)^2 \\
u_{k|k} &= u_{k-1|k-1} + v_{k|k} \Delta t \\
P^n_{k|k} &= P^n_{k|k} \left( V_{\text{max}} / \|v_{k|k}\| \right)^2
\end{align*}$$

(14)

The Algorithm 1 describes the whole scheme.

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**Algorithm 1 Information fusion with speed detection**

- Initial state at time $t_0$ :
  $$\begin{align*}
u_{0|0} &= u_0, P^u_{0|0} = P^u_0, v_{0|0} = v_0, P^v_{0|0} = P^v_0
\end{align*}$$

- Input
Fingerprints: \( R \), RSS measurement at time \( t_k \): \( z_k \)

Position and velocity estimation at time \( t_{k-1} \): \( u_{k-}\|k-1\|, P^u_{k-\|k-1\|}, v_{k-\|k-1\|}, P^v_{k-\|k-1\|} \)

- **Output**

  for \( k = 1 \) to \( T \)
  
  1) position prediction by motion model: (6)
  2) position estimation by RSS measurement: (7), (10)
  3) position update by information fusion: (11)
  4) velocity update by Kalman filter: (12), (13)
  5) velocity detection and position correction: (14), (10)

end for

The method of information fusion with speed detection (IFSD) simultaneously considers the information from the RSS measurements and the prior positioning from the motion model. The indoor pedestrian speed is further set as a constraint to detect the outliers. Compared with the point Kalman filter, which only puts the mean \( u_k \) as the input to the Kalman filter, the information fusion step in the IFSD considers the covariance estimation of the RSS measurements \( P^r_{k\|k-1} \).

**EXPERIMENTS**

This section introduces results of experiments conducted in a Bluetooth network with the motion restricted fusion filter.

**Bluetooth RSS Data Collecting System**

In this study, a Bluetooth RSS data collecting system is developed for indoor positioning. The system consists of a Bluetooth evaluation kit and a data collecting program developed during the research work (Fig. 1). The basic function of the system is to scan the Bluetooth Access Points (APs) nearby, collect the RSS from the detected APs, and then send the measurements to the laptop via a serial port. The sampling interval can be adjusted within 1.2 – 11.5 seconds with a resolution of 1.28 seconds according to the priority chosen.

The evaluation kit is equipped with a RS-232 and an USB interface, an on-board Pulse Code Modulation (PCM) codec, a 16-pin I/O interface, and a Serial Peripheral Interface (SPI) for upgrading the firmware and parameters. It is powered by a laptop through a USB connection. The core component of the evaluation kit is the Bluegiga WT41 module (Fig. 2), a class 1 Bluetooth® 2.1 plus an Enhanced Data Rate (EDR) module, which contains all the necessary elements from Bluetooth radio to antenna and fulfills a fully implemented protocol stack within the embedded firmware. The module is optimized for long range applications and the effective scanning range is approximately 800 m.
The data collecting program is developed based on a Visual C++ IDE. The flow chart of the program is presented in Fig. 3. The program uses a multi-thread application, with one thread for communicating with the Bluetooth evaluation kit in real-time to collect the RSS from the Bluetooth AP and the other thread for showing the results in a user interface.

**SPAN High Accuracy GPS-IMU System**

To evaluate the positioning accuracy of different algorithms, a reference trajectory, used as the ground truth, is obtained via NovAtel’s high-accuracy SPAN system. SPAN technology is a tightly couple solution of a precision Global Navigation Satellite System (GNSS) receiver with a robust Inertial Measurement Unit (IMU) from NovAtel. It can provide reliable, continuously available measurements including position, velocity, and attitude even through short periods of time when no GNSS satellites are available. During the tests, the GPS receiver of the SPAN system is a NovAtel DL-4plus, containing the NovAtel OEM-G2 engine. A dual-frequency NovAtel GPS-702 antenna is applied. The inertial measurement unit is a tactical-grade, ring laser gyro based IMU. The SPAN system can operate either in Real-Time Kinematic (RTK) mode or
Virtual Reference Station (VRS) mode for real-time and post-processing applications to get trajectories with centimeter level of accuracy.

Field Test

Indoor tests were carried out in a corridor of an office-building at the Finnish Geodetic Institute. During the test, the indoor corridor was equipped with 13 Bluetooth access points. Fig. 4 shows the corridor from the inside. Fig. 5 shows the testing platform with the floormap, the position of the Bluetooth APs, and the test route in the corridor.

Figure 4 Interior of the glass, concrete, and steel office building, which is the pedestrian navigation testing environment.

Figure 5 Floormap, the position of the Bluetooth APs and the testing equipment.
Two tests were carried out in the scenario. In both tests, a tester walked along the corridors back and forth with the test cart. Test 1 lasts about 6 minutes, while with a relatively faster speed, test 2 only lasts for 3 minutes. The Bluetooth priority scale is set to 6, which corresponds to a sampling interval \( \Delta t \approx 9 \) s. The maximum horizontal speed is set to 2 m/s, which is typical for pedestrian indoor motion [15].

Results

We compare the proposed information filter with speed detection (IFSD) with the Bayes static estimation (BSE) method, which only uses the current measurements to estimate the posterior mean and covariance of the position (Sec. III.B) and the point Kalman filter (PKF) method, which uses a Kalman filter to further smooth the position results obtained by the BSE. A stationary motion model is used in the PKF to formulate the movement [13]. In our tests, the covariance of the process noise in the PKF is set as \( Q_{PKF} = (V_{max} \cdot \Delta t)^2 I_2 = 18^2 I_2 \) and the measurement covariance \( R_{PKF} = 9* I_2 \). In the IFSD, we set \( \sigma_x = \sigma_y = 1/\Delta t \), which means that the changes in the velocity over a sampling interval are in the order of 1 m/s in each direction. The initial position of the IFSD and the PKF is obtained from the first output of the BSE. The initial covariance for the position estimation is \( 9* I_2 \) and the initial velocity for the IFSD is 0 m/s with covariance \( I_2 \). Fig. 5 and 7 represent the estimated trajectories of the 3 different algorithms in a North-East coordinate frame including also the SPAN reference track as the ground truth. Fig. 6 and 8 show the position error vs. time epoch of the three algorithms. Position errors are compared in Table I. From the results, the mean error of the BSE is about 5 m. The PKF smooths the positions obtained by the BSE. Based on the stationary motion model, the estimation errors are reduced in several epochs, e.g. \( k = 8, 10, 13 \) in Fig. 6 and \( k = 4, 5, 7, 9 \) in Fig. 8. However, the improvement of the PKF is very slight, only 0.1 m. The reason for this may lie in the fact that the \( Q_{PKF} \) is relatively large due to the long sampling interval of the Bluetooth. Thus, the prior information from the motion model has little impact on the position estimation at each epoch. In comparison, the positioning error of the IFSD is 4.2 m on the average, about 1 m less than BSE and 0.8 m less than the PKF. Significant improvements can be observed at \( k = 13 \) in test 1 and \( k = 4 \) to 10 in test 2, where the large errors are detected by the indoor pedestrian speed constraint and filtered out.

Thus, according to the test results, it is clear that the proposed IFSD can effectively correct the large outliers in position estimation and achieves the best position accuracy among the three algorithms. This is achieved by combining the estimation information (mean and covariance) from the measurements with the prior information from the motion model, together with the speed detection and position correction.
Figure 5 Position estimate in Test 1

Figure 6 Position error vs. time epoch in Test 1
Figure 7 Position estimate in Test 2

Figure 8 Position error vs. time epoch in Test 2
CONCLUSIONS

This paper studied the fingerprinting method for positioning in an indoor Bluetooth network. An information filter with speed detection method was proposed. The method simultaneously considered the Bayesian static estimation results and the pedestrian motion model. By exploiting the fact that the pedestrian indoors has a limited walking speed, speed detection was further assisted to correct the outliers of the position estimation. Field tests showed that the proposed method was effective and achieved an improved accuracy when compared with the Bayesian static estimation method and the point Kalman filter.

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