WLAN-Based Pedestrian Tracking Using Particle Filters and Low-Cost MEMS Sensors

Hui Wang, Henning Lenz, Andrei Szabo, Joachim Bamberger, Uwe D. Hanebeck

***Abstract*— Indoor positioning systems based on Wireless LAN (WLAN) are being widely investigated in academia and industry. Meanwhile, the emerging low-cost MEMS sensors can also be used as another independent positioning source. In this paper, we propose a pedestrian tracking framework based on particle filters, which extends the typical WLAN-based indoor positioning systems by integrating low-cost MEMS accelerometer and map information. Our simulation and real world experiments indicate a remarkable performance improvement by using this fusion framework.**

***Index Terms*—Indoor Positioning, Pedestrian Tracking, Particle Filter, MEMS**

I. INTRODUCTION

POSITIONING and navigation systems have achieved great success in a broad category of so-called location-based services (LBS), such as personnel security, tracking of assets and people, intelligent guidance, location-aware multimedia services and many others [1-4]. Generally, these systems can be separated into three groups: satellite based systems, local network based systems and sensor based systems. Satellite systems, such as the well-known GPS or Galileo systems, focus on the outdoor positioning [5, 6]. However, these systems suffer from the attenuation, reflection and refraction of buildings and walls when used indoors. Another category of positioning systems makes use of existing communication network infrastructures, such as Wireless LAN (WLAN), Ultra-Wideband (UWB) or DECT networks [7-10]. The received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA) and angle of arrival (AOA) are typically used to infer the user's location. The advantage using such systems is that they can be deployed both indoors and outdoors. In addition, they make use of available networks and does not need additional hardware, thereby keeping the installation and maintenance cost at a low level. But still, current network-based systems suffer from the noisy characteristics of wireless channel and multi-path distortion, leading to a coarse accuracy. The last category of systems uses various dedicated sensors. These sensors either sense the absolute location related information, such as magnetic sensors, laser sensors, ultrasonic and infrared sensors, or sense the change of location related information, such as inertial sensors or barometric sensors [5, 11, 12, 14].

Since inertial sensors can only provide relative information, they are often combined with other positioning systems. For instance, the GPS/INS solution uses GPS as a supervisor to correct the accumulative errors of inertial sensors, and on the other hand, inertial navigation systems (INS) also improve the performance of GPS, especially in tunnel or other scenarios where GPS signals are temporally blocked [5, 13]. Traditional inertial navigation systems are big and expensive, which limits their integration with indoor navigation systems. However, the emerging MEMS technology makes low-cost and small size inertial sensors a reality [16]. One example are MEMS accelerometers, which are available at a price lower than 10 dollar today and have successfully been integrated into mobile devices [15].

In this paper, we propose a fusion framework based on particle filters. Different from other expensive IMU assisted systems [23, 24], our framework integrates the typical WLAN pedestrian positioning system with only a low cost accelerometer and map information, as shown in Fig. 1. The remainder of the paper is organized as follows. In Section II, we briefly introduce the RSS-based WLAN positioning system. In Section III, we analyze the useful information from MEMS accelerometer. Our particle filtering algorithm is proposed in Section IV. We also discuss other filters for the purpose of comparison in this section. Experimental results based on both simulation and real world test data are given in Section V. Finally, Section VI concludes the paper.

II. POSITIONING ALGORITHM BASED ON RSS MEASUREMENTS

In network based localization systems, RSS is most often used as the input of the positioning algorithm because it is much easier to obtain than the time or the angle information. The popular localization algorithm for the RSS based systems is the so-called pattern matching or *K*-nearest neighbors (KNN) algorithm [7]. This algorithm includes the following two steps:

1. In the offline step, the received power vectors from several access points (APs) at calibration points are measured

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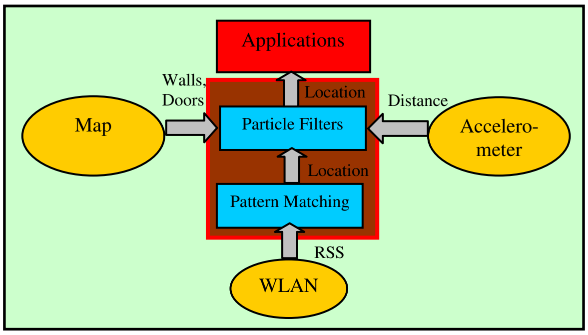


Fig.1. Structure of Indoor Tracking Framework

and recorded as the fingerprints of the calibration points.

2. In the online step, the received power vector is then compared with the fingerprint of calibration points using the distance metric in Equation (1). The K calibration points which have the closest distances with the received power vector are finally chosen and averaged as the final estimation.

$$d(\mathbf{x}) = \frac{1}{Q}\sum_{q=1}^{Q}\left\{\left(P_q^{\,m} - P_q(\mathbf{x})\right)^2\right\}, \qquad (1)$$

where $P_q^{\,m}$ is the measured power from access point q, $P_q(\mathbf{x})$ is the q^{th} element of the fingerprint at the calibration point $\mathbf{x}$. Q is the number of APs.

III. MEMS Accelerometer and Movement Model

The accelerometer is a device for measuring the acceleration of moving objects. Thanks to the fast development of MEMS technology, the small and cheap MEMS accelerometers are already available [16]. Fig. 2 gives an example of the raw measurement of a stay-walking-stay behavior using the commercial Freescale MMA7260Q 3-axis accelerometer. Theoretically, the moving speed and distance can be obtained by integrating the acceleration signal. But for indoor pedestrian walking, the acceleration is small, so it can hardly be separated from sensor noise, offset drift, and tilt variation. An alternative approach is to detect the walking steps. While people walk, the vertical acceleration fluctuates periodically due to the motion mechanism. This periodical signal stands for the steps people walked, as shown in Fig. 3. So we need to identify the steps and step size to obtain the walking distance

$$D = Step\_Size \times Num\_Steps\,. \qquad (2)$$

In our paper, we use a simple zero-crossing algorithm to detect the number of steps. We know that the vertical acceleration signal crosses the zero line twice every step. Hence, we can count the number of zero crossing points and divide it by two, deriving the number of walked steps *Num_Steps*. The step size is calculated by an empirical equation proposed by engineers from Analog Device [21], as shown in Equation (3).

$$Step\_Size \approx \sqrt[4]{A_{\max} - A_{\min}} \times C\,, \qquad (3)$$

where $A_{\max}$ and $A_{\min}$ are the maximum and minimum acceleration in one step, respectively; C is a constant value, which can be obtained from walking training. Some more accurate, but also more complex models for calculating the number of step and step size can be found in the literature [17, 20]. In Section V, we will see that our filtering algorithm is not sensitive to the estimation error of walking distance, which favors the use of a simple model for the distance estimation.

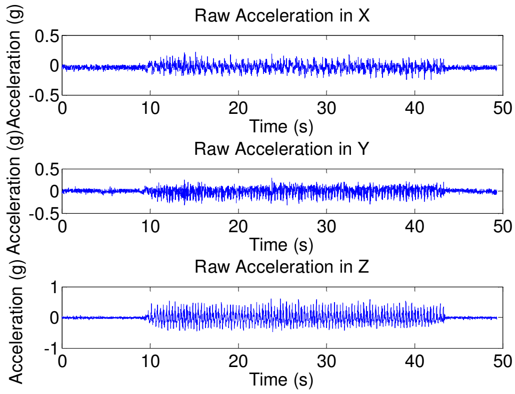


Fig. 2. Raw Measurement of Acceleration
(The offset g in z-axis is already compensated)

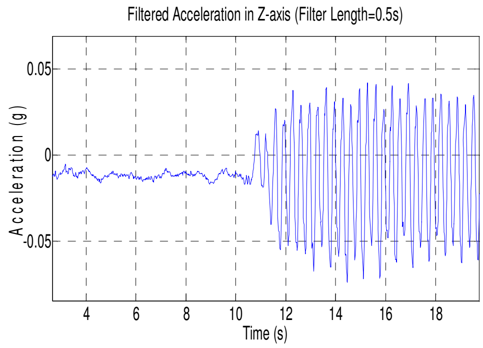


Fig. 3. Filtered Acceleration in Z-axis
(The offset g in z-axis is already compensated)

IV. Filtering Algorithms

In indoor positioning systems, the fluctuation of RSS measurements leads to a coarse estimation accuracy. When the mobile device needs to be localized continuously, the filtering can help to smooth the trajectory and to reduce the estimation error. A Kalman filter is commonly used in tracking applications. The drawback of Kalman Filter is also obvious. Its main assumption, i.e. the linear model, is hardly fulfilled in real life. The Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are proposed to solve the non-linear estimation problem by linearizing all the non-linear models. But they are only reliable for systems which are almost linear. Distributed information like the map information is impossible to be integrated for tracking by EKF or UKF. As an alternative to Kalman filter and its derivatives, particle filters are attracting more and more attention recently [22]. Particle filters are based on Monte-Carlo sampling and thus can deal with non-linear and non-Gaussian estimation problems. Using Particle filters additional information like walking distance and map information can be straightforwardly integrated. This holds although the map information is non-linear and distributed in space and although the walking distance characterizes only one part of the movement behavior, i.e., information on the orientation is missing. In the following, we will briefly introduce the Kalman filter model as a reference for comparison. Then we focus on the particle filter model as well as its integration with accelerometer and map information.

A. Kalman Filter

Kalman filter models a discrete-time controlled process using the following linear stochastic difference equations for state $\mathbf{x}(k)$ and measurement $\mathbf{z}(k)$:

$$\mathbf{x}(k) = \mathbf{A}\mathbf{x}(k-1) + \mathbf{B}\mathbf{u}(k) + \mathbf{n}(k-1) \tag{4}$$

$$\mathbf{z}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v}(k) \tag{5}$$

Here, the matrices, $\mathbf{A}$, $\mathbf{B}$, $\mathbf{H}$ defines the linear transition and measurement processes, while the random vector $\mathbf{n}$ and $\mathbf{v}$ represent the process and measurement noise respectively. They are assumed to be independent, white, and with normal distributions

$$p(\mathbf{n})\sim N(\mathbf{0}, \mathbf{Q}), \tag{6}$$

$$p(\mathbf{v})\sim N(\mathbf{0}, \mathbf{R}). \tag{7}$$

Here, $\mathbf{Q}$ and $\mathbf{R}$ are covariance matrices of state error and measurement error, respectively. For the RSS based systems, we define the parameters as follows:

$$\mathbf{x}(k) = \begin{bmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{bmatrix}, \mathbf{A} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{n}(k) = \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix} \begin{bmatrix} a_x(k) \\ a_y(k) \end{bmatrix}, \mathbf{z}(k) = \begin{bmatrix} x_{RSS}(k) \\ y_{RSS}(k) \end{bmatrix},$$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \mathbf{v}(k) = \begin{bmatrix} e_x(k) \\ e_y(k) \end{bmatrix},$$

where x and y are the position in x-axis and y-axis; v_x and v_y are the speed in x-axis and y-axis; a_x and a_y are the acceleration which is regarded as noise; $\mathbf{z}$ is the estimated position from RSS measurements. And $\mathbf{v}$ can be seen as the error of RSS-based positioning algorithms. Then the estimated state $\hat{\mathbf{x}}$ can be calculated using the following prediction and correction steps [5, 22]:

$$\hat{\mathbf{x}}^-(k) = \mathbf{A}\hat{\mathbf{x}}(k-1), \tag{8}$$

$$\mathbf{P}^-(k) = \mathbf{A}\mathbf{P}(k-1)\mathbf{A}^{\mathrm{T}} + \mathbf{Q}, \tag{9}$$

$$\mathbf{K}(k) = \mathbf{P}^-(k)\mathbf{H}^T(\mathbf{H}\mathbf{P}^-(k)\mathbf{H}^T + \mathbf{R})^{-1}, \tag{10}$$

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k)(\mathbf{z}(k) - \mathbf{H}\hat{\mathbf{x}}^-(k)), \tag{11}$$

$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H})\mathbf{P}^-(k), \tag{12}$$

where $\mathbf{P}^-(k)$ is the covariance matrix corresponding to the predicted state and $\mathbf{P}(k)$ is the covariance matrix corresponding to the estimated state that already includes the recent measurement.

B. Particle Filters

(1) General Algorithm

Different from the Kalman filter, the particle filters directly estimate the posterior probability density function (pdf) of the state $\mathbf{x}(k)$ given the past observations $\mathbf{Z}(k)$ using the following equation [22]:

$$p(\mathbf{x}(k) \mid \mathbf{Z}(k)) \approx \sum_{i=1}^{N} w^i(k)\delta\big(\mathbf{x}(k) - \mathbf{x}^i(k)\big), \tag{13}$$

where $\mathbf{x}^i(k)$ is the i-th sampling point or particle of the posterior probability. $w^i(k)$ is the weight of the particle.

The biggest advantage of the particle filter is that it can solve non-linear and non-Gaussian estimation problems. Many forms of particle filters are available in the literature [22]. Here we consider the commonly used Sequential-Importance-Resampling (SIR) particle filter. This filter comprises of the following steps [22]:

a) *Initialization*: Sampling N particles $\{\mathbf{x}^i(0),\ i=1\ldots N\}$ according to the initial pdf $p(\mathbf{x}(0))$.
b) *Prediction Sampling*: For each particle $\mathbf{x}^i(k)$, get a new particle $\mathbf{x}^i(k+1)$ from the transition pdf $p(\mathbf{x}(k+1)|\mathbf{x}^i(k))$.
c) *Importance Sampling*: For each new particle $\mathbf{x}^i(k+1)$, calculate $w^i(k+1)= p(\mathbf{z}(k+1)|\mathbf{x}^i(k+1))$.
d) *Normalization and Resampling*: The weights are normalized and finally re-sampled. In the resampling step, particles with low weight are deleted and particles with high weight are duplicated such that each particle has the same weight. A detailed description of the resampling algorithm can be found in [22].

From the above description, we see that for particle filters, the transition density function $p(\mathbf{x}(k+1)|\mathbf{x}(k))$ and the update density function $p(\mathbf{z}(k+1)|\mathbf{x}(k+1))$ should be known to such an extent that enables to do prediction sampling and calculation of weights (see below). But, in general, the pdfs are not required to be Gaussian.

(2) Particle Filter for only RSS Measurement

For comparison with the described Kalman filter, we apply a particle filter also using only RSS measurements. For each old particle $\mathbf{x}^i(k)=[x^i(k)\ y^i(k)\ v^i_x(k)\ v^i_y(k)]^{\mathrm{T}}$, a new particle $\mathbf{x}^i(k+1)$ can be obtained from the following transition function:

$$\begin{bmatrix} x^i(k+1) \\ y^i(k+1) \\ v^i{}_x(k+1) \\ v^i{}_y(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x^i(k) \\ y^i(k) \\ v^i{}_x(k) \\ v^i{}_y(k) \end{bmatrix} + \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix} \begin{bmatrix} a_x(k) \\ a_y(k) \end{bmatrix}, \tag{14}$$

where it is assumed that the movement of a person is governed by inertia which is superimposed by Gaussian acceleration noise, i.e. $a_x(k)$ and $a_y(k)$ are sampled from the normal distribution $N(\mathbf{0}, \mathbf{Q})$. The weights can be computed using Equation (15), which assumes that the position estimated by RSS based pattern matching is Gaussian distributed around the true position.

$$\begin{aligned} w^i(k+1) &= p(\mathbf{z}(k+1) \mid \mathbf{x}^i(k+1)) \\ &= \frac{1}{\sqrt{2\pi}\sigma} e^{\left[-\frac{(x^i(k+1)-x_{RSS}(k+1))^2+(y^i(k+1)-y_{RSS}(k+1))^2}{2\sigma^2}\right]} \end{aligned} \tag{15}$$

(3) Fusion of RSS Measurement and Accelerometer with a Particle Filter

When an accelerometer is used, the extra information, walking distance $d(k)$ between two RSS samples can be obtained using the algorithm in Section III. This information cannot be directly integrated with Kalman filter because it requires a non-linear prediction function. The particle filter helps to overcome this problem. We use the following prediction sampling equation.

$$\mathbf{x}^i(k) = \begin{bmatrix} x^i(k) \\ y^i(k) \end{bmatrix} = \begin{bmatrix} x^i(k-1) + d^i(k)\cos\theta^i(k) \\ y^i(k-1) + d^i(k)\sin\theta^i(k) \end{bmatrix}, \tag{16}$$

where $d^i(k)$ is sampled from the normal distribution $N(d(k), \sigma_{acc}^2)$, which has mean of walking distance $d(k)$ and standard deviation σ_{acc}^2. Since $\theta^i(k)$ is unknown, we can sample it from a uniform distribution *uniform*(0~2π). The weights are calculated from the same equation as equation (15). With Equation (15) and (16), we manage to fuse the accelerometer and RSS measurement using the particle filter.

(4) Fusion of RSS Measurement, Accelerometer and Map Information with a Particle Filter

With a particle filter, more information than RSS and accelerometer can be fused. In particular, a building map is another very useful information source, since a lot of location-related data can be extracted from the building structure information, such as the distance between floors, the position of walls, doors or elevators. For the tracking problem, this information helps to reduce the uncertainty of the walking trajectory. Using a particle filter, the estimation can be improved by deleting impossible particles, i.e. the particles which would have crossed a wall. Accordingly, the weighting function (15) changes to Equation (17).

$$w^i(k) = \begin{cases} 0, & \textit{if new particle crosses walls} \\ \frac{1}{\sqrt{2\pi}\sigma} e^{\left[-\frac{(x^i(k)-x_{RSS}(k))^2+(y^i(k)-y_{RSS}(k))^2}{2\sigma^2}\right]}, & \textit{otherwise} \end{cases} \tag{17}$$

V. Experiment Results and Analysis

We conducted experiments both in simulated and real world tests in order to better evaluate different filtering techniques. In this section, we will describe the experiments and analyze the results.

A. Simulation Tests

Our simulation platform simulates the RSS distribution in our office environment using a Multi-Wall radio propagation model [25, 26]. Five APs are available in the test floor. The positions of APs are marked with stars in Fig. 4. Reference points are selected uniformly with the resolution of 1 meter. KNN algorithm is used to make the initial estimation. Different filters are then used to smooth the trajectory and reduce the location error. For a fair comparison, we haven chosen eight different walking trajectories, as shown in Fig. 4, including walking straight with constant velocity (Test 1), walking straight with variable velocity (Test 2), walking with 90° turn (Test 3), walking with 180° turn (Test 4), walking with 45° turn (Test 5), walking in a circle (Test 6&7) and walking randomly (Test 8). The means and standard deviations of estimation errors in simulation are shown in diagram 1. The algorithm parameters can be found in the appendix.

From the simulation, we notice that the particle filter itself, when only RSS measurements are considered, performs comparable with the Kalman filter. After integrating the extra information walking distance, a significant improvement is achieved. A comparable, but slightly worse result is obtained, when instead of the acceleration signal only the map information is added to the RSS information. From the simulation results, we see that the last particle filter, combining accelerometer and map, is in average more than 40% better than the KNN estimation and around 30% better than the Kalman filtering, both in the sense of mean and standard deviation of location error.

We also test the particle filter algorithm with respect to the sensitivity of the step size estimation. Therefore Test 8 has been performed with different step sizes, simulating a wrong step size estimation. Fig. 5 shows the mean error in Test 8 when different step sizes are used. We see that 10-20% step size errors do not cause a too large deviation from the best localization accuracy.

B. Real Walking Test

We also verified all the algorithms using real RSS and acceleration measurements. The test environment is the same as described in the simulation. The walking trajectory is the same as the one simulated in Test 8. We use a Lucent Orinoco Gold Card to collect RSS measurements and use the Freescale MMA7260Q 3-axis MEMS accelerometer to collect the acceleration measurements. The acceleration data is processed by the movement model algorithm and the determined walking distance is shown in Fig. 6. We give the result of different filters in Table I and the cumulative density function in Fig.7.

The real world test approves the results found by the simulations. Using a filtering algorithm – Kalman filter or particle filter – the localization accuracy can be improved by about 10%, in comparison with the plain RSS-based nearest neighbor localization. Further improvements of about 25% are obtained, when the particle filter gets extra information from an acceleration sensor and from a building map.

VI. Conclusions

In this paper, we proposed a particle filter framework to extend the typical RSS based indoor positioning systems by using an MEMS accelerometer and map information. The walking distance is estimated using a motion model based on a zero-crossing algorithm, which avoids a large accumulative error induced by sensor noise. The SIR particle filter is used to integrate the non-linear information from accelerometer and building map. Our simulation and real walking test indicates a remarkable improvement compared to Kalman filtering in the sense of mean and standard deviation of estimation errors. In addition, this fusion algorithm is robust with respect to a wrong step size estimation. Since the estimated positions are not limited to those obtained from the RSS-based WLAN positioning systems, our framework can also be used for tracking and fusing in other network based systems, e.g. UWB, DECT or GSM systems, or with other sensing methods, e.g. TDOA, TOA or AOA.

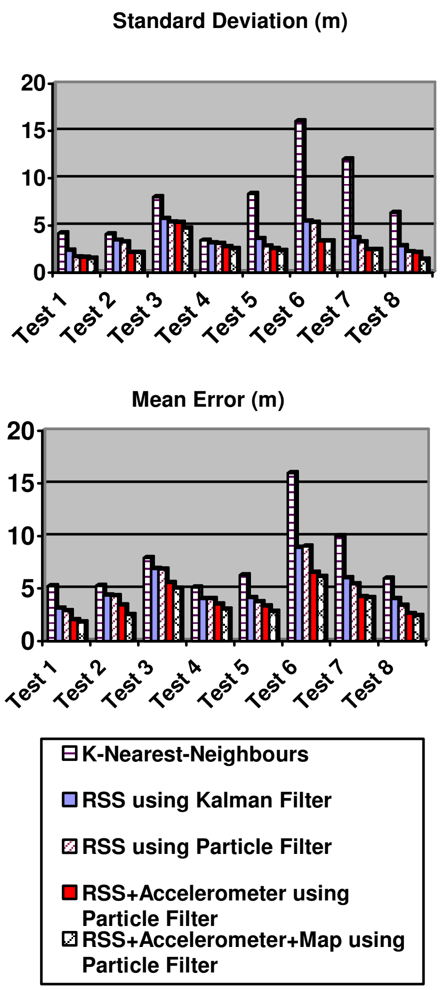


Diagram 1. Comparison of Standard Deviations and Mean in Simulation

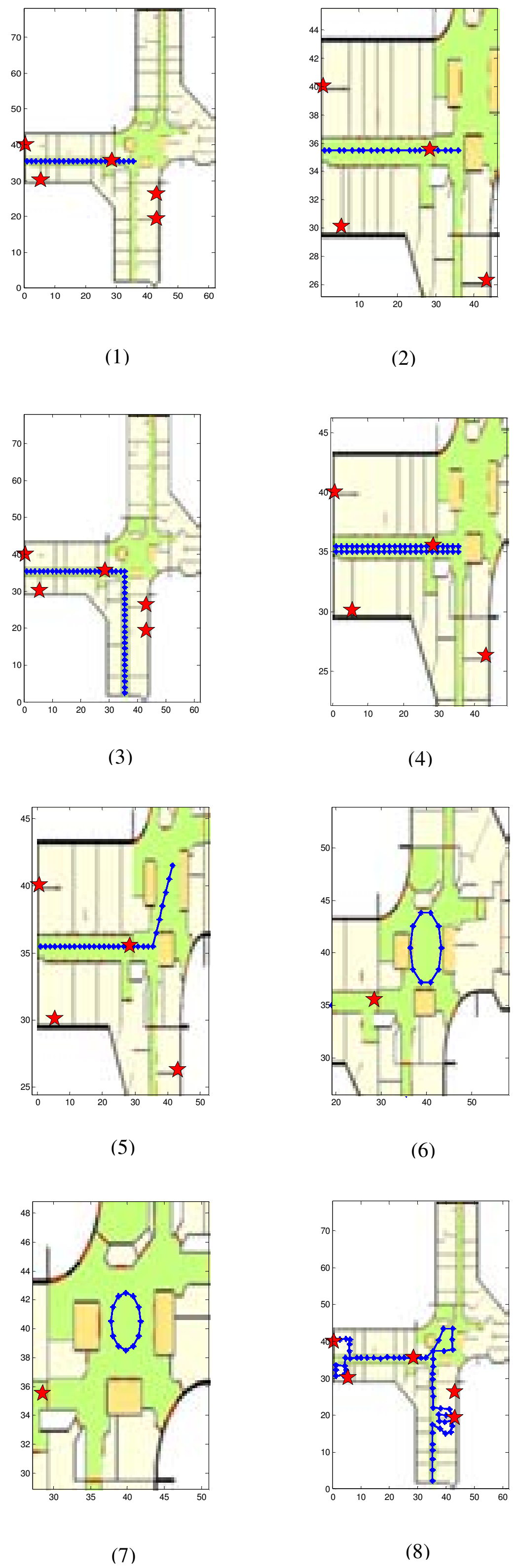


Fig. 4 Simulation environment and test routes (Stars represent the APs.)

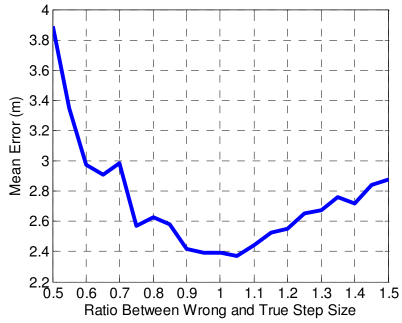
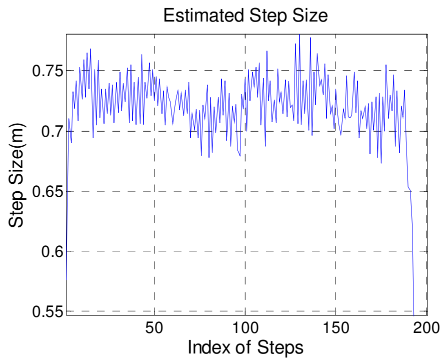
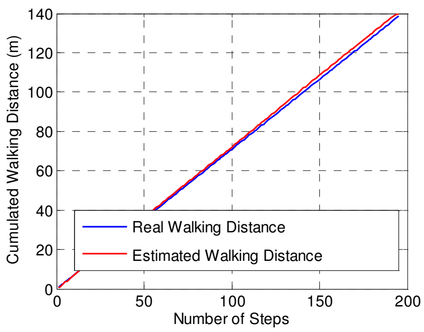


Fig. 5 Results Using Different Step Sizes in Simulated Test 8



(a)



(b)

Fig. 6 Estimated Walking Distance from Real Acceleration Measurements

TABLE I
RESULTS OF REAL WORLD TEST

	Mean Error(m)	Standard deviation(m)
KNN	6.44	6.84
Kalman Filter(KF)	5.81	4.07
Particle Filter(PF)	5.57	3.9
PF+Accelerometer	4.54	3.52
PF+Accelerometer+Map	4.30	2.80

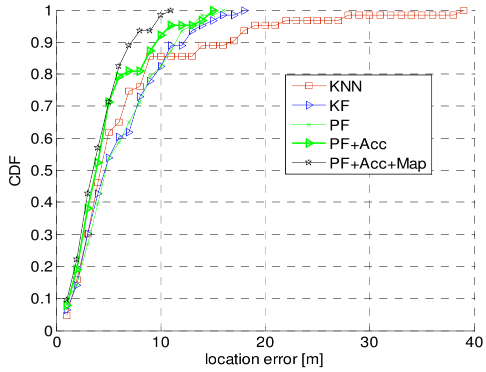


Fig. 7 CDF of Location Error of Real World Test

APPENDIX

TABLE II
PARAMETERS OF ALGORITHMS

	Simulation	Real World
KNN	K=7	
Kalman Filter	$Q=\begin{bmatrix}\frac{\Delta t^2}{2} & 0\\ 0 & \frac{\Delta t^2}{2}\\ \Delta t & 0\\ 0 & \Delta t\end{bmatrix}\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}\begin{bmatrix}\frac{\Delta t^2}{2} & 0\\ 0 & \frac{\Delta t^2}{2}\\ \Delta t & 0\\ 0 & \Delta t\end{bmatrix}^T (\mathrm{m}^2)$, $R=\begin{bmatrix}25 & 0\\ 0 & 25\end{bmatrix}(\mathrm{m}^2)$	
Particle Filter	$Q=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}(\mathrm{m}^2)$, σ=5m	
PF+Accelerometer	$\sigma_{acc}=0.5$m, σ=1m	$\sigma_{acc}=0.5$m, σ=0.5m
PF+Accelerometer+Map	$\sigma_{acc}=0.5$m, σ=1m	$\sigma_{acc}=0.5$m, σ=0.5m

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