PEDESTRIAN NAVIGATION BASED ON INERTIAL SENSORS, INDOOR MAP, AND WLAN SIGNALS

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ABSTRACT

As satellite signals, e.g. GPS, are severely degraded indoors or not available at all, other methods are needed for indoor positioning. In this paper, we propose methods for combining information from inertial sensors, indoor map, and WLAN signals for pedestrian indoor navigation. We present results of field tests where complementary extended Kalman filter was used to fuse together WLAN signal strengths and signals of an inertial sensor unit including one gyro and three-axis accelerometer. A particle filter was used to combine the inertial data with map information. The results show that both the map information and WLAN signals can be used to improve the pedestrian dead reckoning estimate based on inertial sensors.

Index Terms— Dead reckoning, Indoor environments, Kalman filters, Particle filters, Inertial navigation

1. INTRODUCTION

While GPS provides pedestrian positioning solution for outdoor environments, the optimal strategy for pedestrian indoor positioning is still an open issue, as the indoor environment severely degrades the accuracy of satellite positioning or makes it totally impossible. Several alternative information sources for pedestrian indoor positioning have been proposed. Microelectromechanical systems (MEMS) based sensors have been used to obtain dead reckoning estimate of the position, which is based on previous known position together with distance traveled and direction of travel [1, 2, 3, 4]. Relatively short range radio communication signals, such as WLAN or Bluetooth signals have been used to obtain indoor position estimates [5, 6, 7]. The use of map information is common practice in car navigation [8], and similar principles have also been proposed for indoor positioning [9].

All the mentioned approaches for indoor positioning have their strengths and weaknesses, and often a weakness of one system is strength of another, so that combination of several sources brings better performance than a single source alone. To combine information from several sources, a suitable data fusion algorithm is needed.

In this paper, we propose nonlinear Bayesian filters for fusing pedestrian dead reckoning (PDR) based on MEMS sensors with WLAN based positioning, indoor map information, or both. The sensor unit includes a heading gyro and a 3D-accelerometer. For the fusion of PDR with WLAN positioning we propose Complementary Extended Kalman Filter (CEKF). For the fusion of map information with other measurements, we propose a particle filter.

In many reports that consider indoor positioning, the field tests have been conducted in office environments consisting of corridors and rooms. We present results of field test conducted in a university library, where radio signal propagation pattern is different; there are few walls that totally block the signals while at the same time there are lot of obstacles that distort the signal propagation causing either non-line-of-sight conditions or strong signal attenuation. However, these obstacles provide lot of map information for data fusion algorithm. In the following sections we describe the models and algorithms and give positioning results based on real data from a pedestrian test walk.

2. INFORMATION SOURCES

The length of the distance traveled can be obtained by performing double integration of an accelerometer signal. Unfortunately, this approach suffers from unbound error growth due to, e.g., tilt errors of the sensor unit. In pedestrian navigation such errors can be avoided by using step detection algorithm and step length estimation based on accelerometer signal pattern [2, 3, 10].

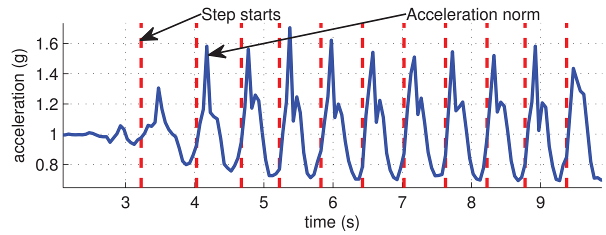
To avoid the effect of the tilt in the acceleration signal, we use the norm of the measured acceleration for step detection and step length estimation since the norm is insensitive to the orientation of the sensor unit. The procedure for step detection consists of the following steps: (1) Low pass filtering and resampling of the signal to the frequency of 20-50 Hz, (2) Computation of the norm of acceleration components, i.e. $a\left(t\right)=\sqrt{a_x\left(t\right)+a_y\left(t\right)+a_z\left(t\right)}$, (3) Detection of a step start when the acceleration norm crosses g (gravitational acceleration) so that it is followed by rise rate and peak height that exceed the preset limits, (4) Detection of a step end at the start of the next step or 0.9 s after the previous step start, which ever happens earlier. The use of acceleration norm for step detection is illustrated in Fig. 1(a).

To obtain the calibration parameters for presenting the step length as a function of step frequency [1], ten sets of walking data were collected in a straight corridor using an accelerometer triad. The straight leg of a known length was walked ten times. To obtain step samples with different step lengths, the walker tried to adjust the walking speed to normal, slower than normal, slow, faster than normal, and fast, as it is known that the step length is also a function of the walking speed [1]. With the data, the steps were detected from the acceleration norms and step intervals were determined. Using step intervals averaged over each walk, the number of detected steps per walk, and the known length of total traveled distance per walk, a linear fit can be found between average step frequencies and step lengths of each test data set, as shown in Fig. 1(b).

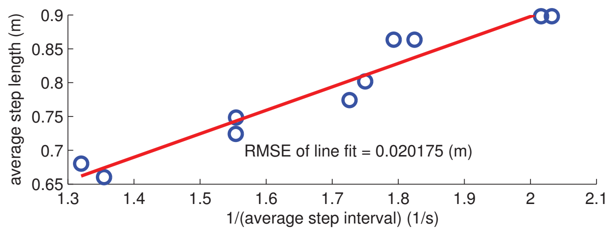
The sensor based PDR estimate is computed by starting from initial coordinates, x_0, y_0, and initial heading angle ψ_0. The heading and horizontal coordinates are propagated by

$$\begin{bmatrix} \psi_k \\ x_k \\ y_k \end{bmatrix} = \begin{bmatrix} \psi_{k-1}+\omega_k \Delta t_k \\ x_{k-1}+\Delta s_k \cos\psi_k \\ y_{k-1}+\Delta s_k \sin\psi_k \end{bmatrix} \tag{1}$$

where ω_k is the angular rate measurement by the gyro, Δs_k is the distance traveled on the step with index k, and Δt_k is the length



(a) Step detection based on acceleration norm.



(b) Step length calibration using test data sets. Observations shown with circles.

Fig. 1. Estimation of travelled distance

of the sample interval, which in this case is the same as the step interval; Δt_k varies according to the walking style and speed of the pedestrian.

The utilization of an indoor map for pedestrian navigation differs from the way street maps are used in car navigation. In car navigation, the roads represent the possible locations of the car, and the task of the positioning algorithm is to use some clever method to force the position estimate to the most probable road segment [8]. In indoor navigation, instead of defining possible routes the indoor map gives information about impossible locations and movements: the positioning algorithm uses information about walls and obstacles that the pedestrian is not able walk though [9]. These are presented by line segments defined by the coordinates of their starting and ending nodes.

WLAN signals can be used in several ways to estimate position. In this paper, we use WLAN fingerprinting [5, 11], where experimentally defined radio map is generated to locally model the relation between the user position and strengths of the WLAN signals received by the user. The implemented probabilistic estimation algorithm uses WLAN fingerprints which include histogram approximations of probability density functions of the WLAN signal strength [11].

3. PROPOSED ALGORITHMS AND MODELS

In this paper, we propose a complementary EKF (CEKF), i.e., an EKF implemented in complementary mode [12] for fusing PDR and WLAN positioning estimates; complementary filtering is useful in combining redundant measurement data. We propose a CEKF configuration where the filter uses PDR measurements to propagate the state of the filter and WLAN based position estimates as measurement updates of the filter.

A simple process model with errors modeled as white noise is applied, which does not require special error states; the elements of the state vector $\mathbf{x}_k$ are the following: x_1 = heading, x_2 = x-coordinate, and x_3 = y-coordinate, and therefore the state propagation resembles the dead reckoning presented in (1). The filter is started from initial estimate $\hat{\mathbf{x}}_0$ and initial covariance $\mathbf{P}_0$, which are set according to the best available estimate about the initial position and the uncertainty of the position information. The state is propagated by using

$$\hat{\mathbf{x}}_k^- = \hat{\mathbf{x}}_{k-1} + \begin{bmatrix} \omega_k \Delta t_k \\ \Delta s_k \cos \hat{x}_{1_{k-1}} \\ \Delta s_k \sin \hat{x}_{1_{k-1}} \end{bmatrix} \quad (2)$$

where $\hat{\mathbf{x}}_{k-1}$ denotes the posterior estimate after the measurement update using the $k-1$th measurement samples, while $\hat{\mathbf{x}}_k^-$ is the prior estimate for kth time step. The definitions of ω_k, Δs_k, and Δt_k are the same as in (1) and $\hat{x}_{1_{k-1}}$ is the previous posterior estimate of heading. The state matrix $\mathbf{F}_k$, needed for covariance propagation, is obtained by taking a partial derivative of (2):

$$\mathbf{F}_k = \begin{bmatrix} 1 & 0 & 0 \\ -\Delta s_k \sin \hat{x}_{1_k}^- & 1 & 0 \\ \Delta s_k \cos \hat{x}_{1_k}^- & 0 & 1 \end{bmatrix}. \quad (3)$$

As the effect of the step length uncertainty is multiplied by sin and cos functions of the heading, the state noise $\mathbf{Q}_k$ is also approximated on every propagation step:

$$\mathbf{Q}_k = diag\left(\begin{bmatrix} V_\omega \\ \cos^2\left(\hat{x}_{1_k}^-\right) V_{\Delta s} \\ \sin^2\left(\hat{x}_{1_k}^-\right) V_{\Delta s} \end{bmatrix}\right) \quad (4)$$

where V_ω is the variance of angular rate measurement and $V_{\Delta s}$ is the variance of step length estimate. The covariance propagation to obtain the prior covariance $\mathbf{P}_k^-$ is now

$$\mathbf{P}_k^- = \mathbf{F}_k \mathbf{P}_{k-1} \mathbf{F}_k^T + \mathbf{Q}_k, \quad (5)$$

where $\mathbf{P}_{k-1}$ is the posterior covariance from the previous time step. The measurement input of the filter is $\mathbf{z}_k = [x_{W_k}\ y_{W_k}]^T$, consisting of the x and y coordinates estimated using WLAN fingerprints, and measurement matrix is

$$\mathbf{H} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Now the equations for measurement update of state $\hat{\mathbf{x}}_k$ and covariance $\mathbf{P}_k$ are

$$\begin{aligned} \mathbf{K}_k &= \mathbf{P}_k^- \mathbf{H}^T \left(\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R}\right)^{-1} \\ \hat{\mathbf{x}}_k &= \hat{\mathbf{x}}_k^- + \mathbf{K}_k \left(\mathbf{z}_k - \mathbf{H}\hat{\mathbf{x}}_k^-\right) \\ \mathbf{P}_k &= \left(\mathbf{I}_{3x3} - \mathbf{K}_k \mathbf{H}\right) \mathbf{P}_k^- \end{aligned} \quad (6)$$

where $\mathbf{R}$ is the covariance of WLAN based coordinate estimates and $\mathbf{I}_{3x3}$ is identity matrix.

The map information about the walls and obstacles is difficult to formulate so that it could be applied with EKF. In particle filters, this kind of information can be taken into account easily: after each propagation step the algorithm can check whether the particles ended into obstacles or out of the room through the walls. If they did, their weight can be set to zero so that in the next resampling they will not survive.

In this paper, we propose a bootstrap particle filter [13] where the particles are propagated using the same equation (2) as with CEKF, except that now the noise components of angular rate measurement and step length estimate are simulated using a random number generator and then added to the particle states. The noise components are generated using the same variance values for angular rate and step length as were used in CEKF; also the likelihoods of the particles are evaluated using the same measurement variances for WLAN based x and y coordinate estimates that were used in CEFK.

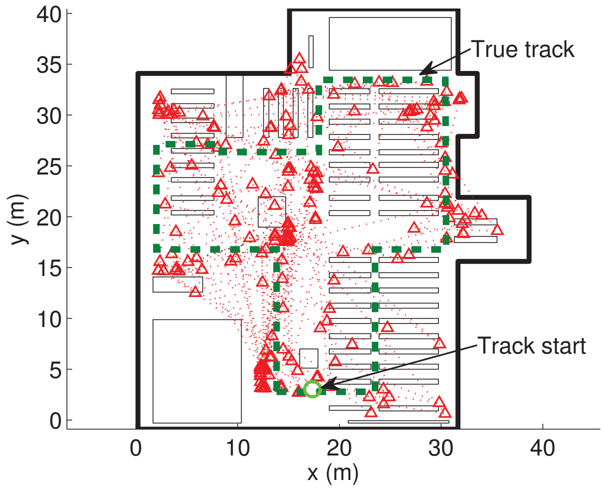


Fig. 2. WLAN based position estimates shown with triangles. Transitions between consecutive estimates shown with narrow dotted lines.

4. FIELD TESTS AND RESULTS

A test walk was conducted in the library of the Tampere University of Technology. The test route consisted of four loops in the library and it took 17 min to walk it. In the library only the outer walls totally block radio signals, but there are lot of book shelves that cause either strong attenuation or non-line-of-sight conditions for the radio signal propagation. On the other hand, as the book shelves are obstacles that the pedestrian cannot walk though they provide useful map information for the particle filter.

The inertial sensor unit used in pedestrian navigation test was a MEMS based sensor described in [14]. It includes an accelerometer triad and one gyro. In the test, the sensor unit was attached to the back of the test walker and aligned so that the sensitive axis of the gyro was vertical, i.e., it was able to measure heading changes.

The WLAN signal strengths were collected using a mobile handset, which outputs WLAN scan results at 2.3 s intervals. The position estimates computed from WLAN signal strengths that were collected along the test walk are shown in Fig. 2. From the figure we can see that the estimates are not evenly spread along the route, but rather concentrated in the center of the library area. The average position error is about 12 m.

The result of the unaided PDR estimate is shown in Fig. 3. It can be seen that during the first loop the traveled distance gets longer and the heading starts to get distorted. After the first loop, the three following loops seem to be quite similar in size and orientation. The maximum errors are 5 m in distance and 24° in heading angle.

The result of CEKF processing of the PDR and WLAN based position estimates is shown in Fig. 4. The CEKF was initialized with the same initial heading and coordinates as the unaided PDR estimate. It can be seen that CEKF can correct some of the skewness in PDR loops. The maximum errors can be estimated as 4 m in distance and 16° in heading.

In the first particle filter test, the filter was used to fuse PDR and map information, while in the second test, it was used to fuse also WLAN estimates with PDR and map information. The number of particles used in the tests was 500. The particle states were initial-

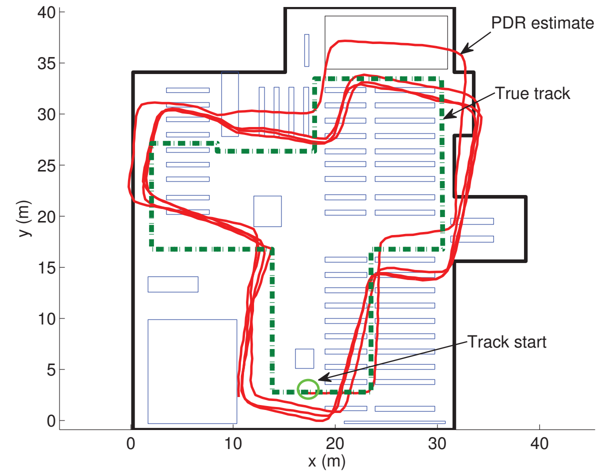


Fig. 3. Unaided pedestrian dead reckoning.

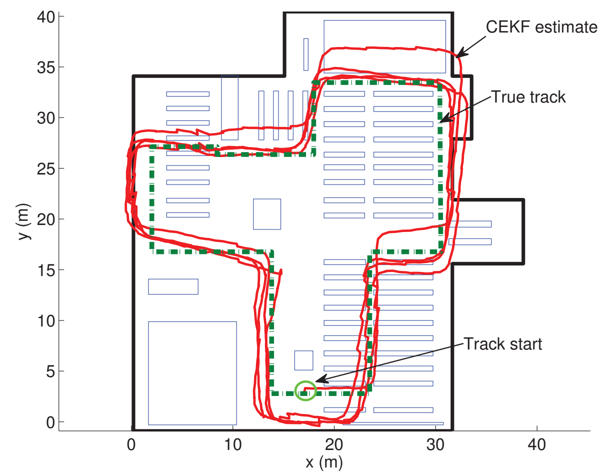


Fig. 4. Complementary EKF using PDR and WLAN data.

ized with the same initial values as the CEKF. The results of the tests are shown in Figures 5 and 6. The plotted particle filter track is the Minimum Mean Square Estimate (MMSE) computed from particle positions at each sampling instance. The maximum errors estimated are less than 3 m in distance and 12° in heading for both particle filters. However, the estimated track in Fig. 6 seems to follow the true track better than the track in Fig. 5, especially in upper and lower edges of the route. The reason for this can be seen in Fig. 2: there are many correct WLAN based position estimates available just before entering to these route segments, and therefore the WLAN estimates are able to improve the result.

5. CONCLUSIONS

In this paper, we proposed methods for combining information from inertial sensors, indoor map, and WLAN signals for pedestrian indoor navigation, and presented field test results obtained using the

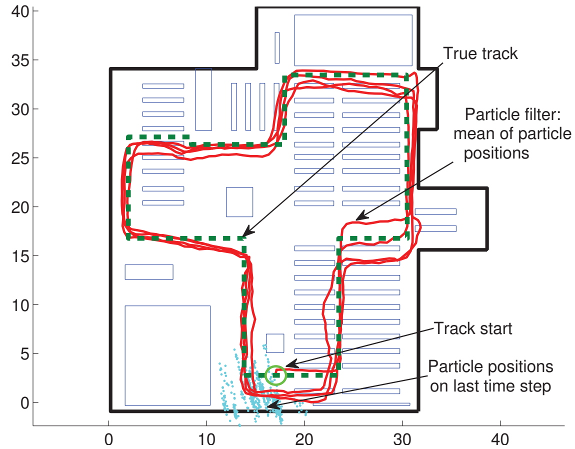


Fig. 5. Particle filter using PDR data and map information.

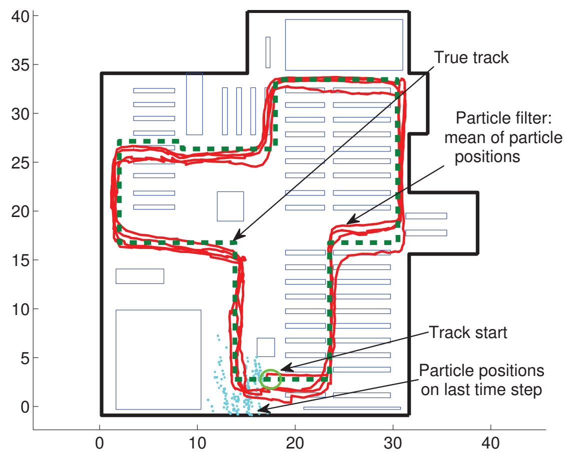


Fig. 6. Particle filter using PDR and WLAN data and map information.

proposed algorithms. For the fusion of the PDR with WLAN positioning we proposed complementary Extended Kalman Filter and for fusion of the map information with other measurements we proposed a particle filter.

The inertial sensor unit used in these tests performed relatively well even as an unaided PDR system. However, fusing it with either WLAN positioning or map information improves accuracy. The quality of the WLAN position data is quite poor. Still the WLAN based position estimate includes some useful information to the data fusion filter. The WLAN based positioning is also complementary with map information: map information is relatively useless in open areas, where walls and obstacles cannot guide the particles, while in areas with high density of obstacles this information is frequently available. Just the opposite, in areas dense with obstacles there is lot of disturbances present in WLAN signals which distort even a positioning algorithm using fingerprints, while in open areas the quality of WLAN based position estimate is better.

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