Development and Evaluation of a Combined WLAN & Inertial Indoor Pedestrian Positioning System

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BIOGRAPHY

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ABSTRACT

In this paper we have presented an indoor positioning system for pedestrians combining Wireless LAN fingerprinting with foot mounted inertial and magnetometer sensors. To achieve a system capable of real-time processing we have employed a hierarchical Bayesian filtering approach using cascaded extended Kalman filters. The accuracy of the combined system was quantitatively evaluated in a real building against ground-truth. Our results show that accuracy is much higher than using Wireless LAN fingerprinting alone; in our experiment we achieved a positioning error (standard deviation) of roughly 1.6 meters. The approach requires only minimal fingerprinting effort since the high accuracy is achieved by the support of the inertial-based step estimation in the overall estimation process.

1 INTRODUCTION

Reliable and accurate indoor positioning remains as one of the greatest challenges in the area of personal navigation. Outdoors, in areas of adequate visibility of GPS satellites, the use of dedicated portable navigation devices or cell phones and PDAs equipped with GPS receivers has increased dramatically over the last few years providing personal navigation in vehicles and also pedestrian navigation in cities and recreational environments.

The indoor environment is problematic for two reasons: firstly, the desired accuracy for meaningful location dependent services is often very much higher than outdoors; and secondly, the difficulty of GPS reception results in much greater deficiencies in accuracy and availability. Infrastructure based approaches are being used indoors, as well as additional sensors worn by the user. Infrastructure systems fall into two categories: dedicated wireless arrangement (for example the Cricket system [1] or Ubisense [2]), or adaptation/usage of existing communications infrastructure like Wireless LANs [3, 4, 5, 6]. In the majority of buildings in which people require personal navigation (e.g. to be guided to a certain room or office) there now exists a dense installation of WLAN infrastructure, often operated by different operators, for example in airports, public buildings, and company premises.

In order to achieve truly ubiquitous personal positioning and navigation indoors, we believe a successful approach will need to be *as autonomous as possible*, requiring a minimal amount of additional standardization and dedicated infrastructure, whilst building on the rapid advances in portable data processing and sensors. Additionally, techniques where the location is actually computed partially or fully in the infrastructure will always remain questionable in terms of privacy considerations.

In this paper we will present a novel approach that combines an existing WLAN infrastructure with a simple inertial and magnetometer sensor suite mounted on the shoe of the pedestrian user. The goal is to obtain and process all the sensor data locally, and *without any need of registration with the local infrastructure*. Since we will employ WLAN fingerprinting based on the signal power (e.g. [7]), the only information needed at the local device will be a fingerprinting database for the local building, which can be maintained and distributed by an entity independent of the local wireless infrastructure domain. The goal is to use as few calibration locations as possible and to rely on the short-term accuracy of foot mounted inertial dead-reckoning (for instance Zero Update based techniques, [8]) "in between" these points. The role of the WLAN positioning here is therefore to provide long term accuracy in the area of interest. In contrast, in the work of Woodman et al. [9] very coarse WLAN positioning was only used to reduce the initial ambiguities of map aided inertial navigation. Suitable (approximate) Bayesian sensor fusion algorithms provide a close-to-optimal estimate of the position that can be efficiently implemented on the end-user's device. The work in [10] describes how fingerprinting can be simplified by using an INS (not foot mounted) during calibration and how actual performance is enhanced during positioning. Our approach using a foot mounted *Inertial Navigation System (INS)* will perform better in situations where WLAN positioning is not available for any significant length of time during which a standard INS approach (no foot mounting; no zero update) would drift too far. This also applies to the work of [11] in which no true 6-degrees-of-freedom ZUPT based inertial processing was performed, but only stride estimation (angular change and stride detection). Furthermore, the particle filter used in [11] relied on a known building layout. The use of WLAN fingerprinting fulfills the requirement of needing no association with the actual access points and is relatively energy efficient. Importantly, the scheduling of the WLAN receiver's duty cycle can in principle be controlled by the fact that the user's motion can be detected from the foot mounted sensors - meaning that WLAN reception is only needed when the user is walking. The fingerprinting itself is a very simple process, requiring measurement of the available WLAN stations approximately every 5 meters that each lasts just a few seconds. The large rectangular office floor used in our actual experiments was thus added to the database in a matter of minutes. Finally, we must add that estimation of the *orientation* of the user is important for any real-time navigation service. This is very difficult without the use of additional sensors such as the ones proposed in this paper.

Our work presents both the pre-processing of the WLAN and dead-reckoning sensors (Sections 2 and 3) as well as theoretical basis for the overall sensor fusion (Section 4). We have adopted a hierarchical approach whereby the inertial system is processed by its own Bayesian filter to estimate individual steps of the user; these estimates are then combined with the estimate of the location from fingerprinting. This decoupling [12] allows the estimation filters to run at their local sampling rates and reduces overall complexity without suffering from significant loss of final estimation accuracy; this coupling of two Kalman filters in this context is novel to the authors' knowledge. The software and hardware implementation of our real-time positioning system is described in Section 5, along with a quantitative evaluation of positioning accuracy that was tested against ground-truth locations. We achieved results that are as accurate as those in [11], but we did not need maps and use a system that has inherently lower complexity.

Our Bayesian estimation algorithms were in fact integrated in a larger context management framework that schedules and gathers sensors' inputs and triggers the pluggable estimation processes. This will allow additional sensors to be readily added in the future. The resulting system was shown to provide sufficient accuracy to allow a particular office to be found by the user. The paper concludes with recommendations for extensions and directions of further work in Section 6.

2 WLAN POSITIONING

There are two primary methods for location determination from Wireless LAN [13, 14] based around Received Signal Strength Indicators (RSSI). One method is based on propagation models, using estimated degradation of signal strength over distance in space from the known location of access points and transmit power - typically using an indoor modelled as established by the COST 231 standards [15], these calculated distances are then typically used to estimate a location through trilateration [4]. The other is empirical, relying on storing pre-recorded calibration data in order to generate an RF map of a building [16, 3, 17, 18]. The location of a Mobile Station (MS) can be estimated by correlating its RSSI measurements with the RF-map constructed, from here on this method shall be called 'Location Fingerprinting'.

Location Fingerprinting requires time to train, and results can be dependant on the time of training as obstructions created by differing numbers of people can affect calibration sample data, however wireless infrastructure information, such as the exact location of the BSs/APs, is not required. Only the reference location of the RSS samples collected during the RF-map construction is needed. Furthermore, fingerprinting can operate using only one active BS/AP - but it will likely produce poor results over large areas. The main drawback of this method is that generation and maintenance of the RF-map is time-consuming and expensive when performed over wide areas, but it typically results in higher accuracy over deterministic methods. Furthermore, location fingerprinting algorithms can be classified into two main categories: deterministic and probabilistic. Deterministic algorithms are using a set of constant location fingerprints, which includes mean vectors and standard deviation vectors of RSSI. Probabilistic algorithms (as used for WLAN location estimation herein) model the location calibration points with RSSI probability distributions.

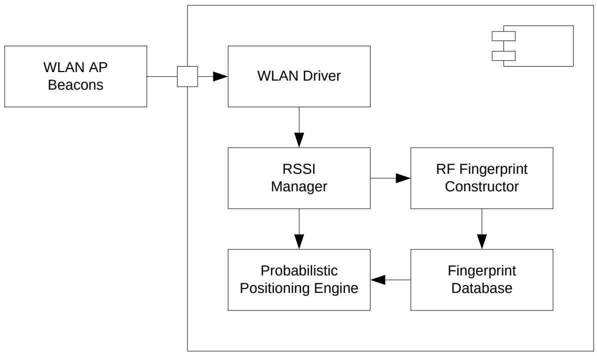

Figure 1. System overview of the WLAN fingerprinting subcomponent

The system has two phases of operation, a calibration phase, and a location calculation phase, which can be initiated after calibration. During the calibration phase a database of location fingerprints is established using RSSI measurements, at a number of calibration points, each referenced to a physical location. This can be seen in Fig. 1, with the RSSI Manager collecting readings from the WLAN driver, and processing this information to establish a fingerprint, which is then stored into the fingerprint database. This process is then repeated until calibration points have been set for the entire area of interest. The more calibration points used, the greater the accuracy of the system. However if calibration points are place too close together, such that there is little difference between RSSI variation of access points, i.e. they have very similar fingerprints, little advantage is gained, and training time becomes infeasible for large areas. In the positioning phase, continual scans from the wireless driver are processed by the RSSI manager. These readings are passed directly through to the positioning engine, which calculates a distance for each of the calibration points, comparing each one to the observed readings. The distance for each calibration point is defined by the following equation:

$$\mathbf{D_p} = \sum_{\mathbf{i}} \sum_{\mathbf{j}} |(\mathbf{x_{ir}} - \mathbf{x_{ij}})\mathbf{p_{ij}}| \tag{1}$$

where x_{ir} is the observed RSSI for the access point i, x_{ij} is the recorded RSSI stored in the fingerprinting database, and p_{ij} is the probability of measuring the reading at the given calibration point. Summing over all access points, then gives a distance calculation for each calibration point denoted $\mathbf{D_p}$. The results are collated, and the minimum distance is taken as the location estimation. To increase stability of the given location, a best-of-three approach is used to establish the estimated location. If no dominant location is determined, the latest estimate is returned as the current location.

3 INERTIAL NAVIGATION FOR PEDESTRIANS

The use of inertial sensors is becoming widespread for pedestrian navigation, especially for indoor applications. Basically two approaches can be distinguished. The pedometer-approach employs an accelerometer for detecting individual steps whilst the stride length and stride direction are themselves estimated using additional sensors, such as global navigation satellite systems (GNSS), or a priori information. Given a detected step, its length and its direction, a person's position can be determined by dead-reckoning [19, 20, 21]. Other methods have been studied in [22]. The latest approaches are based on full six degree of freedom (6DOF) inertial navigation. A foot-mounted 6DOF strapdown inertial platform comprising triads of accelerometers and gyroscopes is used to dead reckon via a conventional strapdown navigation algorithm. An Extended Kalman filter (EKF) runs in parallel to the strapdown algorithm. Rest phases of the foot, which are detected from the accelerometer signals, trigger zero-velocity (virtual) measurements that are used to update the filter (ZUPT). Due to the regular ZUPT measurements we can estimate and correct the drift errors, which accumulate in the strapdown solution [8, 23, 24, 25]. It was shown in [8] that this *pedestrian dead-reckoning (PDR)* approach can achieve very good performance even with today's low-cost micro-electro-mechanical (MEMS) sensors, because the ZUPTs are so frequent that errors build up only slowly during each step the pedestrian makes.

The benefit of combining foot-mounted inertial sensors with nonlinear map-matching techniques or additional nonlinear / non-Gaussian sensors typically used in an indoor scenario has been revealed in [26] and [27]. Comparable results were shown for a 2.5 D environment in [9]. The benefit of integrating a pair of platforms that are mounted on each of the pedestrians' feet respectively has been studied in [12]. In these sensor fusion approaches foot displacement and heading change values from the foot's PDR filter are computed at each step and are exploited as measurements within a higher-level main fusion filter. In the following the details of the inertial PDR filter are addressed.

3.1 ALGORITHM FUNDAMENTALS

A strapdown navigation algorithm [28] processes the vector of acceleration and turn rate measurements $\mathbf{z}_l = [\mathbf{a}_l \ \boldsymbol{\omega}_l]^T$, which is provided by the inertial sensors, to compute position $\mathbf{r}_l$, velocity $\mathbf{v}_l$, and attitude $\boldsymbol{\Psi}_l$. In parallel an EKF is used to estimate the errors of the strapdown calculations [29]. In our simple implementation 9 states are estimated by the filter: position errors $\delta\mathbf{r}_l$, velocity errors $\delta\mathbf{v}_l$ and attitude errors $\delta\boldsymbol{\Psi}_l$. In a more elaborate estimation one could also estimate accelerometer biases $\delta\mathbf{a}_l$ and gyroscopic biases $\delta\boldsymbol{\omega}_l$. Additionally, our implementation incorporates a magnetometer to align and stabilize the heading as an additional measurement. Hence the inertial filter provides estimates of position, velocity, and attitude in terms of a Gaussian *Probability Density Function (PDF)*. In the subsequent processing only position and heading are states of interest:

$$\mathbf{x}_l = \begin{pmatrix} \mathbf{r}_l \\ \Psi_l \end{pmatrix} , \tag{2}$$

where Ψ_l is the yaw angle derived from $\boldsymbol{\Psi}_l$. From the posterior PDF of the inertial filter the (marginalized) posterior $p(\mathbf{x}_l|\mathbf{z}_l, \ldots, \mathbf{z}_0)$ can be derived straightforward.

3.2 REST PHASE DETECTION

The reliable identification of the foot's rest phases is crucial for the update of the PDR filter. Different approaches have been proposed to trigger the ZUPT measurement [8], [23]. Here we basically follow these ideas and monitor the magnitude of the acceleration vector, which is sensed by the accelerometer triad. If the signal remains within a threshold interval around earth acceleration for a certain time interval ZUPTs are triggered until the threshold condition is violated.

3.3 THE STEP SENSOR

The inertial filter is used to process the high rate inertial measurements. To exploit them in a further main fusion filter a (virtual) step sensor is derived from the output of the inertial filter, which provides a measure of the traveled distance and the change in heading for each step the pedestrian makes, see Fig. 2. To provide the step measure the following operations need to be performed: Each time a new ZUPT is triggered the expectation of the inertial filter $\hat{\mathbf{x}}_l$ is stored in the variable $\hat{\mathbf{x}}_L \widehat{=} \hat{\mathbf{x}}_l$. Introducing the step displacement variable $\Delta\mathbf{x}_L = \mathbf{x}_L - \mathbf{x}_{L-1}$ we may write for the displacement with respect to the coordinate system of the inertial filter

$$\begin{aligned} \Delta\hat{\mathbf{x}}_L &= \hat{\mathbf{x}}_L - \hat{\mathbf{x}}_{L-1} \\ &= \begin{pmatrix} \Delta\hat{\mathbf{r}}_L \\ \Delta\hat{\Psi}_L \end{pmatrix} \ . \end{aligned} \quad (3)$$

As final step measure the displacement with respect to the

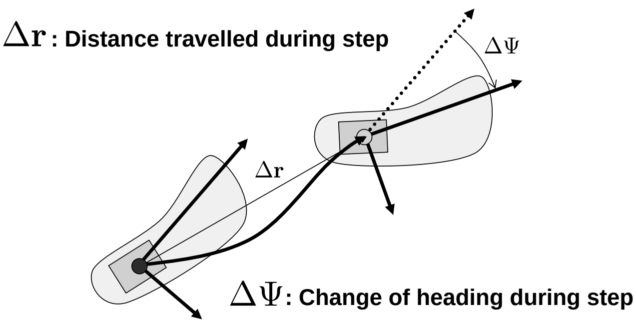

Figure 2. The INS is used to calculate an estimate of the pedestrian's step in the form of a foot displacement vector.

heading before the step is computed and we have

$$\Delta\mathbf{x}_k = \begin{pmatrix} \mathbf{C}^T(\Psi_\varepsilon)\mathbf{C}^T(\hat{\Psi}_{L-1})\Delta\hat{\mathbf{r}}_L \\ \Delta\hat{\Psi}_L \end{pmatrix} \ , \quad (4)$$

with

$$\mathbf{C}(\bullet) = \begin{pmatrix} \cos(\bullet) & -\sin(\bullet) \\ \sin(\bullet) & \cos(\bullet) \end{pmatrix} \ . \quad (5)$$

The average heading misalignment of the inertial sensor platform with respect to the pedestrian's heading is given by the angle Ψ_ε, which has to be fixed initially.

4 JOINT SENSOR DATA FUSION

The objective in our system is now to integrate the WLAN-fingerprinting with the inertial step-sensor. This is done via a main integration filter, in which we keep track of the pedestrians position $\mathbf{r}_k$ and her heading Ψ_k. The overall signal processing is illustrated in Figure 3. The state vector can thus be written as

$$\mathbf{x}_k = \begin{pmatrix} \mathbf{r}_k \\ \Psi_k \end{pmatrix} \ . \quad (6)$$

To alleviate the incorporation of the step-sensor we furthermore consider the change in position $\Delta\mathbf{r}_k$ and the change in heading $\Delta\Psi_k$ per each step the pedestrian makes through the step measure

$$\Delta\mathbf{x}_k = \begin{pmatrix} \Delta\mathbf{r}_k \\ \Delta\Psi_k \end{pmatrix} \ . \quad (7)$$

4.1 MOVEMENT MODEL

The movement model is used to characterize the temporal evolution of the state $\mathbf{x}_k$ in order to reflect the physical constraints that are imposed on the movement of a pedestrian. In particular in an indoor environment this may include also any restrictions which are imposed by the building layout. The benefit of this approach was shown in [26], [27]. Nevertheless in our application scenario the building layout is not known. Hence formally, the new state $\mathbf{x}_k$ is assumed to depend only on the previous state $\mathbf{x}_{k-1}$, the current step-measure $\Delta\mathbf{x}_k$ and a noise term $\mathbf{n}_s$:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \Delta\mathbf{x}_k, \mathbf{n}_s) \ , \quad (8)$$

where we have chosen that the new location and heading depend on the past state and on the step-measure through

$$\begin{aligned} \mathbf{r}_k &= \mathbf{r}_{k-1} + \mathbf{C}(\Psi_{k-1})\Delta\mathbf{r}_k + \mathbf{n}_{s,r} \ , && (9) \\ \Psi_k &= \Psi_{k-1} + \Delta\Psi_k + n_{s,\Psi} \ , && (10) \end{aligned}$$

where $\mathbf{C}(\Psi_{k-1})$ is the rotation matrix given in (5). The noise processes $\mathbf{n}_s = [\mathbf{n}_{s,r}^T, n_{s,\Psi}]^T$ and $\mathbf{n}_{s,r} = [n_{s,x}, n_{s,y}]^T$ are zero-mean uncorrelated Gaussian noise processes of variance $\sigma_{s,x}^2$, $\sigma_{s,y}^2$, and $\sigma_{s,\Psi}^2$ respectively, which are adjusted to reflect the uncertainty of the step-measure.

4.2 MEASUREMENT MODEL

The position estimate obtained by the WLAN fingerprinting filter is used as an position measurement $\mathbf{z}_k$ in the main integration filter and is assumed to depend only on the current state $\mathbf{x}_k$ and a noise term $\mathbf{n}_\Delta$:

$$\mathbf{z}_k = h(\mathbf{x}_k, \mathbf{n}_w) \ . \quad (11)$$

In particular we assume

$$\mathbf{z}_k = \mathbf{r}_k + \mathbf{n}_w \ , \quad (12)$$

with $\mathbf{n}_w = [n_{w,x}, n_{w,y}]^T$ being zero-mean uncorrelated Gaussian noise. The respective variances $\sigma_{w,x}^2$ and $\sigma_{w,y}^2$ are adjusted to reflect the uncertainty of the WLAN-fingerprinting-based position estimate.

4.3 FILTER DESIGN

Since we do not make use of the building layout or further sensors there is no need to incorporate any further nonlinear constraints than the one given by (9). But this relation

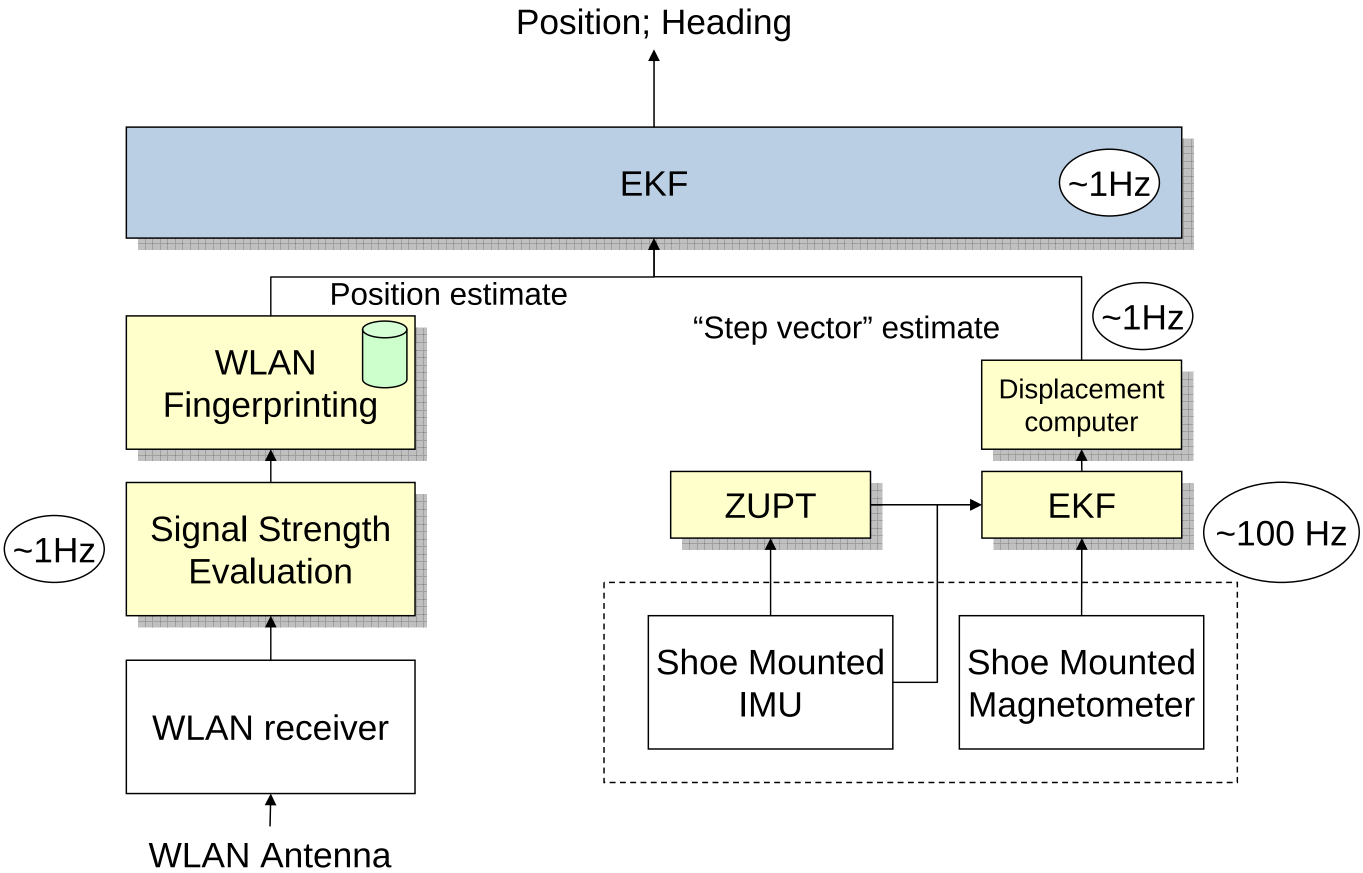

Figure 3. This figure shows the complete system with two layers of processing: a lower one for the WLAN position estimate and step computation which are then fused in an upper EKF

is rather moderate with respect to nonlinarity and thus an Extended Kalman filter (EKF) [30] is adequate to implement our main integration filter, in particular as all relevant noise sources are Gaussian. We may now follow straighforward the well known implementation of the EKF: Given the initial mean $\mathbf{x}_0 = \bar{\mathbf{x}}_0$ and the associated intial covariance $\mathbf{P}_0 = \bar{\mathbf{P}}_0$ we compute at each filter iteration in the *prediction step* recusively the parameters of the Gaussian prior PDF, which are mean

$$\hat{\mathbf{x}}_k^- = f(\hat{\mathbf{x}}_{k-1}, \Delta\mathbf{x}_k, \mathbf{0}) \ , \tag{13}$$

and covariance

$$\mathbf{P}_k^- = \mathbf{\Phi}_k \mathbf{P}_{k-1} \mathbf{\Phi}_k^T + \mathbf{Q}_k \ , \tag{14}$$

where the Jacobian of the system dynamics is given by

$$\begin{aligned} \mathbf{\Phi}_k &= \left. \frac{\partial f(\mathbf{x}_{k-1}, \Delta\mathbf{x}_k, \mathbf{0})}{\partial \mathbf{x}_{k-1}} \right|_{\mathbf{x}_{k-1}=\hat{\mathbf{x}}_{k-1}} \\ &= \begin{pmatrix} 1 & 0 & g_1 \\ 0 & 1 & g_2 \\ 0 & 0 & 1 \end{pmatrix} \ . \end{aligned} \tag{15}$$

The terms g_1 and g_2 are the respective elements of the vector

$$\mathbf{g} = \mathbf{C}'(\Psi_{k-1})\Delta\mathbf{r}_k \ , \tag{16}$$

where the derivative of the rotation matrix is

$$\mathbf{C}'(\Psi) = \frac{\mathrm{d}\mathbf{C}(\Psi)}{\mathrm{d}\Psi} \ . \tag{17}$$

In the subsequent *update step* the parameters of the Gaussian posterior PDF are computed recursively at each iteration. The posterior mean computes with

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k \left(\mathbf{z}_k - h(\hat{\mathbf{x}}_k^-, \mathbf{0})\right) \ , \tag{18}$$

and the posterior covariance with

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)\mathbf{P}_k^- \ , \tag{19}$$

where the Kalman gain is given by

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}\mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1} \ , \tag{20}$$

with the Jacobian of the measurement equation

$$\begin{aligned} \mathbf{H}_k &= \left. \frac{\partial h(\mathbf{x}_k^-, \mathbf{0})}{\partial \mathbf{x}_k^-} \right|_{\mathbf{x}_k^- = \hat{\mathbf{x}}_k^-} \\ &= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \ . \end{aligned} \tag{21}$$

For the other matrices we have

$$\mathbf{R}_k = \mathrm{diag}([\ \sigma_{w,x}^2 \quad \sigma_{w,y}^2\ ]) \ , \tag{22}$$

$$\mathbf{Q}_k = \mathrm{diag}([\ \sigma_{s,x}^2 \quad \sigma_{s,y}^2 \quad \sigma_{s,\Psi}^2\ ]) \ . \tag{23}$$

5 IMPLEMENTATION AND EVALUATION

5.1 TEST ENVIRONMENT

To test the presented system, we chose an university building. It is equipped with eleven WiFi access points on one

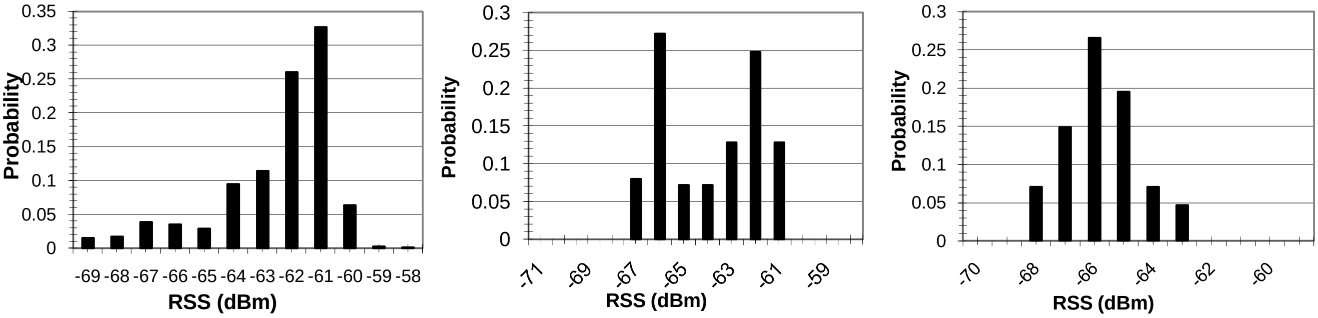

Figure 5. Example PDFs of One Calibration Point for Different Access Points

floor as can be seen (black dots) in Fig. 4, for public internet access, as well as for research purposes in the labs. Detection of different offices and rooms was expected to be fairly easy by WiFi fingerprinting as infrastructure (in particular walls) should produce a significantly different fingerprint than in other rooms. So we concentrated for testing on a circular walk (4 laps) in the hallway. We were provided with a floor plan whose coordinates in pixels were used as absolute position with a known conversion factor to meters.

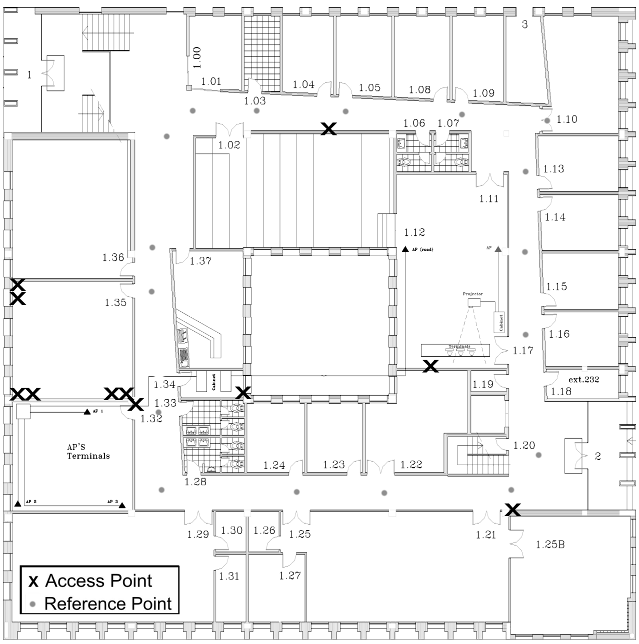

Figure 4. Floor plan of the test building with eleven Access Points (black crosses) and 17 reference points (grey dots)

Fingerprinting calibration points were taken approximately every $2.5\ m$ and were in the corridor, with signal strength readings being taken once per second. Measurements were taken by holding a laptop at a fixed height (approx. $1.2\ m$), with slight motion to build up a PDF over a small region. A sample size of 60 was used for each calibration point. At each point, a minimum of three access points are always recorded. An example of the output for a single calibration point for three particular access points can be seen in Fig. 5. The calibration point was defined by clicking on a floor plan to designate the physical location.

For the evaluation we defined 17 reference points on the floor plan and marked them on the floor of the building, which were followed then precisely.

5.2 IMPLEMENTATION

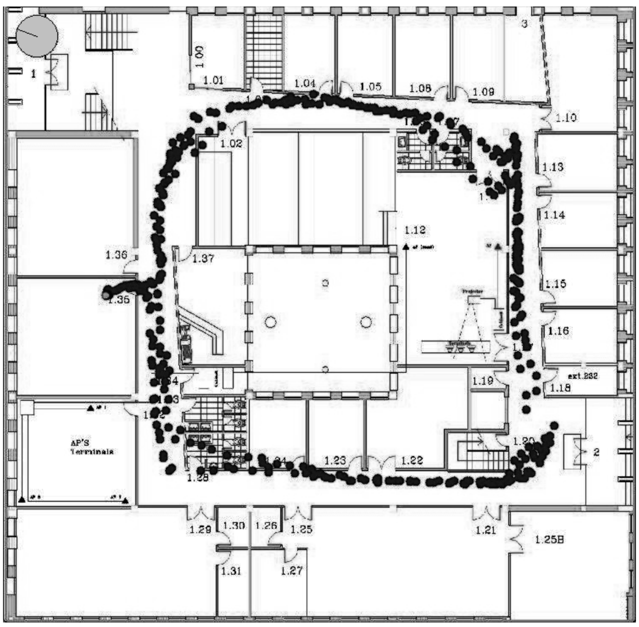

Figure 6. Visualisation of recorded track

The implementation of the positioning system was realised in the three separate part systems we explained in the last sections and installed on two laptops. They communicated in Client-Server mode as both sensor connections were implemented in `C` while the higher level Kalman filter was implemented in `Java`, as well as a visualisation application. Laptop 1, with a Windows OS (for driver reasons), implemented the INS connection and the low level filter and the client part of the connection. Laptop 2 was running Linux with two wireless network cards for the Fingerprinting part. One network card was used for scanning to ensure consistent results during the training stage, and to allow channel hopping without disrupting network communications. A second wireless card was used to send real time location updates to other displays for live presentation of data. Furthermore, Laptop 2 had the connection server implemented in Java, which fed the Kalman filter with the newest measurements. The fusion filter, after calculating a new position, stores it in a file and passes it in addition to the visualisation application, also on Laptop 2. Its output can be seen in Fig. 6. To reduce network related delays, both laptops were connected by an ethernet cable throughout the walk.

In order to be able to evaluate properly the data, all data together with their timestamp (in milliseconds) were recorded. Raw INS output on Laptop 1, input (from fingerprinting and low level filter) and output of the sensor fusion on Laptop 2. During the test walk furthermore we recorded the timestamps when we passed the reference points marked on the floor. Those data were used then for the evaluation presented in the following subsection.

5.3 EVALUATION

Evaluation goals were to:

- determine the accuracy of the WLAN standalone approach in our configuration,
- determine the accuracy of the fused position
- compare both approaches.

To evaluate the gathered data, we compared the pedestrian's position calculated with WLAN and the fused position at one point in time with the known, absolute position at that moment. Our measure for the accuracy was the absolute distance (line of sight) of the calculated position to the reference point in meters. Fig. 5.3 (left) shows those results for each of the 49 recorded points. Results for WLAN standalone are presented by the dashed line, the fused position error is shown with the complete line. It is obvious that the fused result is influenced strongly by the WLAN result, in particular with regards to the fingerprinting "errors", when wrong sample points were identified as current position and hence the error was particularly high. From both techniques we calculated the arithmetic mean error for our test track:

- 3.1777 meters for pure WLAN fingerprinting
- 1.6468 meters for the fusion of fingerprinting and shoe data.

All in all the fused result is more stable than the fingerprinting approach: the INS is preventing big jumps that are possible with pure fingerprinting. Using INS alone would lead to significant drift over time with increasing errors. Therefore it is not a sensible stand alone approach and therefore not evaluated specifically. On the other side fingerprinting partially provides very good results - when the absolute reference points were very close to correctly detected fingerprinting sample points. This can be also seen in the right picture of Fig. 5.3, that shows the cumulative probability distribution: Fingerprinting provides more than 20% of errors below half a meter, but also 20% of errors over 4 meters - which appear in the fused results only with a frequency below 5%. It can be seen that the majority of the calculated errors of the fusion lie around one meter.

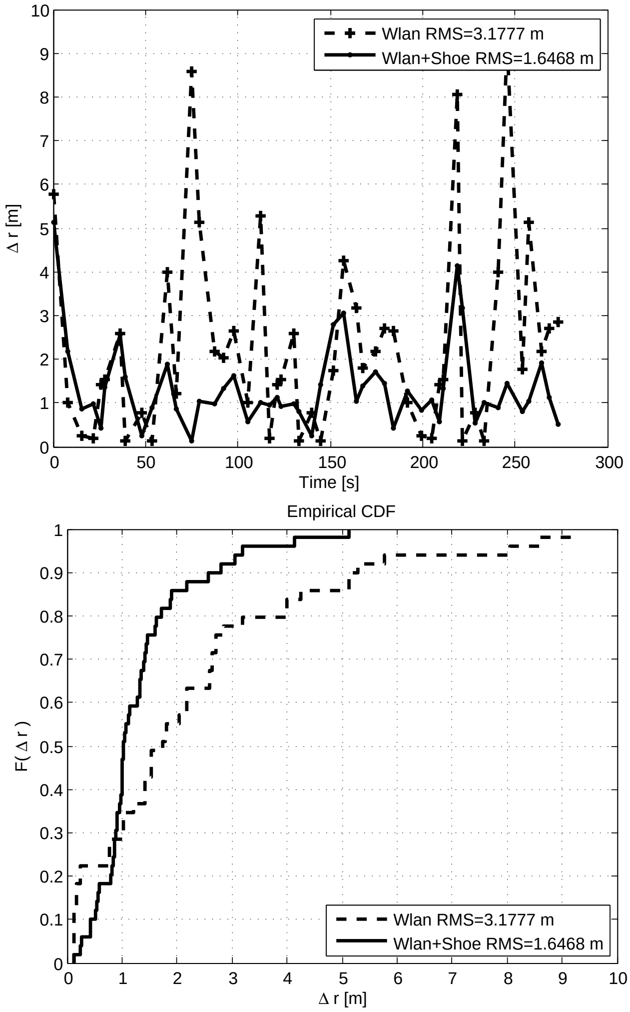

Figure 7. Position error distribution over walking time (left) and cumulative probability distribution (right)

6 CONCLUSIONS

In this paper we have presented an indoor positioning system for pedestrians combining WLAN fingerprinting with foot mounted inertial and magnetometer sensors. The approach requires no processing outside of the local device and minimal a-priori fingerprinting effort. We have employed a hierarchical Bayesian filtering approach using cascaded extended Kalman filters to achieve a real-time implementation. The accuracy of the combined system was quantitatively evaluated in a real building and shows that it is much higher than that of the fingerprinting alone; in addition it also provides an estimate of the orientation of the user.

Further work should focus on an extension to three dimensions as well as investigating different building layouts. Additionally, other sensors could be incorporated, as well as information of the floor plan, as in [26, 9, 12], or pseudorange measurements from GPS. Such additional information might mandate the use of other algorithms for the upper fusion layer, such as Sequential Monte Carlo (SMC) techniques (i.e. particle filters).

From a practical perspective, scheduling of the WLAN fingerprinting receiver triggered by the estimator could save required power usage, and an investigation of the tradeoff between different densities of fingerprinting and accuracy could guide the necessary calibration effort. Also, WLAN base stations are sometimes relocated, and the radio propagation may change, after calibration. An approach that uses the current estimate of users' positions to perform incremental adaptation of the fingerprinting could in future address these issues. It will also be valuable to gauge how much the fingerprinting effort can be reduced while still maintaining reliable positioning.

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REFERENCES

[1] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system." in *Proc. of the Sixth Annual ACM International Conference on Mobile Computing and Networking (MOBICOM) 2000*, Aug. 2000.

[2] Pete Steggles, "The ubisense smart space platform; a ubisense white paper," Ubisense, Tech. Rep., May 2005.

[3] V. Zarimpas, B. Honary, and M. Darnell, "Indoor 802.1x based location determination and real-time tracking," in *The IET International Conference on Wireless, Mobile and Multimedia Networks (ICWMMN 2006)*, Hang Zhou, China, November 2006.

[4] A. Kotanen, M. Hännikäinen, H. Leppäkoski, and T. D. Hämäläinen, "Positioning with IEEE 802.11b wireless lan," in *Personal, Indoor and Mobile Radio Communications, 2003. PIMRC 2003. 14th IEEE Proceedings on*, vol. 3, 2003, pp. 2218– 2222.

[5] T. Roos, P. Myllymäki, H. Tirri, P. Misikangas, and J. Sievänen, "A probabilistic approach to wlan user location estimation," *International Journal of Wireless Information Networks*, vol. 9, pp. 155–164, 2002.

[6] I. J. Quader, B. Li, W. (patrick Peng, and A. G. Dempster, "Use of fingerprinting in wi-fi based outdoor positioning," 2007.

[7] M. Ocana, L. Bergasa, M. Sotelo, J. Nuevo, and R. Flores, "Indoor robot localization system using wifi signal measure and minimizing calibration effort." in *Proceedings of the IEEE International Symposium on Industrial Electronics, 2005.*, Jun. 2005, pp. 1545–1550.

[8] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Computer Graphics and Applications*, vol. 25, no. 6, pp. 38–46, Nov. 2005.

[9] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proceedings of the 10th International Conference on Ubiquitous Computing, UbiComp 2008*, Seoul, South Korea, Sep. 2008, pp. 114–123.

[10] J. Seitz, L. Patiño-Studencka, B. Schindler, S. Haimerl, J. G. Boronat, S. Meyer, and J. Thielecke, "Sensor data fusion for pedestrian navigation using wlan and ins." in *Proc. of Gyro Technology Symposium 2007*, Sep. 2007.

[11] F. Evennou and F. Marx, "Advanced integration of WIFI and inertial navigation systems for indoor mobile positioning," *EURASIP J. Appl. Signal Process.*, pp. 164–164, January 2006.

[12] B. Krach and P. Robertson, "Cascaded estimation architecture for integration of foot-mounted inertial sensors," in *Proceedings of the 2008 IEEE/ION Position, Location, and Navigation Symposium, PLANS 2008*, Monterey, California, USA, May 2008.

[13] ISO/IEC 8802-11, "Wireless lan medium access control (MAC) and physical layer (PHY) specifications," 1999.

[14] IEEE Std 802.11b-1999, "Supplement to IEEE 802.11 standard, higher-speed physical layer extension in the 2.4 GHz band," 1999.

[15] COST, "Action 231, digital mobile radio towards future generation systems, (final report)," in *Office for official publications of the European Communities*, 1999.

[16] V. Zarimpas, B. Honary, D. Lund, C. Tanriover, and N. Thanopoulos, "Location determination and tracking using radio beacons," in *3G 2005*, The IEE, Savoy Place, London, November 2005, pp. 207–211, iSBN 0-86341-572-5.

[17] M. A. Youssef, A. Agrawala, and A. U. Shankar, "Wlan location determination via clustering and probability distributions," in *In IEEE PerCom 2003*, 2003.

[18] P. Bahl and V. N. Padmanabhan, "Radar: An in-building RF-based user location and tracking system," in *INFOCOM (2)*, 2000, pp. 775–784. [Online]. Available: http://citeseer.ist.psu.edu/bahl00radar.html

[19] V. Gabaglio and B. Merminod, "Real-time calibration of length of steps with GPS and accelerometers," in *Proceedings of the ENC GNSS 1999*, Genova, Italia, Oct. 1999, pp. 599–605.

[20] Q. Ladetto, "On foot navigation: continuous step calibration using both complementary recursive prediction and adaptive Kalman filtering," in *Proceedings of the 13th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GPS 2000*, 2000.

[21] J. Collin, O. Mezentsev, and G. Lachapelle, "Indoor positioning system using accelerometry and high accuracy heading sensors," in *Proceedings of the 16th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GPS/GNSS 2003*, Portland, Orgeon, USA, Sep. 2003.

[22] D. Kubrak, C. Macabiau, and M. Monnerat, "Performance analysis of MEMS based pedestrian navigation systems," in *Proceedings of the 18th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GNSS 2005*, Long Beach, California, USA, Sep. 2005.

[23] S. Godha, G. Lachapelle, and M. E. Cannon, "Integrated GPS/INS system for pedestrian navigation in a signal degraded environment," in *Proceedings of the 19th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GNSS 2006*, Fort Worth, Texas, USA, Sep. 2006.

[24] S. Beauregard, "Omnidirectional pedestrian navigation for first responders," in *Proceedings of the 4th Workshop on Positioning, Navigation and Communication, 2007, WPNC07*, Hannover, Germany, Mar. 2007, pp. 33–36.

[25] P. D. Groves, G. W. Pulford, C. A. Littlefield, D. L. J. Nash, and C. J. Mather, "Inertial navigation versus pedestrian dead reckoning: Optimizing the integration," in *Proceedings of the 20th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GNSS 2007*, Fort Worth, Texas, USA, Sep. 2007, pp. 2043—2055.

[26] B. Krach and P. Robertson, "Integration of foot-mounted inertial sensors into a Bayesian location-estimation framework," in *Proceedings of the 5th Workshop on Positioning, Navigation and Communication, 2008, WPNC08*, Hannover, Germany, Mar. 2008.

[27] Widyawan, M. Klepal, and S. Beauregard, "A back-tracking particle filter for fusing building plans with PDR displacement estimates," in *Proceedings of the 5th Workshop on Positioning, Navigation and Communication, 2008, WPNC08*, Hannover, Germany, Mar. 2008.

[28] D. H. Titterton and J. L. Weston, *Strapdown inertial navigation technology*, 2nd ed., ser. IEE Radar, Navigation and Avionics Series. London: Peter Peregrinus Ltd., 2004, vol. 5.

[29] M. Grewal, L. Weill, and A. Andrews, *Global Positioning Systems, Inertial Navigation, and Integration*, 2nd ed., ser. IEE Radar, Navigation and Avionics Series. New York: John Wiley & Sons, Inc., 2001, vol. 5.

[30] P. Maybeck, *Stochastic Models, Estimation and Control, Volume I*, ser. Mathematics in Science and Engineering. New York: Academic Press, Inc., 1979, vol. 141.