Sensor Data Fusion for Pedestrian Navigation Using WLAN and INS

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Abstract

This paper presents a sensor fusion approach for pedestrian navigation based on a WLAN positioning system and an inertial navigation system (INS). Using sensor fusion of WLAN and INS data, WLAN position estimates will be improved and smoothed. Furthermore, movements of the pedestrian can be followed more accurately and orientation information can be added, enhancing significantly the WLAN positioning system.

The low-cost MEMS-based INS is inaccurate and can diverge very fast over time due to typical intrinsic errors like bias, misalignment and scaling. However, the INS has the advantage of high availability, high data rate, and it is immune to external disturbances. In contrast to the INS system, the positioning rate of the fingerprinting-based WLAN system is comparably low and susceptible to external disturbances which lead to erratic, but bounded positioning errors. Due to the complementary error behavior, data fusion of WLAN and INS is appropriate.

The paper shows that WLAN positioning can be improved in two respects by INS data. Firstly, INS navigation data can speed up significantly the necessary creation of a fingerprint database of WLAN access-points field-strength measurements. During the database set-up phase a fixed-interval INS smoothing algorithm is applied to annotate the field strength measurements with position information. Secondly, later in the operational phase, the RSSI values measured by the user are used to extract from the database the best fitting field strength fingerprints and the annotated location information is fused with the INS navigation data by means of a Kalman filter to determine the position of the user.

Measurements for a realistic scenario are carried out to demonstrate the performance of the integrated system. The results are analyzed and the system strengths and weaknesses are discussed.

1. Introduction

The integration of GPS and inertial navigation systems has a long history and is used in many applications, e.g. to provide accurate position information during GPS reception gaps [1]. Inertial measurement units (IMUs) based on MEMS (Micro Electro-Mechanical Systems) have become more and more attractive due to cost reasons. However, due to their poor performance the reception gaps which can be bridged are rather short. In urban and particularly in indoor environments the GPS outages tend to be long. Therefore, an integrated GPS/INS navigation system based on a low-cost IMU does not provide yet an adequate solution to indoor pedestrian navigation. Partially, this statement holds also for urban environments, because pedestrian navigation cannot benefit as much from maps, speed and limited degrees of freedom in motion as GPS-based vehicle navigation does.

WLAN systems have found widespread use for communications. Thus, a high density of WLAN access points can be found in city centers. It has been shown that WLAN access points can be used also for positioning purposes [2]. The ubiquitous availability of WLAN access points in cities and indoors poses the question, whether integrated WLAN/INS navigation systems are more adequate than GPS/INS navigation systems in such environments. A couple of proposals for an integrated WLAN-INS navigation system have popped up recently, e.g. [3],[4]. In [3] a WLAN-INS fusion algorithm for pedestrian navigation based on a particle filter is presented. The inertial signals are used to count steps and with information on step size a position is obtained, which is fused with the WLAN position. A similar approach is presented in [4]. Both of these approaches exploit map information besides the WLAN position and inertial data.

Our proposal for pedestrian navigation is not based on counting steps, but on an integration of a rather conventional INS mechanization [5] with the WLAN positioning system [6]. Most commonly, WLAN positioning systems are based on the fingerprinting principle [2], [7]. A drawback is the huge database of field strength measurements. This database needs to be filled and maintained. Therefore, we want to address in this paper besides the integration of the INS and WLAN, the setup of the pivotal fingerprint database, which can be aided by an INS.

In Section 2 a new approach is proposed to speed up the fingerprint database setup by INS aiding. Section 3 discusses our approach to WLAN and INS data fusion during operational mode. In both sections measurements are presented. Finally, conclusions are drawn in Section 4.

2. INS-Assisted Database Creation

The setup of the fingerprint database is a tedious and time consuming task. The positions of the reference points, which are entered into the database, must be precise and the field strength measurements must be cleaned from noise and disturbances due to multipath propagation by averaging. Figure 1 shows the result of such a standard database set-up, i.e. mean RSSI values taken at equidistant reference points in a corridor of our building. As can be seen from the figure the spacing was 3 m. There are two sets of averaged RSSI values corresponding to two different WLAN access points, marked by crosses "+" and "x", respectively. The solid curves will be addressed at the end of the section. Of course, for precise positioning a fingerprint of more than two WLAN access points is typically required.

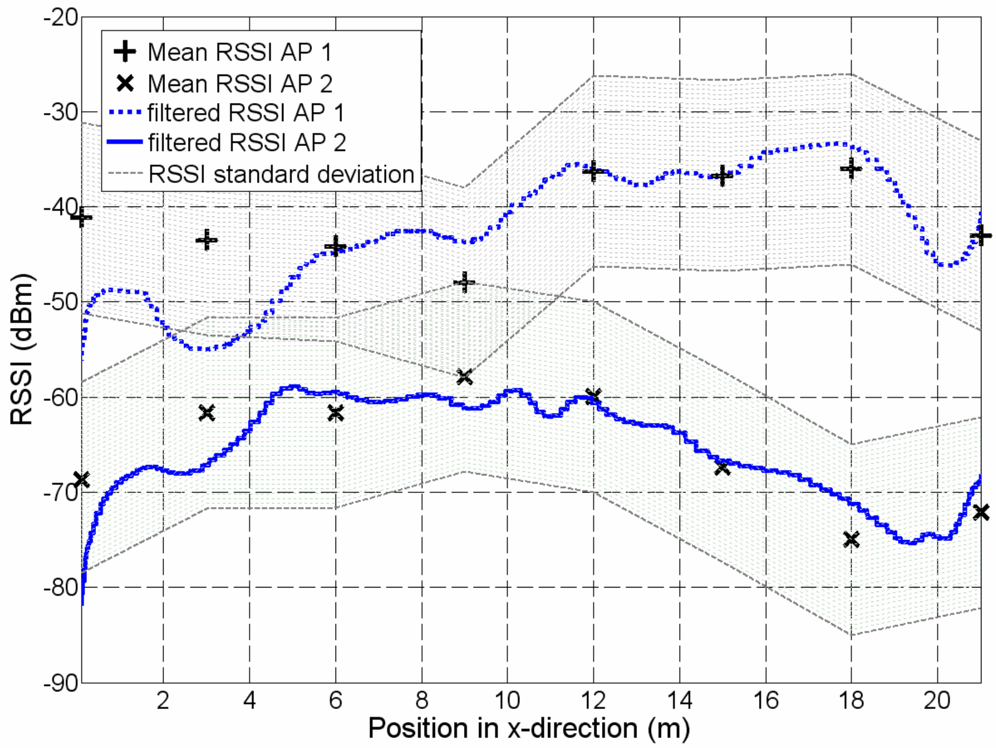

Figure 1: RSSI values of standard reference points ('+' ; 'x') and automatically generated, smoothed RSSI tracks (lines)

During a normal set-up phase, some reference points are easily positioned due to their characteristic location, e.g. at an intersection of two corridors. With the help of an accurate map, their position can be easily and half-automatically calculated after clicking at the corresponding map position. For the other reference points a method of automatic positioning would be helpful. To this end we propose an INS-aided process. Firstly, RSSI values and IMU measurements have to be collected synchronously while the user is walking between two reference points in the area of interest, in our case along the corridor. Now there are no stops at intermediate reference points as before and only the positions of the first and last reference point in the corridor have been assumed to be known. If the IMU measurements are processed by means of a basic INS, the calculated x and y positions diverge very fast due to the poor performance of the low-cost IMU (forward filtering), cf. Figure 2, dashed line. The figure shows that in our example after 35 seconds the calculated y-position deviates from the true y-position by 40 m, a clearly unacceptable result. The same is true if a backward filtering approach is used starting from the end reference point; again cf. Figure 2, dotted line. The IMU we have used was a low-cost MEMS-based unit developed at Fraunhofer IIS comprising three 1-axis accelerometers, three 1-axis gyroscopes and three 1-axis magnetic field sensors. However, if fixed-interval smoothing is applied, which combines forward filtering and backward prediction, the deviation is reduced drastically as Figure 2 clearly shows (solid line). Thus, precisely positioned reference points 35 s apart will now suffice to provide intermediate reference positions with an accuracy of roughly 1 m. Assuming a typical walking speed of 1 m/s, a reference point every 35 m instead of every 3 or 5 m will be now enough.

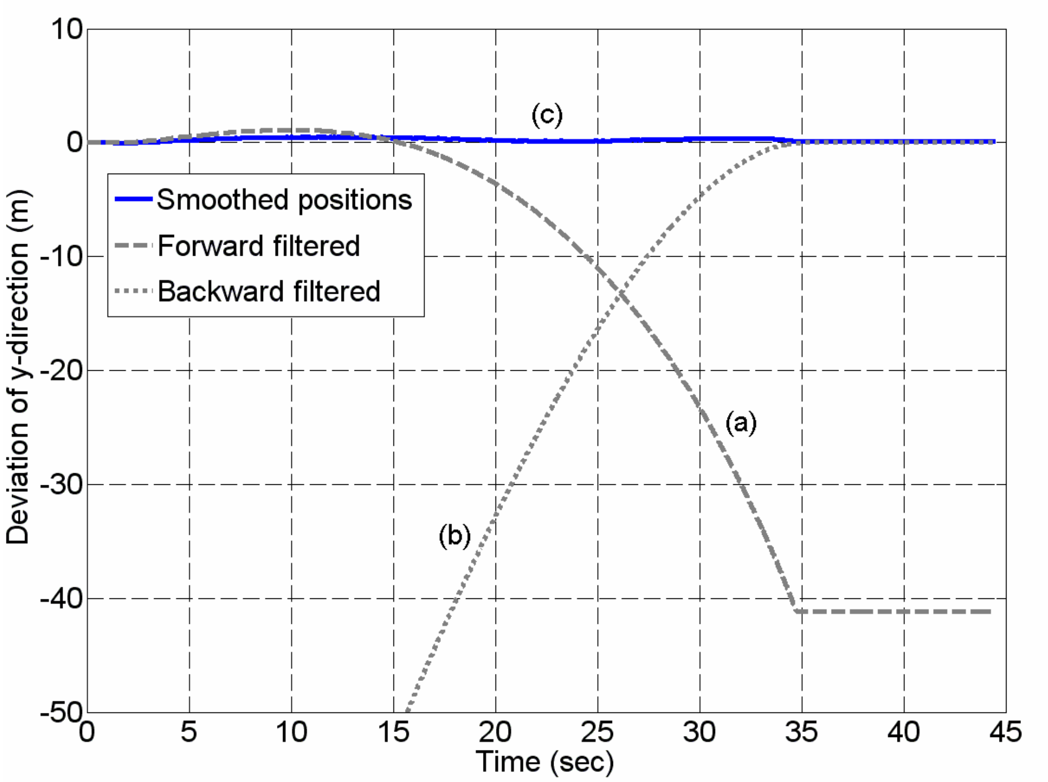

Figure 2: Deviation of calculated y-position for, (a) forward filtering only, (b) backward filtering only, and (c) smoothing

With this approach a very acceptable track (+) is obtained as shown in Figure 3. The deviation from the true track is below 0.5 m. The standard reference points, marked by dots, which have not been used in the calculations, are shown for reference only. The RTS algorithm (Rauch, Tung, Striebel) combining forward filtering and backward prediction has been taken from [8] and is originally due to Fraser (1967).

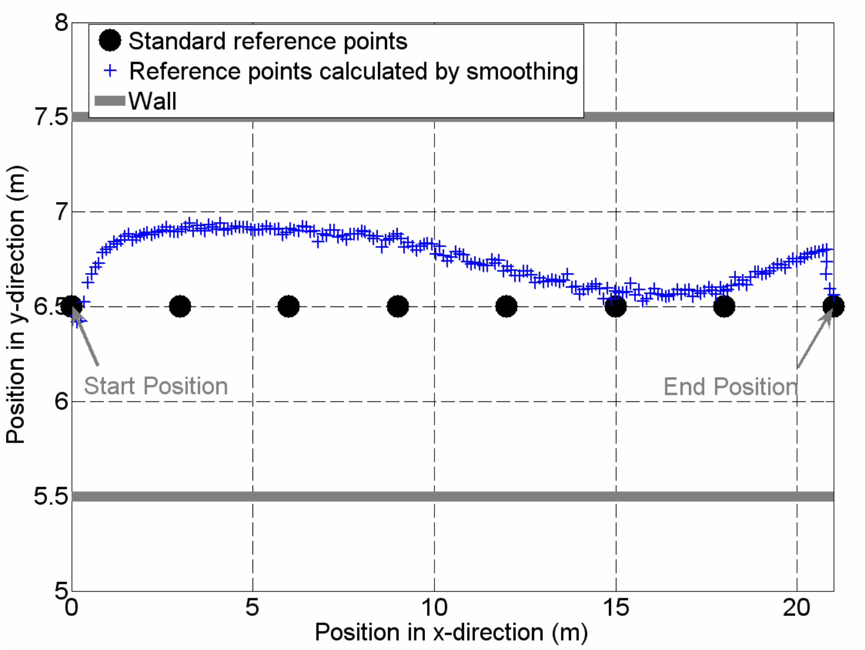

Figure 3: Standard reference points and automatically generated reference track

Combining now the position track with the low-pass filtered RSSI values of the two access points yields the dotted and the solid line in Figure 1. Both curves stay in a ±10 dB corridor around the reference points ('+' and 'x') of the standard database set-up approach. The long-term shadowing characteristic, which is so essential for WLAN field strength fingerprints, is preserved. The field-strength tracks obtained by this method can be sub-sampled according to the needs of the WLAN positioning to fill the fingerprint database. The benefits of this new approach are time savings and an easy automation of the database setup.

3. Fusion of WLAN and INS

WLAN positioning systems will benefit from integration with INS in three respects at least:

i. Database setup as discussed in the previous section.
ii. Attitude information, as briefly discussed in the next section.
iii. Improved positioning and tracking.

In contrast to [3] and [4] the integration of WLAN and INS proposed in this paper is based on a Kalman filter, labeled tracking filter in the block diagram of Figure 4. A quality indicator is calculated in the block labeled motion detection and passed to the tracking filter together with the WLAN positions. The block attitude calculation computes attitude quaternions from angular rates and transforms the measured accelerations from body frame into navigation frame.

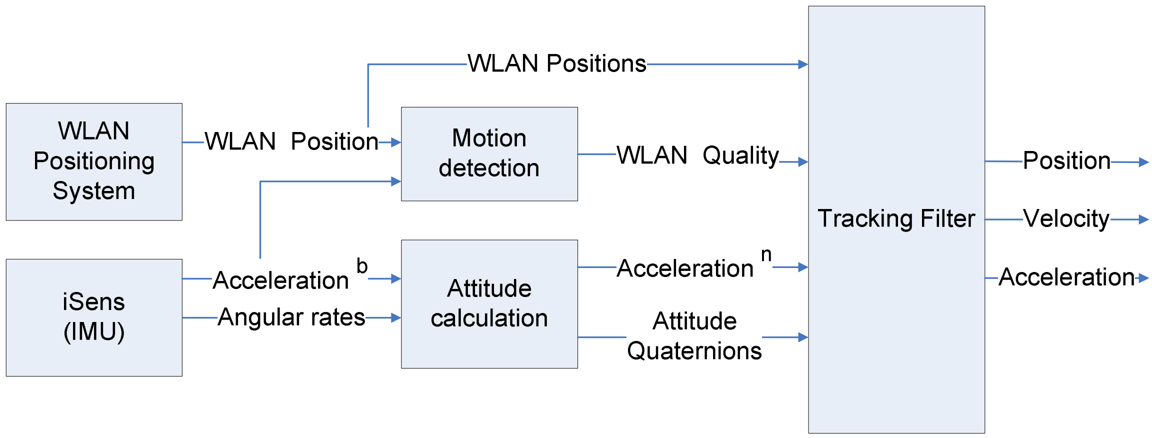

Figure 4: Block diagram of the WLAN/INS integration

a. *Attitude calculation*

The most essential contribution of INS to WLAN positioning is the attitude. In pure WLAN systems it is impossible to determine the attitude; it is only possible to calculate the heading by subsequent position fixes. This heading can be quite inaccurate if the environment is changing fast and the position fixes are noisy. With the inclusion of inertial sensors, the attitude can be determined independently of external disturbances.

b. *Fusion algorithm*

The fusion algorithm is in charge of combining the acceleration signal, the estimated attitudes and the WLAN positions. A Kalman filter with 9 states has been selected. The state vector is composed of position, velocity and acceleration. The state transition matrix of the time-discrete process has been chosen as

$$\Phi = \begin{bmatrix} \mathbf{I} & \delta t\ \mathbf{I} & \frac{\delta t^2}{2}\ \mathbf{I} \\ \mathbf{0} & \mathbf{I} & \delta t\ \mathbf{I} \\ \mathbf{0} & \mathbf{0} & \mathrm{DCM}_{k-1,k} \end{bmatrix}$$

Noteworthy is the $\mathrm{DCM}_{k,k\text{-}1}$ sub-matrix in the lower right corner relating the accelerations at time instant k-1 and k. The underlying model assumption is that the acceleration does not change magnitude from time instant to time instant (except for random changes), but only direction as measured by the gyroscopes. This setting yielded slightly better results for pedestrian navigation than an identity matrix, i.e. the assumption that the acceleration does not change between time instants. It should be noted as well that attitude calculations of the IMU have been three dimensional though WLAN does only deliver two-dimensional positions.

The measurement equation of the Kalman filter relates the state vector comprising position, velocity and acceleration to the measurement vector comprising position, as measured by the WLAN system, and acceleration, as measured by the IMU. Since the IMU has a data rate higher than the WLAN system, a valid WLAN position is available only occasionally. The measurement equation of the Kalman filter has to be adapted accordingly.

The position estimates delivered by the WLAN system cannot be modeled as a random process disturbed by white Gaussian noise as implicitly assumed by the Kalman filter. Given the nature of the perturbations it is necessary to continuously adapt the measurement covariance matrix to assure that damaged or very erroneous WLAN position estimates are less weighted than good estimates. A quality estimator was implemented: Two motion indicators are calculated from the WLAN positions and the IMU accelerations. If both indicate motion the WLAN positions are passed to the Kalman filter for fusion. If both indicators disagree the INS data is dominating the fusion.

c. Experimental results

To verify the fusion algorithm, measurements were taken in our office building. In the sequel we show two examples: (1) A walk along a corridor and (2) a walk along the same corridor, but with a short detour into a room.

Figure 5 shows the results for the walk along the corridor. The dots in Figure 5(a) and 5(b) indicate the *x*- and *y*-positions versus time *t*, respectively, as estimated by WLAN, where x is along the corridor. The solid curves are the result of the fusion with the IMU data. The along-track acceleration component can be seen in Figure 5(c). At first the motion detection indicates a standstill, because the acceleration values up to time $t = 20$ s are very low. Consequently, the influence of the WLAN position estimates on the calculated track is suppressed. Then, within 30 seconds the person walks along the corridor until he stops at $t = 50$ s, turns at $t = 80$ s, waits again, and walks back the 19 m long corridor. The periods of movement can be seen clearly from the recorded acceleration data. The *x*-component of the computed track is a good interpolation of the WLAN position estimates. Brief WLAN outages are bridged, e.g. between x-position 3 m and 8 m. It is interesting to note that at $t = 80$ s the turn on the spot is detected leading to a jump-like correction of the fused position. The *y*-component of the computed track fluctuates occasionally by 1 m due to erratic WLAN position estimates, but large outliers are removed by the implemented simple quality estimator.

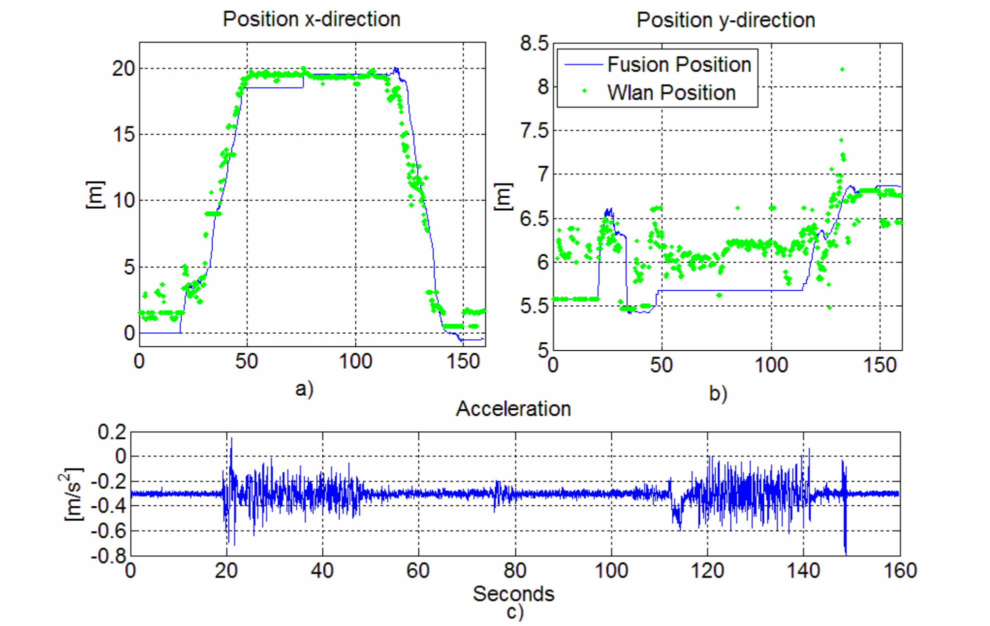

Figure 5: Walk along a corridor
(a) WLAN positions and smoothed track (x component)
(b) WLAN positions and smoothed track (y component)
(c) Accelerometer data along track

In the second example a detour is taken into a room adjacent to the corridor. Figure 6 shows the positions estimated by WLAN (dots), the track calculated by the fusion algorithm (solid line), and approximately the true track (dashed line). Again the WLAN outliers are removed and an acceptable track is obtained in contrast to the positions as estimated by WLAN.

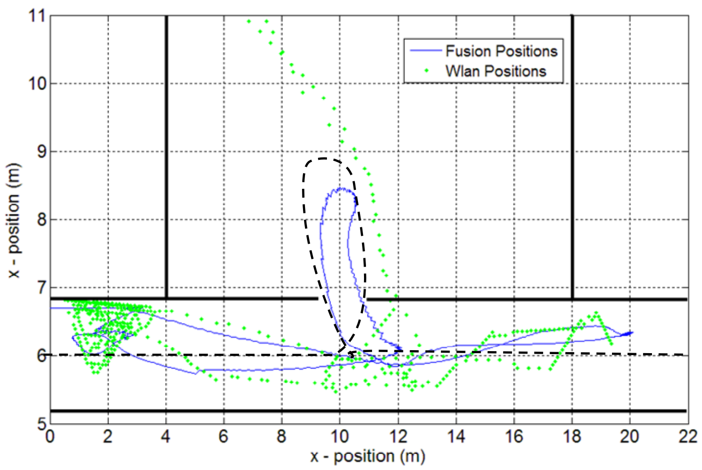

Figure 6: Walk along the corridor with detour into the room

4. Conclusions

WLAN positioning has been demonstrated to benefit from INS in three respects: Firstly, the required fingerprint database can be filled much more rapidly. Field strength measurements can be annotated on the fly with position information by means of a low-cost INS in combination with a fixed-interval smoother. Data can be collected in an automated fashion while walking. The field strength tracks can be processed and sub-sampled according to the design requirements of the WLAN positioning. Secondly, obviously and most importantly, an integration of WLAN with INS adds attitude information to the already available position and heading information of WLAN. Thirdly, an integration of WLAN and INS by means of a Kalman filter has been demonstrated to provide smoothed tracks bridging WLAN outages. The crucial point is to filter out unreliable WLAN positions which violate the implicit white Gaussian noise assumption of the Kalman filter and which do not match to the measured INS data.

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