Fusion of RSS and Inertial Measurements for Calibration-Free Indoor Pedestrian Tracking

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***Abstract*— RSS-based localization techniques are widely used in indoor environments to estimate the position of people or objects. Recent work proposes to combine this localization technique with a dead reckoning strategy (using inertial sensors on the person or object to be tracked) to improve the accuracy of the localization results and, at the same time, track the position of the user continuously. The RSS-based subsystem of most of the proposed hybrid systems rely on a time consuming calibration phase to build a radio map of the environment, which is used to find a correspondence between the RSS measurements and the position. However, due to the changing environmental dynamics, the behavior of the channel may change after some time, thus, recalibration processes are necessary to maintain the positioning accuracy. In order to avoid these calibration and re-calibration needs, this paper proposes to use a nearly calibration-free RSS channel modeling localization approach and fuse it with the inertial measurements through a Kalman filter. The proposed strategy is tested through numerical simulation and experimental tests, showing accuracy gains with respect to other strategies. Furthermore, the proposed method has a low deployment cost, as very little calibration is needed prior to the operation.**

Keywords—Pedestrian tracking; indoor localization; inertial sensors; RSS-based localization; Kalman filtering; calibration

I. INTRODUCTION

Received Signal Strength (RSS) based localization is one of the most popular techniques for inferring the relative positions of people or objects in indoor environments. However, these techniques do not usually have a very good accuracy, due to the variability of the RSS. In order to improve the localization accuracy of plain RSS-based localization techniques, hybrid localization systems have been proposed, which combine RSS-based localization with other technologies. In particular, the recent successful integration of small inertial sensors, such as accelerometers and gyroscopes, into mobile devices (PDA, mobile phones) has boosted the interest in hybrid localization techniques combining RSS and inertial measurements.

Inertial sensors can be used to continuously estimate the position, orientation, and speed of a moving object without the need for external references. This is achieved by using a dead reckoning approach (estimating the trajectory of the object by continuously adding its movements from a given starting point). The main disadvantage of using inertial sensors for dead reckoning is that the integration of their bias and noise results in errors that accumulate quickly. Despite this drift with time, the accuracy of inertial navigation over short periods of time can be quite high and therefore, they can be used to enhance the performance of other localization systems, such as those based on the measurement of the RSS.

In this paper we present a hybrid localization technique for pedestrian tracking that fuses RSS information and inertial measurements through a Kalman filter. Typical hybrid approaches for pedestrian tracking (e.g.[1][2][3]) rely on the use of a fingerprinting or map-based RSS localization technique. This approach requires a costly and time-consuming calibration phase to create a radio map of the environment, which is then used to find the position of the mobile node by matching its measurements with those stored in the map. In many practical scenarios, this calibration might be unfeasible or inconvenient, and, even when it is possible, the initial calibration may not be accurate enough after some time due to the dynamic behavior of the propagation channel. In contrast, we present in this paper a hybrid localization technique that uses a *channel modeling approach*. Channel model based techniques use a propagation channel model to establish a relation between the RSS and the distance between two nodes; then, a triangulation or positioning algorithm is used to calculate the position of a node from a set of distances to some anchor nodes with known positions. Although this approach is not as accurate as fingerprinting techniques, it has minimal calibration cost. In this paper, we show that fusing channel-based localization with inertial measurements can be a valid alternative to fingerprinting in terms of localization accuracy, while being much more practical and inexpensive.

The structure of the paper is as follows. Section 2 reviews previous work on hybrid localization systems for indoor pedestrian tracking. Section 3 describes the localization scenario and the proposed fusion algorithm, which is tested in Section 4 and 5 through a number of numerical simulations and real-field experiments, respectively. Finally, Section 6 concludes the work.

II. RELATED WORK

Inspired by automotive navigation, the first hybrid systems for pedestrian tracking [4][5][6] were based on complementing GPS navigation with inertial sensors when the GPS signal was not available. Due to the use of GPS receivers these systems were mainly targeted at outdoor environments.

For indoor environments, several hybrid localization systems have been proposed combining inertial sensors with ultrasound localization systems [7] or UWB-based localization [8][9][10]; but the most interesting ones are those combining the inertial sensors with RSS-based indoor localization systems, since this technique is currently available in most off-the-shelf wireless devices.

The authors of [1] proposed one of the first systems featuring inertial sensors and RSS-based indoor localization. Their proposal is based on the fusion of WiFi signal strength measurements and inertial measurements provided by an accelerometer, a gyroscope and an atmospheric pressure sensor, which are attached to the belt of the user. The accelerometer is used to count the number of steps, which is then multiplied by an average step length to obtain the traveled distance, while the angular velocity provided by the gyroscope is integrated to keep track of the rotation around the vertical axis. The pressure sensor is used to detect if the mobile node is going upstairs or downstairs. These inertial measurements are fed into a Kalman filter to reduce noise. Apart from that, the WiFi RSS measurements are used to provide a first estimation of the user position by means of a fingerprinting algorithm. Finally, a particle filter combines the information given by the WiFi positioning system with the filtered inertial information. The reported experimental results show that the root mean square error using this technique can be around 1.5 m.

The authors of [2] propose another pedestrian tracking framework based on particle filters. In particular, they integrate a WLAN-based indoor positioning system based on fingerprinting with map information and a low-cost MEMS accelerometer that provides walking distance estimations using a step counting approach. The localization accuracy is improved by about 25% with respect to the plain fingerprinting system, achieving an average localization error of 4.3 m.

A similar approach was described by [3]. In this case, a foot-mounted inertial unit, a detailed building model, and a particle filter are combined to provide absolute positioning, despite the presence of drift in the inertial unit and without knowledge of the user's initial location. A fingerprinting algorithm using WiFi signal strength is only used to initialize the localization algorithm. The results from their experimental tests show that a user can be tracked throughout a 8725 m^2 building spanning three floors to within 0.5 m 75% of the time, and to within 0.73 m 95% of the time.

A different approach was proposed by [11]. In the previous cases, the inertial measurements were used to provide distance information through a step counting algorithm. Conversely, the inertial navigation system in [11] provides position estimates coming from the integration of the inertial measurements. To avoid the inherent drift of these systems, they combine these position estimates with those provided by a RSS-based channel modeling localization system implemented on a wireless sensor network. A Kalman filter with forward/backward smoothing is used to combine the position estimates provided by both systems. Experimental results on a moving cart show considerable improvements in accuracy of the location estimates, however, this approach would probably not be valid for pedestrian tracking, as the direct integration of inertial measurements would yield high positioning errors.

III. DESCRIPTION OF THE LOCALIZATION SYSTEM

The goal of our localization system is to provide accurate indoor positioning information by combining an almost calibration-free RSS-based localization technique and a pedestrian dead reckoning (PDR) system through a Kalman filter.

RSS-based localization systems for indoor environments usually feature a collection of anchor nodes deployed in known positions, and one or several mobile nodes carried by the person or object to be localized. Our system follows this configuration and uses a channel modeling technique to provide periodic position estimates of the mobile node without the need of costly initial calibration or recalibration processes.

PDR systems typically collect the information provided by inertial sensors carried by the person to be tracked (acceleration and angular speed) and provide a continuous estimate of the position, speed and orientation of the user. Depending on the position of the inertial sensors (foot-mounted, waist-mounted, etc.), the PDR algorithms may be different. In our case, we have considered waist-mounted sensors and used a simple step counting approach to continuously estimate the speed (modulus and direction) of the user.

Despite the simplicity of the approach and the little calibration required to make it work, the fusion algorithm provides good localization and tracking results. We describe next the two localization systems and the fusion algorithm.

A. *RSS-based localization system*

There are two main approaches for indoor RSS-based localization, namely, fingerprinting or map-based techniques and channel modeling techniques. Map-based techniques ([12], [13]) create a radio map of the environment by gathering, for each anchor node, a set of RSS measurements in different test points. When a mobile node needs to be localized, its RSS measurements are matched against the ones stored in the map, in order to find the closest correspondence. Channel modeling techniques ([14], [15]) use a propagation channel model to establish a relation between the RSS and the distance between two nodes; then, a triangulation or positioning algorithm, such as the ones in [16] or [17], is used to calculate the position of a node from a set of distances to some anchor nodes with known positions. Clearly, fingerprinting techniques require a costly and time-consuming calibration phase, whereas calibrating a channel model is much simpler, as only a few parameters have to be selected (which can be done with a few measurements in the deployment area or even established theoretically, using later an automatic updating technique [18]). For this reason, we have selected this last approach for our system.

For the RSS to distance conversion we have used the lognormal channel model [19], which establishes the following relation between the received power P_{RX} (in practice, the RSS) and the distance d between transmitter and receiver:

$$P_{RX}(dBm) = A - 10\eta \log \frac{d}{d_0} + N(0,\sigma) \qquad (1)$$

where A and η are the parameters of the channel model and N is a zero-mean Gaussian random variable with standard deviation σ. A depends on the antenna gains, the transmission power and the power loss for a reference distance d_0, and needs to be experimentally adjusted. The path loss exponent η has to be experimentally determined too. If all the anchor nodes have the same characteristics, the whole propagation environment can be characterized by only one value of A and one value of η.

Given A and η, the distance between the mobile node and an anchor node can be estimated from the received P_{RX} using (1). Then, from a set of, at least, three estimated distances to different anchor nodes, the node's position can be calculated by using any positioning algorithm (for example, the ones proposed in [16] or [17]). In our system, we used the weighted hyperbolic positioning algorithm proposed in [17]:

$$\bar{x}_{RSS} = \left(H^T S^{-1} H\right)^{-1} H^T S^{-1} \tilde{b} \qquad (2)$$

with:

$$H = \begin{bmatrix} 2x_2 & 2y_2 \\ \vdots & \vdots \\ 2x_N & 2y_N \end{bmatrix}$$

$$\tilde{b} = \begin{bmatrix} x_2^{\,2} + y_2^{\,2} - \tilde{d}_2^{\,2} + \tilde{d}_1^{\,2} \\ \vdots \\ x_N^{\,2} + y_N^{\,2} - \tilde{d}_N^{\,2} + \tilde{d}_1^{\,2} \end{bmatrix}$$

$$S = \begin{bmatrix} \tilde{d}_1^{\,4} + \tilde{d}_2^{\,4} & \tilde{d}_1^{\,4} & \cdots & \tilde{d}_1^{\,4} \\ \tilde{d}_1^{\,4} & \tilde{d}_1^{\,4} + \tilde{d}_3^{\,4} & \cdots & \tilde{d}_1^{\,4} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_1^{\,4} & \tilde{d}_1^{\,4} & \cdots & \tilde{d}_1^{\,4} + \tilde{d}_N^{\,4} \end{bmatrix}$$

where (x_i, y_i) is the position of anchor node i ($i = 1, \ldots, N$) and $\tilde{d}_i$ the distance estimation to anchor node i.

In our system, the anchor nodes send beacon messages periodically, with a period ΔT. The mobile node listens to these transmissions, measures their RSS and estimates its own position using (1) and (2). In this way, the RSS-based position estimates are updated every ΔT seconds.

B. Inertial tracking system

Gyroscopes and accelerometers, measuring angular velocity and linear acceleration respectively, can be used to track the position and orientation of an object relative to a known starting point, orientation and velocity.

In principle, it is possible to track the orientation of an object by integrating the angular velocity signals provided by the gyroscopes. This orientation can then be used to transform the acceleration samples from the *body reference frame* (in which all the measurements are taken) into a *global frame of reference*, from which acceleration due to gravity can be subtracted. The remaining acceleration can then be integrated twice to obtain the position of the object relative to the initial position and speed.

Unfortunately small errors in the accelerometer and gyroscope signals, after being integrated, cause *drift*, an error in the calculated position that grows rapidly with time (proportionally to t^3). The drift incurred by a MEMS IMU will typically exceed 150 meters after 1 minute of operation [20]. The situation may be worse in pedestrian navigation, that is, when the object to be tracked is a person, since the inertial sensors are attached to the body and suffer from many movements during walk, including possible changes in their position with respect to the user.

One way to mitigate the drift problem consists of using foot-mounted inertial sensors and leveraging the fact that the foot is in contact with the ground at some precise moments. These moments can be detected from the acceleration signal of a foot-mounted accelerometer and zero velocity updates (ZVUs) can be then applied to correct accumulated errors during the previous step [6][21][22]. The application of such constraints replaces the t^3-error growth with an error accumulation that is linear in the number of steps [6].

An alternative approach consists of detecting the walking steps. In this case, the inertial sensors may be located in a waist pack. While people walk, the acceleration signal fluctuates periodically due to the motion mechanism. The information contained in the acceleration signals, such as the frequency, maximum and minimum amplitudes, etc. is related to the walking dynamics of the user, and thus, can be used to estimate the traveled distance. The most common and intuitive way to measure the distance is to count the number of steps and multiply this number by an average step length. Step counting is easily performed by detecting the peaks in the vertical acceleration signal [23], which is usually smoothed first with a low pass filter. Step length can be either assumed to be constant, or calculated from the acceleration signal in several ways, for example, with the empirical equation proposed in [24] and further used in [25] and [2]:

$$l = K \cdot \left(A_{\max} - A_{\min}\right)^{1/4} \qquad (3)$$

where A_{max} and A_{min} are the maximum and minimum vertical acceleration in a single stride and K is a constant, which can be obtained from walking training. Experimental results show that the application of this simple approach replaces the t^3-error growth with an error that is proportional to the traveled distance, where the reported values of the proportionality constant range between 1% and 10%.

In our system, we applied this last approach to first estimate the step length using (3) and then obtain the corresponding speed v by dividing by the elapsed time. In this way, a new value of the modulus of the speed is obtained when a new step is detected. On the other hand, the heading angle (or speed direction) θ is obtained by integrating the gyroscope data, using the following equation:

$$\theta_i = \theta_{i-1} + \delta T \cdot \omega_{z_i} \qquad (4)$$

where ω_{z_i} is the component of the angular speed in the vertical axis at time instant i and δT is the inverse of the gyroscope sampling frequency. Note that the speed direction is updated at the sensors sampling frequency, whereas the speed magnitude is only updated at every new step.

C. Fusion algorithm

The proposed localization system uses a Kalman filter to fuse the position estimates provided by the RSS-based localization system and the speed measurements provided by the inertial sensors.

At each time instant k, the state of the user is represented by its position vector $\bar{x}_k$ = $[x_k\ y_k]^T$. The Kalman filter estimates the *a posteriori* state $\bar{x}_{k|k}$, given all available observations ($\bar{z}$ = $\{\bar{z}_1 \ldots \bar{z}_k\}$). In our system, we used the following state model:

$$\bar{x}_k = \bar{x}_{k-1} + \Delta T \cdot \bar{v}_k + w_k \tag{5}$$

where ΔT is the time between measurements (in our case, the time between RSS-based position estimates), $\bar{v}_k$ are the speed measurements provided by the inertial tracking system ($\bar{v}_k = [v_k \cdot \cos\theta_k \quad v_k \cdot \sin\theta_k]^T$), which are used as a control input, and w_k is the process noise, which follows a zero-mean bivariate Gaussian distribution ($w_k = \Delta T \cdot \Delta v_k + 1/2 \cdot \Delta T^2 \cdot \Delta a_k$) with covariance matrix:

$$Q_k = I \cdot \left(\frac{1}{2} \sigma_a \Delta T^2 \right)^2 + I \cdot (\sigma_v \Delta T)^2 \tag{6}$$

where I is the identity matrix, σ_a = 0.1m/s^2 and σ_v = 0.1m/s. The values of these parameters have been experimentally tuned.

On the other hand, the observation $\bar{z}_k$ of the real state $\bar{x}_k$ is modeled according to the following expression:

$$\bar{z}_k = \bar{x}_k + r_k \tag{7}$$

where r_k is the observation noise, which is assumed to follow a zero-mean normal distribution with covariance matrix $R_k = I \cdot \sigma_p^2$, with σ_p = 2m. The value of this parameter has also been tuned experimentally.

For each new measurement or observation $\bar{z}_k$ (in our case, $\bar{z}_k = \bar{x}_{RSS}$, i.e. the observation is the position estimate provided by the RSS-based localization system at instant k), the Kalman filter executes two steps: prediction and update. Using the standard equations of the Kalman filter [26], the predicted state estimate and the predicted estimate covariance in our case are given by:

$$\hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} + \Delta T \cdot \bar{v}_k \tag{8}$$

$$P_{k|k-1} = P_{k-1|k-1} + Q_k \tag{9}$$

Finally, the *a posteriori* state estimate and the *a posteriori* covariance matrix are calculated in the update phase as:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \cdot \tilde{y}_k \tag{10}$$

$$P_{k|k} = (I - K_k) P_{k|k-1} \tag{11}$$

where $\tilde{y}_k$ is the innovation ($\tilde{y}_k = z_k - \hat{x}_{k|k-1}$), whose covariance matrix is $S_k = P_{k|k-1} + R_k$, and K_k is the optimal Kalman gain, given by:

$$K_k = P_{k|k-1} S_k^{-1} \tag{12}$$

We predict the position through the Kalman filter whenever a new RSS-based position estimated is obtained (every ΔT seconds). The predicted position is calculated from the previous filtered position estimate using the last collected speed value. In the periods between RSS-based localizations, the mobile node position is estimated using the previous position estimate and the measurements of the inertial tracking system:

$$\hat{x}_i = \hat{x}_{i-1} + \delta T \cdot \bar{v}_i \tag{13}$$

IV. NUMERICAL PERFORMANCE EVALUATION

In this section we evaluate the performance of the proposed technique in terms of accuracy through detailed simulation. The simulation environment comprises a sensor network composed of N reference nodes deployed on a rectangular grid covering an area of S m^2. The mobile node (the user) was simulated to follow a circular trajectory with constant speed.

When the simulation starts, the mobile node performs an initial RSS localization and starts moving according to the selected trajectory. The initial localization result is used as the starting point for the PDR system, which provides a continuous estimate of the user's position (13). After ΔT seconds, a new RSS localization is performed. The new position estimate $\bar{x}_{RSS}(t)$ and the speed estimated by the inertial system at this moment ($v_x(t)$, $v_y(t)$) are introduced in the Kalman filter to correct the user's position.

RSS-based localization is simulated in the following way. The log-normal channel model (1) is used to transform the real distances between the nodes into RSS measurements. Once n values of the RSS for each mobile-reference node pair are obtained, those RSS values that are below the sensitivity threshold are discarded and those above the threshold are averaged and used to obtain the distance estimation between the different pairs of nodes. Finally, these estimated distances and the known positions of the reference nodes are used to estimate the position of the mobile node using the weighted hyperbolic positioning algorithm (2).

Inertial tracking is simulated in the following way. From the simulated trajectory of the node, the real accelerations and angular rates in the mobile reference system are obtained (with a sampling rate of f_s). The steps are simulated by adding a sinusoid with appropriate frequency and amplitude to the real acceleration of the mobile node. The frequency of this sinusoid is calculated from the step length l as $f = v/l$, where v is the real speed of the node. The amplitude is also calculated from the step length according to (3). The step length l is known to increase with the walking speed. In order to have an approximate relation for the simulator, we carried out a few experiments in which we measured the average step length of a person for different walking speeds. The relation was found to be approximately linear, with the following least-square fit:

$$l = 0.32+0.26v$$

Therefore, the speed of the mobile node is used to determine both the amplitude and the frequency of the sinusoid representing the steps. Noise and bias are then added to generate the simulated inertial measurements. From this signal, the steps were detected by first smoothing the signal with a low-pass filter and then searching for local maxima and minima as done in [19]. Then, the step length is calculated from the amplitude of the signal using (3). The traveled distance is then obtained by multiplying the number of steps by the step length. On the other hand, the orientation is obtained by integrating the gyroscope measurements in the vertical axis.

In the following figures we present the performance of the proposed system for a simulation environment with N = 9 anchor nodes in an area of S = 400 m^2. The mobile node follows a circular trajectory centered in the simulation area, with radius equal to 8 m. The inertial measurements are affected by acceleration noise (σ = $5.7575\cdot10^{-2}$ m/s^2) and gyroscope bias (B = 10º/h) and are taken at a sampling frequency f_s = 50 Hz. The value of K for the step length estimation was set to 0.45. The propagation channel is modeled using the log-normal model, with parameters $\eta = 2.5$, $\sigma = 5$ dB and A = -60 dB (coverage radio around 25 m, as the sensitivity was set to S = -95 dBm).

Figure 1 shows the cumulative density function of the localization error for a circular movement with a speed of 1m/s (typical speed for a pedestrian) and Figure 2 shows the evolution of the average localization error for the same simulation environment. The localization error is calculated as the Euclidean distance between the real and the estimated position.

The results in these figures correspond to the stationary state of the filter and were obtained by averaging the results of 100 simulations in the same conditions. The performance of the proposed system is compared against two other almost-calibration-free methods:

1) Using the RSS-based localization system alone: as RSS-based localization is performed periodically, at a given time, the user is considered to be located at the position of the last localization.

2) Combining the RSS and the PDR systems without filtering: the user is tracked with the inertial system between RSS-based localizations, and when a new position estimation is obtained, the tracking system is reset.

As it can be seen, the introduction of the Kalman filter improves around 1.5 m the localization accuracy. In 90% of cases, the localization error is below 2.4 m.

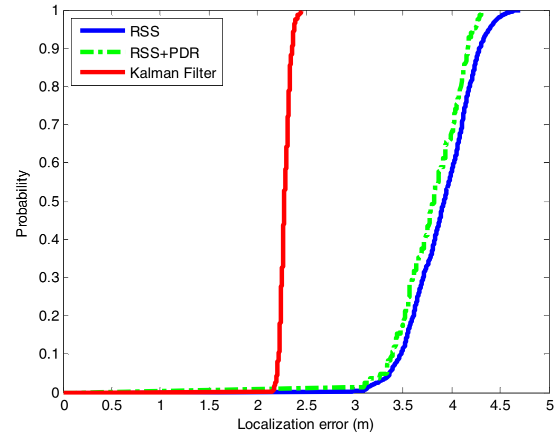

Fig. 1. Cumulative density function of the localization error for a circular movement with v = 1m/s.

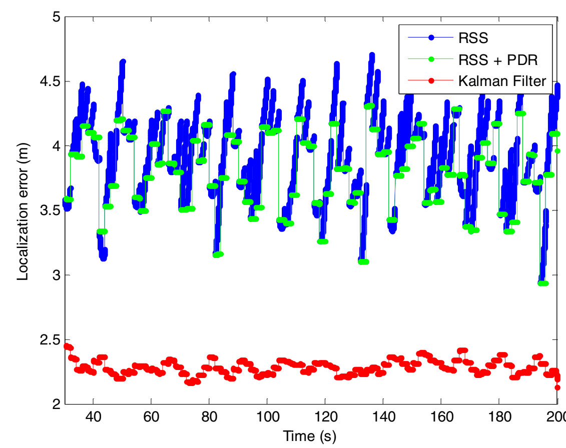

Fig. 2. Evolution of the localization error for a circular movement with v = 1m/s.

V. Experimental Evaluation

In this section we describe the results of some experimental tests that were carried out to evaluate the accuracy of the proposed algorithm in a real indoor environment using a sensor network based on the IEEE 802.15.4 standard.

The experiments were carried out in a 100 m^2 office area characterized by non line-of-sight propagation due to the presence of walls and furniture. N = 9 reference nodes (MicaZ motes) were deployed at different positions of the testing area and a mobile node (a Shimmer mote), provided with inertial sensors, was used to obtain RSS and inertial measurements. The mobile node was mounted on the waist of several users, who followed a predefined trajectory at different speeds.

Figure 3 shows the deployment area with the position of the reference nodes and the trajectory of the user (the user started to walk at the bottom-left corner, then made a right 90-degree turn and continued till the end of the room, where he stopped, made a left 180-degree turn and followed the same trajectory towards the starting point).

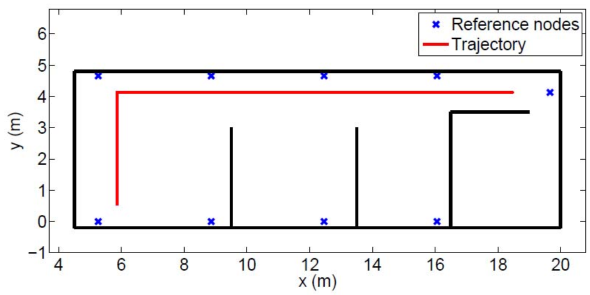

Fig. 3. Deployment area of the localization experiments.

The inertial sensors were programmed with a sampling rate of 50 Hz, and RSS localization was performed every 2 s. The RSS measurements and the inertial data were saved in a SD card on the Shimmer mote, together with a synchronization signal to mark the real position of the user. This information was then processed offline in order to evaluate the resulting localization accuracy.

Tables 1 and 2 present a comparison of the performance of the considered methods in terms of average and maximum localization error for several experiments.

It can be seen that the proposed Kalman filter approach has a quite good performance, achieving better results than the other calibration-free approaches. Although these results come from single realizations of short-time experiments and, therefore, cannot be taken as a general evaluation, these examples together with the results obtained by simulation are quite encouraging.

Based on these results, we can state that the proposed localization strategy would lead to results comparable to those obtained with more complex systems, such as fingerprinting-based strategies. For example, our results are similar to the ones reported in [1] and [2], which localize a person with an average localization error of 1.53 m and 4.30 m, respectively. Notice that those systems embed both fingerprinting, accelerometer measurements and map information, while we do not need any map information nor a costly calibration stage. Moreover, they use a particle filter to fuse the different measurements, so our approach is more efficient from a computational point of view. On the other hand, more sophisticated methods such as the one in [3] yield error values below 1m; however, they require the use of foot-mounted sensors, thus cannot be directly compared to our approach, which is targeted at a more common configuration (waist-mounted sensors).

TABLE I. AVERAGE LOCALIZATION ERROR (M)

User	1	2	3	4	5	6	7	8
RSS	3.31	2.68	2.48	3.83	2.59	2.82	3.72	2.70
RSS + PDR	3.05	2.54	2.32	3.60	2.47	2.48	3.42	2.61
KF	2.39	2.26	1.64	2.92	2.30	2.22	2.63	2.22

TABLE II. MAXIMUM LOCALIZATION ERROR (M)

User	1	2	3	4	5	6	7	8
RSS	11.06	6.45	8.03	10.60	6.58	5.98	7.75	5.87
RSS + PDR	11.17	6.20	8.03	9.93	6.33	5.97	7.67	5.61
KF	3.91	4.36	4.02	4.30	4.65	4.33	3.92	4.62

VI. CONCLUSION

We have proposed a hybrid pedestrian localization technique for indoor environments that combines a RSS-based localization system and a PDR system through a Kalman filter. The proposed technique has the advantage of a negligible calibration cost compared to other systems. Furthermore, numerical and real-field experiments have shown that the accuracy of the proposed system is better than other calibration-free approaches, and comparable to the accuracy obtained with more complex systems that require a time-consuming calibration phase.

Further work will include a more exhaustive evaluation, using different mobility patterns and different user speeds, in order to extract some guidelines to correctly tune the Kalman filter parameters and models. We are also planning to carry out a quantitative evaluation of the calibration and processing cost in comparison to other methods (fingerprinting, particle filtering, etc.).

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