2013 International Conference on Indoor Positioning and Indoor Navigation, 28-31st October 2013

Robust indoor positioning fusing PDR and RF technologies: The RFID and UWB case

Francisco Zampella, Antonio R. Jiménez R., Fernando Seco
Centre for Automation and Robotics
Consejo Superior de Investigaciones Científicas (CSIC)-UPM
Ctra. Campo Real, Km 0.2, La Poveda, 28500 Arganda del Rey, Madrid-Spain
{francisco.zampella, antonio.jimenez, fernando.seco}@csic.es
www.car.upm-csic.es/lopsi

***Abstract*—Indoor positioning is usually based on individual technologies that provide estimates of the trajectory of the person, or measures the ranges or angles between the user and known positions. Each technique has its advantages and problems, and a common way to overcome the drawbacks of single-technology solutions is to fuse the information from several system, but due to their non linear measurements, there is no optimal linear solution. We propose the use of a particle filter to fuse foot mounted inertial measurements with any additional Radio Frequency (RF) measurement.**

The information fusion is achieved propagating the position of the particles using the relative step displacements obtained from foot mounted Pedestrian Dead Reckoning (PDR), and updating the weights of the particles according to the RF measurements. In our experiments the inertial unit was located in the foot of the user, and the RF system consisted in a Radio Frequency Identification (RFID) receiver in the waist, and an Ultra Wide band (UWB) tag in the chest, but the scheme can be used in any sensor configuration. As the UWB measurements have a significant amount of outliers due to non line of sight conditions generated by the position of the tag in the body, received reflections, etc., we propose a new outlier rejection algorithm based on the compatibility of groups of measurements. The fusion was tested evaluating the inclusion of each of the RF systems and varying the number RFID tags used. The proposed method is able to locate a person with less than 2 m of error (for 90 % of the obtained estimations) in the studied trajectory. This particle filter scheme offers robust indoor positioning with 100 % availability and smooth trajectory estimation thanks to the PDR and limited error due to the RF measurements.

***Index Terms*—Indoor Positioning, Sensor Fusion, Pedestrian Dead-Reckoning, Ultra Wide Band, RFID.**

I. Introduction

The development of new smartphones and improvements in the Global Navigation Satellite Systems (GNSS) have popularized among users the location based services [1] in which the positioning of the person allows them to obtain maps, location oriented offers, routes to a final destination, etc. Outdoors, the GNSS are able to provide that position, but indoors or any other GPS denied areas other technologies must be used.

The most common personal indoor positioning techniques use Radio Frequency (RF) signals between beacons with known positions and the person to locate [2]. Usual measurements include the Received Signal Strength (RSS), Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), etc, that can be related to the position solving the possibly non linear set of equations through different mathematical methods as proposed in [3]. RSS is the most common measurement available in mobile devices, making it cheap to deploy in large buildings, but offers a low accuracy indoors (3 to 30 m of error, [4], [5]). AOA and TDOA methods, on the other hand, require antenna arrays and device's synchronization, respectively, increasing the cost and limiting the surveying area to a few rooms, but with a better accuracy (0.3 to 1 m of error in the AOA/TDOA UWB based system [6] developed by Ubisense).

In the absence of external beacons it is possible to use Inertial Navigation Systems (INS) [7] to reconstruct a trajectory, integrating the acceleration and turn rates obtained from an Inertial Measurement Unit (IMU). Due to the multiple integrations required in the INS, the noise and bias of a low cost consumer grade IMU will generate a position error that grows as the cube of the time [8]. A common solution is the use of the IMU to detect steps and reconstruct the position from those displacements using an Extended Kalman Filter (EKF), making the error growth small and linear with time. This technique is commonly known as Pedestrian Dead Reckoning (PDR) [9], [10] and offers a good navigation solution, but will drift with time and requires the initial position and orientation.

A robust solution requires the fusion of the RF measurements with the movement model of PDR. Renaudin [11] and Jiménez [12] used the RF and magnetometer measurements collected before the start of the movement, to obtain an estimate of the initial position and included the measurements from UWB or RFID, respectively, in the EKF that propagates the PDR algorithm. Systems based in UWB are expensive and are usually installed in limited areas. On the other hand RFID tags are cheap and can be placed in extensive areas, but their measurements errors are higher and the obtained positioning is not as good. In both cases the EKF based filter might fail if the heading error grows too high, because the system is non linear. We propose the use of a simplified Particle Filter (PF) using the movement model from PDR and particle updates from several RF measurements, to solve the problem without initializing the states with other measurements.

978-1-4673-1954-6/12/$31.00

This solution addresses positioning in office buildings where it is possible to encounter multiple signals with a potential use for positioning. In the present paper we will focus in fusing IMU measurements with two systems, the RSS from a RFID system and a UWB real time Positioning system from Ubisense [6] based on TDOA and AOA. The first RF system, is a cheap, easy to deploy system, but with a low precision. The second RF system has a high precision, but is an expensive, line of sight dependant solution, installed only in a 15×25 m laboratory and present non detected outliers. We propose the development of an outlier detection for this system.

This paper is structured as follows, Section II reviews the relevant indoor positioning techniques. Section III propose the PF sensor fusion scheme and the the outlier detection algorithm. Section IV evaluates the proposed algorithm, while Section V draws the conclusion.

II. Indoor Positioning Techniques

The proposed positioning technique is based on the fusion of different measurements from RF and inertial measurements. In this section we will present the different approaches to convert those measurements into information useful in the positioning of a person.

A. RF Measurements

Any RF signals can be treated as an observation related to the position of the person ($r = [r_x, r_y, r_z]^T$) and the beacons. A general representation of a measurement z_i from the beacon i will be:

$$z_i = h_i(r) + \eta_z, \tag{1}$$

where $h_i(r)$ is the observation function according to a given measurement kind, evaluated in the position r, and η_z is a measurement noise. Under a Bayesian approach each measurement will have a probability distribution according to the position r. In the usual case of assuming a Gaussian error with zero-mean and standard deviation σ, the probability will be:

$$p(z_i|r) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(z_i - h_i(r))^2}{2\sigma^2}\right). \tag{2}$$

The most common RF measurements are based in the range between the RF devices or the angle of the received signal. Both techniques will be used in our experiments and are presented next.

1) Range Based Measurements: The distance d_i between a beacon/sensor i (positioned at r_{s_i}) and a person attenuates and delays the received signal, and this effects can be modeled to obtain expected times of arrival or signal strengths. The time t_{TOA_i} depends on the propagation speed of the electromagnetic wave on the air (c), and it can be measured if both emitter and receiver are synchronized as:

$$t_{\mathrm{TOA}_i} = d_i/c \cdot + \eta_t = \|r_{s_i} - r\|/c + \eta_t, \tag{3}$$

where $d_i = \sqrt{(r_{s_i,x} - r_x)^2 + (r_{s_i,y} - r_y)^2 + (r_{s_i,z} - r_z)^2}$ and η_t is the measurement noise.

Indoor it is unusual to have RF systems with synchronization between emitters and receivers, therefore most devices use the Round Trip Time or the TDOA. In the first case the signal must travel in both directions and the response time of the first receiver introduces a response time t_r, therefore the measurement model is:

$$t_{\mathrm{RTT}_i} = 2 \cdot d_i/c + t_r + 2 \cdot \eta_t + \eta_r, \tag{4}$$

where η_r is the variation in the response time.

In the second case the beacons are synchronized, but the sensor of the person is not, therefore each received time can be modeled as:

$$t_{\mathrm{TDOA}_i} = d_i/c + t_0 + \eta_t, \tag{5}$$

where t_0 is the unknown time between the emission of the signal and the start of the count in the receivers. When all the receivers are synchronized, it is possible to avoid the uncertainty of t_0, subtracting the times from 2 different beacons (i and j). The measurement model becomes:

$$t_{\mathrm{TDOA}_{i,j}} = (d_i - d_j)/c + 2 \cdot \eta_t. \tag{6}$$

The RSS is also used to estimate the distance d_i. Outdoors, with line of sight and without reflections the power of a signal decreases as the inverse of the squared distance. Indoors, on the other hand, the non line of sight conditions and the reflections in the walls affect this relationship and the model must be modified. Using the measurements in dBm, the relationship becomes:

$$\mathrm{RSS}_i = \alpha - 10 \cdot \beta \cdot \log_{10}(d_i/d_r) + \eta_{\mathrm{RSS}}, \tag{7}$$

where α is the received RSS at a reference distance d_r, β is the path loss exponent (usually between 1.5 and 6 in indoor environments) and η_{RSS} is the measurement noise.

Each received measurement establishes an equation, having enough relationships generates a non linear set of equations with r, that can be solved using several of the trilateration methods proposed in [3]. In general, (3), (4) and (7) generate spherical regions around each beacon and therefore, positioning with those measurements is called spherical trilateration. The circular regions generated by each beacon can be observed in the red lines in Figure 1. If (6) is used, each pair of distances generates an hyperbolic region and its positioning is usually called hyperbolic trilateration. The green lines in Figure 1 show the possible hyperbolic regions for each pair of measurements from 4 beacons.

2) Angles Based Measurements: With the use of arrays of antennas it is possible to estimate the angle of arrival observing the delays or signal strengths of the received signals in each point of the array [13]. This is one of the principles that allows angle of arrival measurements and in the UWB system used, two angles are available, the elevation φ and azimuth λ of the received signal. Following the deduction of [11], the angles

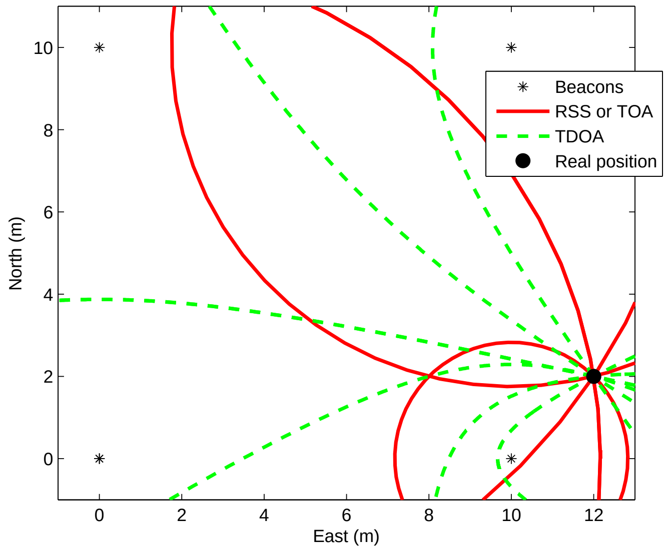

Fig. 1. Distance and difference in distances measurements

are associated to the position of a tag $r^{s_i} = [r_x^{s_i}, r_y^{s_i}, r_z^{s_i}]$ in the reference frame of the i-st sensor (superindex s_i) as:

$$\lambda_i = \tan^{-1}\left(\frac{r_y^{s_i}}{r_x^{s_i}}\right), \tag{8}$$

$$\varphi_i = \tan^{-1}\left(\frac{r_z^{s_i}}{\sqrt{(r_x^{s_i})^2 + (r_y^{s_i})^2}}\right), \tag{9}$$

where r^{s_i} can be obtained knowing the position of the tag r^n in the local reference frame (superindex n), the position of the sensor $r_{s_i}^n$ on the local reference frame and the yaw ψ_i and pitch θ_i of the sensor (the sensor must be installed with roll $\phi = 0$), as:

$$r^{s_i} = R(\theta_i, \psi_i) \cdot (r^n - r_{s_i}^n), \tag{10}$$

where the rotation $R(\theta_i, \psi_i)$ is:

$$R(\theta_i, \psi_i) = \begin{bmatrix} \cos\psi_i \cos\theta_i & \sin\psi_i \cos\theta_i & -\sin\theta_i \\ -\sin\psi_i & \cos\psi_i & 0 \\ \cos\psi_i \sin\theta_i & \sin\psi_i \sin\theta_i & \cos\theta_i \end{bmatrix} \tag{11}$$

The measurements proposed in (8) and (9) are not linear, therefore in the schemes proposed in [11] and [12], they need to be linearized. A better solution can be obtained if the measurements are treated with a non linear filter, and in this paper we propose the use of a particle filter.

B. Pedestrian Dead Reckoning

In the absence of RF measurements it is possible to use the inertial measurements to estimate the movements of the person using INS [7], as:

$$\hat{r}^n(k+1) = r^n(k) + (\dot{r}^n(k) + \dot{r}^n(k+1)) \cdot \Delta T/2, \tag{12}$$

$$\hat{\dot{r}}^n(k+1) = \dot{r}^n(k) + (C_b^n(k) \cdot a^b(k) - g) \cdot \Delta T, \tag{13}$$

$$\hat{C}_b^n(k+1) = C_b^n(k) \cdot \exp([\omega^b(k) \times] \cdot \Delta T), \tag{14}$$

where r^n and $\dot{r}^n$ are the position and velocity of the person on the navigation frame, ΔT is the time interval, C_b^n is the Direction Cosine Matrix (DCM) that rotates the measurements from the sensor or body (index b) to the navigation frame, a^b and ω^b are the acceleration and turn rate measured in the sensor reference frame and $[\omega^b \times]$ is the skew symmetrical matrix of ω^b:

$$[\omega^b \times] = \begin{bmatrix} 0 & -\omega_z^b & \omega_y^b \\ \omega_z^b & 0 & -\omega_x^b \\ -\omega_y^b & \omega_x^b & 0 \end{bmatrix} \tag{15}$$

Due to the integrations used in (12) to (14), this technique requires a tactical grade IMU, but they are too big and expensive to be carried by a pedestrian. Micro Electro Mechanical (MEM) IMUs are smaller and less expensive units that can be used in this case, but the error levels of low cost consumer grade devices require constant external measurements to avoid a divergence.

A common approach to avoid the INS error increment is to identify the no motion states of the walk in order to apply Zero velocity UPdaTes (ZUPT), something easily achievable when the IMU is in the foot of a pedestrian as proposed in [9], [14]. The typical implementations use a 15 or 9 error states EKF and detect the stance phase of the walk observing the magnitude of the turn rates and accelerations registered in the IMU. Refer to [14] for a complete description of the PDR algorithm. In this paper we will use a 9 states EKF to estimate the path of the pedestrian ($X = [\delta\Psi, r^n, \dot{r}^n]^T$, consisting in Attitude error, Position and Velocity). The states can be estimated using (14) and the linearized transition model, as:

$$\hat{X}(k) = \Phi(k-1) \cdot X(k-1) + w, \tag{16}$$

where $\hat{X}(k)$ is the estimate of the states, w is the process noise with covariance $Q = E(w \cdot w^T)$ and Φ is the 9×9 state transition matrix:

$$\Phi = \begin{bmatrix} I_3 & 0_3 & 0_3 \\ 0_3 & I_3 & I_3 \cdot \Delta T \\ -[\hat{C}_b^n a^b \times] \cdot \Delta T & 0_3 & I_3 \end{bmatrix}. \tag{17}$$

The estimate of the covariance of the states $\hat{P}(k)$ can be calculated from the previous covariance $P(k-1)$ as:

$$\hat{P}(k) = \Phi(k-1) \cdot P(k-1) \cdot \Phi^T(k-1) + Q, \tag{18}$$

When a Stance is detected (refer to [15] for a comparison of several techniques), it is possible to implement a ZUPT measurement, with a measurement model:

$$m_{\text{ZUPT}}(k) = H \cdot X(k) + v, \tag{19}$$

where, v is the measurement noise with covariance $R_{\text{ZUPT}} = E(v \cdot v^T)$ and $H = [0_3, 0_3, I_3]$ is the observation matrix. This measurement updates the states as:

$$X(k) = \hat{X}(k) + K_k \cdot (m_{\text{ZUPT}} - H \cdot \hat{X}(k)), \tag{20}$$

where $m_{\text{ZUPT}}(k) = [0, 0, 0]^T$ (zero velocity) and K_k is the Kalman gain, calculated as:

$$K_k = \hat{P}(k) \cdot H^T (H \cdot \hat{P}(k) \cdot H^T + R_{\text{ZUPT}})^{-1}. \tag{21}$$

This way the position and velocity are corrected, and we have an estimate of the attitude error, that can be used to correct the value of $\hat{C}^n_b$, as:

$$C^n_b(k) = \exp([\delta\Psi(k)\times]) \cdot \hat{C}^n_b(k). \tag{22}$$

After the correction, the attitude error is reset to 0. The covariance of the states is updated as:

$$P(k) = (I_9 - K_k \cdot H) \cdot \hat{P}(k). \tag{23}$$

III. Sensor fusion

In a typical building it is possible to encounter several signals useful for positioning (Bluetooth, WiFi, RFID, etc.), focusing in only one technology limits the amount of information and therefore lowers the quality of the position estimation. In many cases a system has a specific coverage area inferior to the total surveying zone, a robust positioning must take into account all of this systems and use all the information available.

The use of RF positioning from several systems offers an absolute positioning, that combined with the movement model obtained with PDR can offer a complete and robust positioning able to overcome non line of sight conditions, offer a 100 % availability and improve the estimation with the incorporation of past information.

The fusion of an UWB system with an inertial system was treated in [11], under an EKF approach, the author used a trunk mounted IMU with step identification. In [12], the author fused RFID measurements with foot mounted PDR, again using an EKF and linearizing the measurements. We believe the introduction of a PF can improve the effect of the movement model and the measurements, offering a simplified fusion scheme to include multiple systems.

In this section we will discuss the proposed fusion scheme using as a basis the step displacements obtained with PDR and the inclusion of any measurements to that algorithm.

A. General fusion scheme

As previously discussed, we will use a PF to integrate the information from the IMU and the RF measurements. A direct fusion at the sampling rate of the IMU (usually 100 Hz), taking into account all the necessary states, will require a significant amount of particles to be processed in a little time, something not possible with our current equipment. We plan to simplify the states and the filter as proposed in [16], but modifying the measurements to use RFID and UWB. We will work with the fusion scheme of Figure 2, where the PF is separated in two parts, the particle propagation and the weights updates. The first is based in the PDR, while the second is based in the external measurements.

The PF will track the unobservable states of the PDR, the position r and the yaw θ, therefore the particle states will be $X = [r_x, r_y, r_z, \theta]^T$, the 3D position and the heading. The IMU measurements are analyzed using a simple PDR algorithm as described in Subsection II-B, when a step is detected, the filter will use the relative displacement $\Delta X = [\Delta r_x, \Delta r_y, \Delta r_z, \Delta\theta]^T$ (measured in the local reference frame rotated according to the yaw of the previous stance) and the characteristics of the step, to generate a movement model. The state's displacement of a particle (p) from the stance n to the stance $n+1$ will be:

$$X^{(p)}(n+1) = X^{(p)}(n) + Rot(\theta^{(p)}(n))(\Delta X(n) + \eta_{\Delta X}), \tag{24}$$

where $\eta_{\Delta X}$ is a Gaussian noise with a covariance according to the characteristics of the step, and the rotation $Rot(\theta)$ is:

$$Rot(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta & 0 & 0 \\ \sin\theta & \cos\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{25}$$

If a measurement z is received in the instant t_z, between the stances n (time $t(n)$) and $n+1$ (time $t(n+1)$), the particles weights $w^{(p)}$ can be updated using (2), according to:

$$w^{(p)} = w^{(p)} \cdot p(z|\hat{r}^{(p)}), \tag{26}$$

where $\hat{r}^{(p)}$ is a lineal interpolation of the position of the particle, calculated as:

$$\hat{r}^{(p)} = r^{(p)}(n) + \frac{(t_z - t(n))}{(t(n+1) - t(n))} \cdot (r^{(p)}(n+1) - r^{(p)}(n)). \tag{27}$$

After all the particle weights have been updated, they need to be normalized such that $\sum w^{(p)} = 1$. The complete process can be observed in Figure 3. A PDR displacement is represented in subplot *a*, where the step obtained using the IMU in the foot will set the path of each particle.

B. RFID measurements

The used RFID system provides RSS measurements between the tags and a reader, and using the measurement model of (2) and (7) the particle weights can be updated. We based our measurement model in the calibration of [12], where $\alpha = -60$ dBm, $\beta = 2.3$ and $\sigma_{RSS} = 6$ dBm. This model approximated the path loss model for RFID tags in an office building, measuring the RSS in 32 positions (1 minute each, ranging 4 different orientations) to 71 different beacons distributed along the whole building (approximately 1 tag every 30 m^2). The differences between each of the paths provides a model with a higher standard deviation of the measurements than a single path measurement, but with a robust behavior against basic changes in the environment, mainly due to the different trajectories taken into account. Due

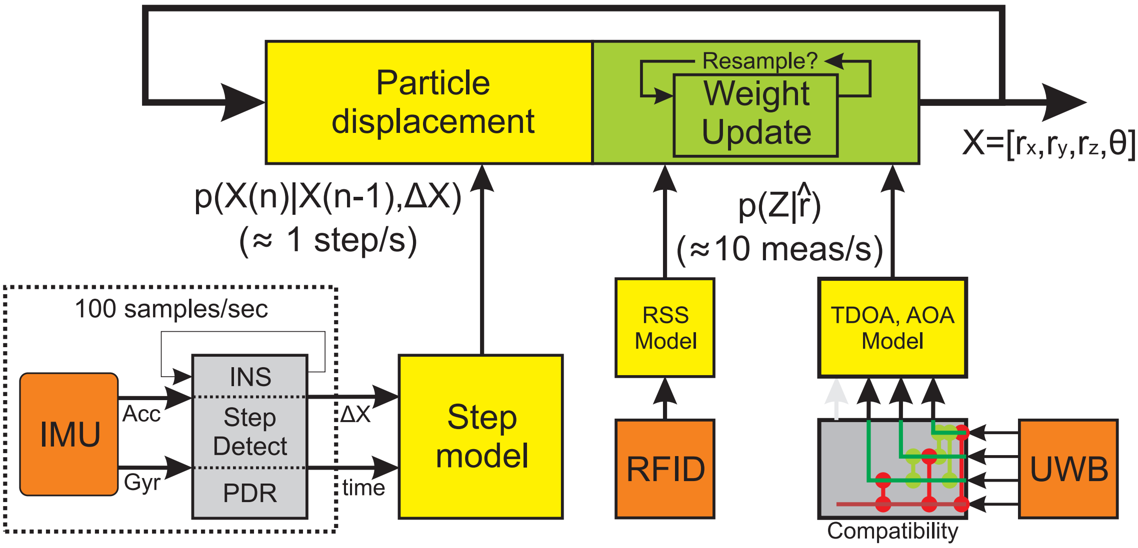

Fig. 2. Fusion scheme. On the left the Step displacement model, using ZUPT-based PDR. On the right, the RF measurements based on UWB and RFID. The UWB measurements have an outlier rejection before their use as measurements.

to the error level typical of RSS measurements indoor, we did not used an outlier rejection for this measurements. Subplot *b* of the figure 3 shows the weight update generated with a RSS measurement

C. UWB measurements, Outliers detection

In the Ubisense UWB RTLS [6], the direct use of the received UWB information as measurements on the PF, might generates a loss of most of the particles if an outlier is detected. This is due to the low probability of the measurements of the outlier, that lower the weights of the particles if the measurements have a low σ, this problem is usually called particle deprivation. The authors in [17] propose the modeling of all the possible sources of error in the error distribution of the measurements, but this will require a non Gaussian distribution of $p(z|r)$, increasing the processing time and complexity of the scheme. We propose an outlier rejection layer, due to the fact that most outliers provide little or no information to the problem, and given enough measurements they can be identified and removed.

Every UWB measurement package consist on measurements from at least 2 sensors, each of the sensors providing TDOA and AOA to the UWB tag, and in most cases at least 1 sensor is receiving non line of sight measurements. If a sensor receives non line of sight measurements all of their measurements will be outliers. We propose to evaluate the groups of sensors with the minimum amount of values to obtain a position (2 sensors) and then include additional sensors' measurements if they are compatible with the original group. We will first obtain an estimate of the position for the measurements from each pair and then observe the compatibility with the measurements.

In general, an estimate of the position $\tilde{r}$ can be obtained from a group of measurements $Z = [t_{TDOA_2} - t_{TDOA_1}, \ldots, t_{TDOA_N} - t_{TDOA_1}, \lambda_1, \ldots, \lambda_N, \varphi_1, \ldots, \varphi_N]^T$

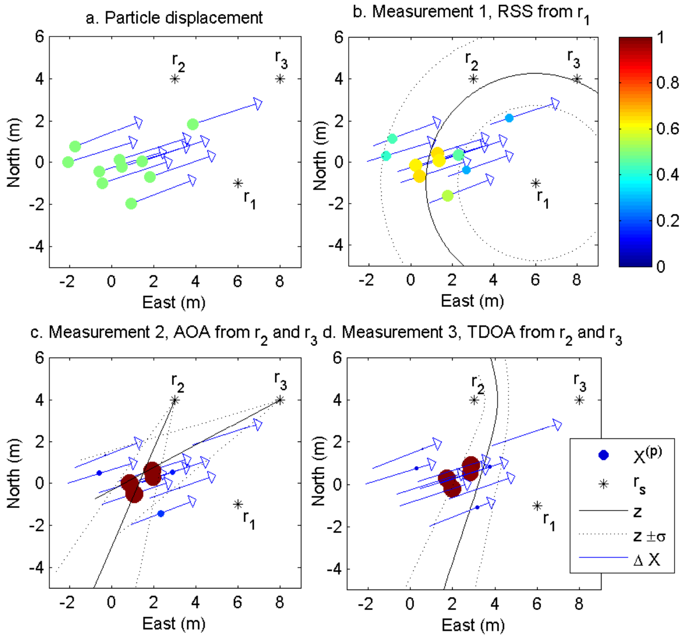

Fig. 3. Steps of the particle filter to fuse PDR and RF measurements. a. Particle displacement (ΔX) from PDR. b, c and d. Measurement updates from RSS, AOA and TDOA measurements (z) with respect to the beacons r_s. The circles represent the particles $X^{(p)}$ position, while their size and color (according to the colorbar) represent their normalized probability

maximizing the probability $p(r|Z)$, such that:

$$\tilde{r} = arg_r \min p(r|Z), \tag{28}$$

but this is a non linear problem that requires an iterative method to be solved, something limitative when we need to evaluate a significant amount of pairs of sensors. We propose to obtain a suboptimal position that can be obtained with a linear method as an alternative. The position of the person obtained using the measurement from the sensor i, can be written as:

$$r_i^n = r_{s_i}^n + R(\theta_i, \psi_i)^T \begin{bmatrix} \cos\varphi_i \cos\lambda_i \\ \cos\varphi_i \sin\lambda_i \\ \sin\varphi_i \end{bmatrix} (t_{\text{TDOA}_i} c - d_0), \quad (29)$$

where $d_0 = t_0 \cdot c$ is unknown but common for all the sensors at that time.

If we know d_0 and have N beacons, each one of them will produce an estimate of r^n. A simple estimate of the position of the person will be the mean of the obtained positions:

$$\bar{r} = \sum_{i=1}^{N} r_i^n / N, \quad (30)$$

but this value depends on d_0. We propose the use of the value d_0 that minimizes the sum of the squared distances between the mean $\bar{r}$ and the estimated points r_i^n, i. e.:

$$d_0 = arg_{d_0} \min \sum_{i=1}^{N} (r_i^n - \bar{r})^T (r_i^n - \bar{r}) \quad (31)$$

Due to the linear relationship between r_i^n and d_0, the problem is a minimization of a quadratic function and its solution is:

$$d_0 = \frac{\sum_i (r_{s_i}^n + v_i \cdot t_{TDOA_i} c - \sum_k r_k^n / N)^T (v_i - \sum_k v_k / N)}{\sum_i (v_i - \sum_k v_k/N)^T (v_i - \sum_k v_k/N)}, \quad (32)$$

where both sum operators ($\sum_i$ and $\sum_k$) range their values from 1 to N, and the vector v_i is:

$$v_i = R(\theta_i, \psi_i)^T \begin{bmatrix} \cos\varphi_i \cos\lambda_i \\ \cos\varphi_i \sin\lambda_i \\ \sin\varphi_i \end{bmatrix}, \quad (33)$$

Using d_0 to find $\bar{r}$, offers a simple method to estimate the position of the person without the need of a non linear minimization using iterative methods. The error level of the estimation can be measured using the squared Mahalanobis distance (MD^2) of the measurement vector $Z = [t_{TDOA_2} - t_{TDOA_1}, \ldots, t_{TDOA_N} - t_{TDOA_1}, \lambda_1, \ldots, \lambda_N, \varphi_1, \ldots, \varphi_N]^T$ to the observations $H()$ in the point $\bar{r}$, as:

$$MD^2(\bar{r}) = (Z - H(\bar{r}))^T R_z^{-1} (Z - H(\bar{r})), \quad (34)$$

where R_z is the covariance of the measurement vector.

A candidate to identify the best pair of beacon measurements is the use of the error level defined by $MD^2(\bar{r})$. Although the estimate of the position ($\bar{r}$) is not a Maximum-Likelihood Estimation, if the measurements pair are not outliers, $\bar{r}$ will have a low Mahalanobis distance, while in most of the cases the outliers will present a higher $MD^2(\bar{r})$. The algorithm will have to obtain the value of the error level in the positions obtained from all the beacon pairs i_1 and i_2 taking into account the measurements from the same beacons, $MD^2_{i_1,i_2}(\bar{r}_{i_1,i_2})$, and select the pair of beacons that have the minimum error level and have an error level below a threshold MD^2_{th} (a Mahalanobis distance of 1 is equivalent to 1 standard deviation on the measurements). Any additional measurements i_3 can be included if the value of the crossed error levels ($MD^2_{i_1,i_3}(\bar{r}_{i_1,i_3})$ and $MD^2_{i_2,i_3}(\bar{r}_{i_2,i_3})$) are also below the threshold MD^2_{th}.

Under some conditions, the outliers can have a low $MD^2(\bar{r})$ due to coincidences in the reflections or refractions. This cases are usually rare but possible and will alter our algorithm. We propose to avoid them studying the value of d_0. When several pairs of beacon measurements are correct, the calculated distance $d_0(i_1, i_2)$ for each pair (i_1 and i_2) should be close to the others, but if the pair presents an outlier, the obtained distance is aleatory. With that in mind, it is possible to estimate the value of d_0 as the median $\hat{d}_0$ of the set of $d_0(i_1, i_2)$ values and detect good measurements if the error $|d_0(i_1, i_2) - \hat{d}_0|$ is under a threshold d_{th}. As a way to improve the median estimation we included in the set, the values of $d'_0(i_1, i_2)$ taking into account the difference:

$$d'_0(i_1, i_2) = t_{\text{TDOA}_{i1}} c - |r_{s_{i1}} - r_{i2}|. \quad (35)$$

The figure 4 shows the sorted distribution of the distances d'_0 of the pairs studied, the real value is close to the median of the distribution.

The proposed algorithm for outlier rejection is:

for $i_1 = 1 : N-1$
  for $i_2 = i_1 + 1 : N$
    Using Z_{i_1} and Z_{i_2},
    - Obtain $d_0(i_1, i_2)$ (32)
    - Obtain $\bar{r}_{i_1,i_2}$ (30)
    - Obtain $MD^2_{i_1,i_2} = MD^2(\bar{r}_{i_1,i_2})$ (34)
    - Obtain $d'_0(i_1, i_2)$ and $d'_0(i_2, i_1)$ (35)
  endfor
endfor
$\hat{d}_0 = \text{median}(d'_0)$
$(i_1, i_2) = arg_{(i_1,i_2)} \min MD^2_{i_1,i_2}$
if $(MD^2_{i_1,i_2} < MD^2_{th} \& |d_0(i_1, i_2) - \hat{d}_0| < d_{th})$
  Good Measurements $\leftarrow \{i_1, i_2\}$
  for $i_3 = \{1 : N\} - \{i_1, i_2\}$
    if (i_3 compatible with i_1 and i_2)
      Good Measurements $\leftarrow \{i_3\}$
    endif
  endfor
else
  no good measurements detected
endif

We have observed that this algorithm is much more restrictive than the one provided by Ubisense, allowing less measurements, but certifying that the measurements are from line of sight conditions. Once the outliers have been identified, the measurements can be applied to the weights of the particles, subplots *c* and *d* of figure 3 shows the weight update generated with AOA and TDOA measurement, respectively.

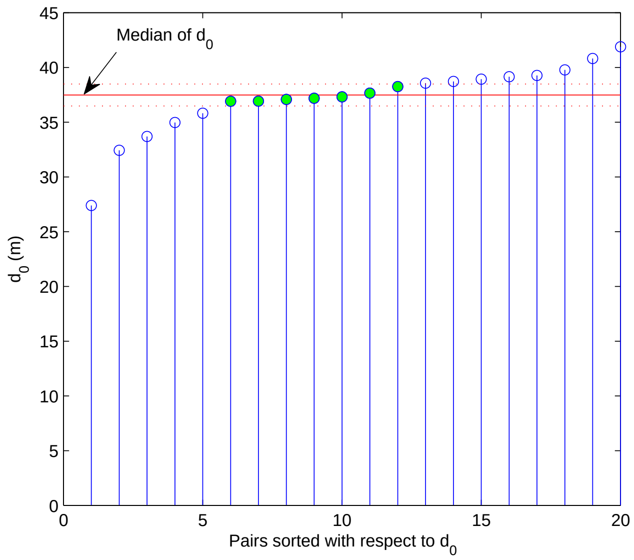

Fig. 4. Sorted d_0 distances for each pair of measurements. The red line indicates the median of the d_o values. Valid d_0 values are marker in green.

IV. Experiments and Results

For the evaluation of the algorithm we recorded several experiments of a pedestrian walking between 2 buildings in the Centre for Automation and Robotics. We wanted to evaluate the improvement introduced by the usage of a high precision system (UWB) placed in a small area and/or a relatively low precision system (RFID) in a wide area, as a way to determine which strategies are better. In this section we will explain the experiment's setup and offer the obtained results.

A. Experimental Setup

For the experiments, the pedestrian carried a XSens MTi IMU in the instep of the foot whose signals were sampled at 100 Hz, a RFCode M220 RFID reader in the waist and a Ubisense UWB tag in the chest. The measurements from the IMU and the RFID reader were recorded using a Motorola Xoom2 tablet (Android) and the measurements from the UWB system were recorded using their proprietary hardware and software, with an offline synchronization. The user walked through a predefined path as a way to obtain the ground truth of the trajectory.

The buildings have 100 installed RFID tags model M100 from RFCode, working at 433 MHz, with an update rate of approximately 1 Hz each, distributed among a $40 \times 65\ m^2$ building and a $15 \times 25\ m^2$ laboratory, both with single floors. 6 Ubisense Series 7000 sensors are installed and used for positioning in the laboratory, where several structures limit the line of sight of the sensors. The sensors used for the experiment can be observed in the figure 5.

For the experiment we will test the inclusion of each of the measurements in the estimation, starting with a basic PDR relative positioning, then including UWB measurements (only in the laboratory). After that we will test the inclusion of RFID measurements in the PDR estimation and finally using all the measurements. We will also evaluate the effect of the number of RFID tags used, activating different sets of tags starting with 12 tags and up to 100 tags.

Fig. 5. Sensors used in the experiment, where it can be observed that one of the UWB sensors does not have a line of sight.

The walking path starts in the laboratory (UWB and RFID) where the pedestrian makes a small path and leaves the area, walking towards the main building (only RFID). There the person makes a counterclockwise trajectory around the main corridors of the building, and 2 turns around a small office before leaving the building and walking towards the laboratory and repeating the trajectory once again. The path starts and finishes in the same point in the laboratory an can be observed in the figure 6 as well as the PDR only positioning knowing the initial position and orientation.

After the first experiments we observed that the UWB system, usually needed around 50 to 60 seconds to detect the tag when we entered the room, while the RFID system was always detecting the signals. This behavior might avoid

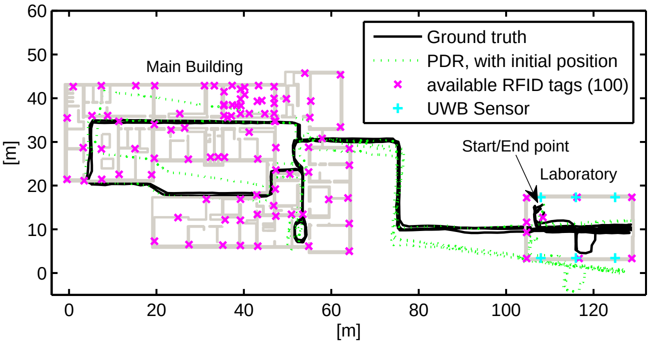

Fig. 6. Trajectory of the experiment and EKF-PDR positioning knowing the initial position and orientation.

the UWB detection if the walks in the laboratory were too short, therefore in our experiments we wandered for at least 120 s before leaving the laboratory to make sure the tag was detected.

B. Results

The obtained trajectories of the weighted mean of the particle clouds can be observed in the figure 7. As previously stated the use of PDR with an UWB positioning system installed only in a small part of the surveying area generates a good estimation in the UWB area (and provides the initial position and orientation), but relies in dead reckoning for the rest of the trajectory, generating an increasing positioning error until a new UWB measurement is detected. The delay in the tag detection increases this effect and we can observe this error in the last path that enters the laboratory, in which, due to a bad dead reckoning the estimation is deviated from the real path until a UWB measurement is detected. The complete sequence will be available in our web page (http://www.car.upm-csic.es/lopsi/static/videos.htm).

The use of PDR with RFID measurements offers a robust solution for the positioning in the studied area, but due to the uncertainty of the RSS measurements the estimation takes some time to converge to the real path or to recover from a bad estimation.

When both measurements are included in the PDR estimation using the PF, the estimation offers a quick convergence of the particles to the real path, and a bounded error level during the whole trajectory. As a way to compare the error levels of each combination and the effect of changing the number of RFID tags, we studied the cumulative distribution function (CDF) of the positioning error against the ground truth of figure 6, obtained using the initial position and orientation, PDR measurements and corrected with the known walking path. The CDFs of the methods are observed in the figure 8. Subplot *a* shows the effect of adding each of the measurements to the estimation, while subplot *b* shows the effect of changing the number of RFID tags used.

As expected the fusion of all the measurements offers the best estimate (2 m of error, 90 % of the time), but we can also note that the use of a low precision system like RFID over a wide area is better than using a high precision positioning system only in a small area of the total walking path. The use of PDR with an UWB system in a small area is recommended only if the walking path is mainly inside the UWB coverage area, due to the fact that outside of that area the estimation relies only in dead reckoning and therefore the error will grow with the traveled distance.

The increase in the density of the RFID tags lower the error level, but we have observed that increasing the number of tags over 34 (in an area of around $3000\ m^2$) does not appear to affect the CDF. As a way to lower the calculation necessary to estimate the position of the person we recommend the use of a RFID tag density of approximately $1\ tag/100\ m^2$.

This algorithm was tested with 100000 particles, in a Intel Core 2 processor (2.83 GHz, using 1 processor) using MATLAB and we were able to process a 730 seconds trajectory in approximately 300 seconds. For the test we used 34 RFID tags (approximately 1 Hz each when available), 6 UWB sensors (up to 10 Hz update rate, but much lower with the proposed outlier detection) and an IMU in the foot (100 Hz sampling rated, approximately 1 step per second). We think this method can be implemented in real time on a smartphone or tablet (reducing the number of particles) or alternatively transmitting RFID, UWB and step information and processing the positioning in a server or any external processor.

V. Conclusion

In this paper we have presented a sensor fusion scheme for Pedestrian Dead Reckoning capable of including measurements with a wide variety of observations and error characteristics. In particular we used the RFID tags (RSS) installed in our buildings and a UWB TDOA/AOA positioning system, installed in one laboratory. Both systems offer different error characteristics and non linear measurement functions, but we were able to use their information to improve the positioning estimations using a particle filter scheme.

The sensor fusion algorithm is based on the step wise information provided by the IMU on the foot. This step displacements and heading changes define the movement model and dispersion of the particles. The information from any external measurements (UWB and RFID) is included in the estimation changing the weighs of the particles according to the probability distribution of the measurement given the position of the particles. This scheme allows to incorporate non linear functions without the need of a linearization.

The proposed fusion does not need an initial position or orientation, and overcomes the limitation of each system, lowering the error level of RFID positioning and accelerating their convergence, and improving the precision of the UWB real time location system outside of the line of sight area.

Any positioning system will have a limitation that must be overcome with the use of additional sensors. Smartphones and tablets presents a basic hardware filled with sensors that

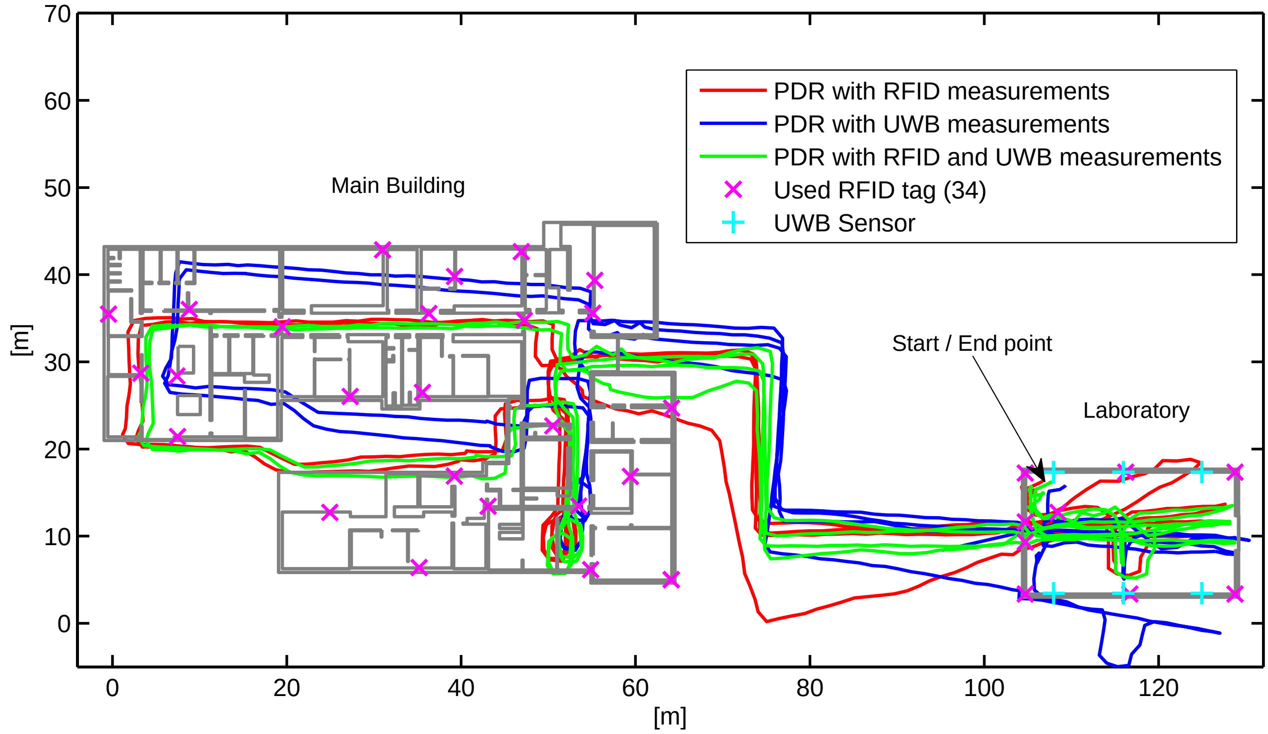

Fig. 7. Estimation of the position using the different methods studied. All the methods were initialized without initial position or orientation.

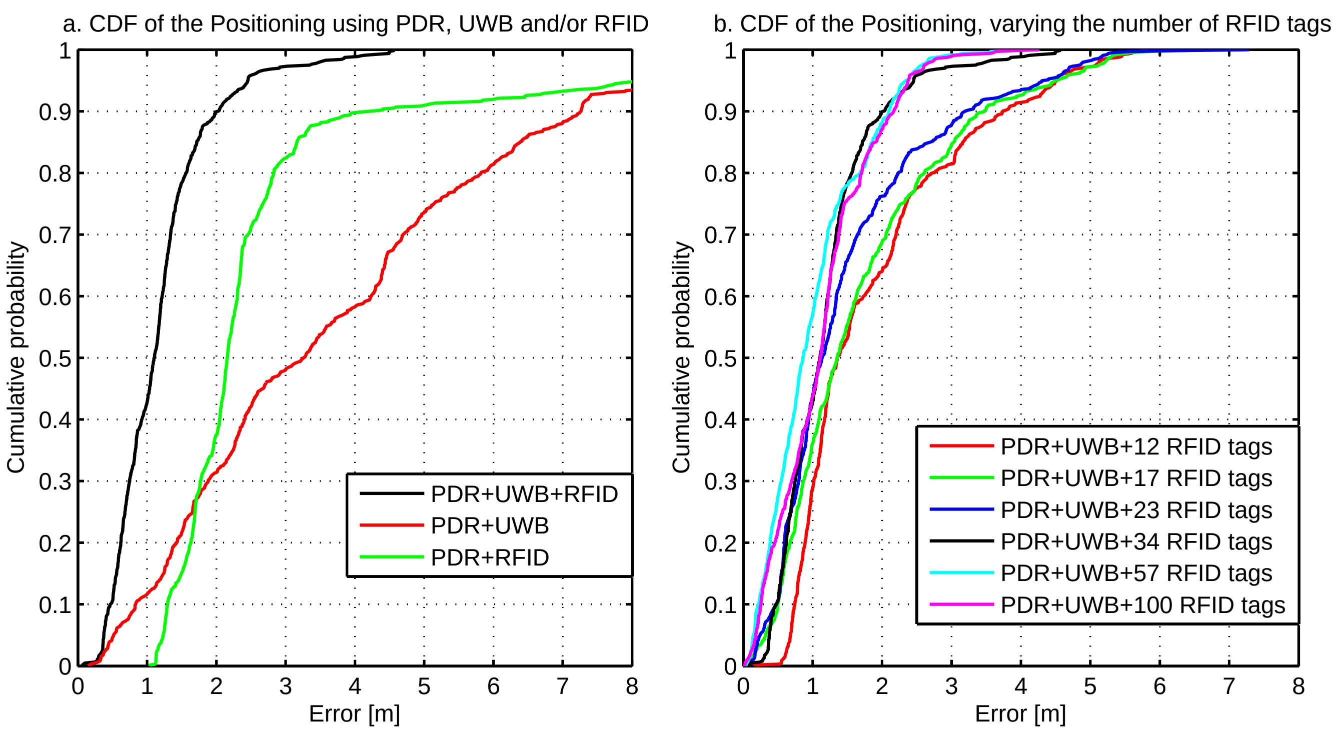

Fig. 8. Cumulative Distribution Functions (CDF) of the position estimation methods based on PDR and RF measurements. a. Changes in the CDF with the inclusion of RFID and/or UWB measurements. b. Changes in the CDF after varying the used RFID tags (PDR with UWB and RFID measurements).

can be used to position a person. The PF scheme offers an structure to fuse all those measurements and any other external measurements (like Ubisense UWB tags) to obtain the best estimate of the position.

Although the obtained error level can be used for indoor positioning purposes, it is clear that additional information can be included in the estimation. Future works can include map-matching [18] and the use of the magnetic information [19], [20].

ACKNOWLEDGMENT

This work was supported by the LEMUR project (TIN2009-14114-C04-02), LORIS project (TIN2012-38080-C04-04), LAZARO project (CSIC-PIE Ref.201150E039) and the JAE PREDoc program.

REFERENCES

[1] K. Michael and M. Michael, "The social and behavioural implications of location-based services," *Journal of Location Based Services*, vol. 5, no. 3-4, pp. 121–137, 2011.

[2] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks," *IEEE Signal Processing Magazine*, vol. 22, pp. 41–53, July 2005.

[3] F. Seco, A. Jimnez, C. Prieto, J. Roa, and K. Koutsou, "A survey of mathematical methods for indoor localization," in *WISP 2009 - 6th IEEE International Symposium on Intelligent Signal Processing*, (Budapest), pp. 9–14, 2009.

[4] F. Seco, C. Plagemann, A. Jiménez, and W. Burgard, "Improving RFID-Based Indoor Positioning Accuracy Using Gaussian Processes," in *International Conference on Indoor Positioning and Indoor Navigation*, pp. 15–17, 2010.

[5] S. Mazuelas, A. Bahillo, R. M. Lorenzo, P. Fernandez, F. a. Lago, E. Garcia, J. Blas, and E. J. Abril, "Robust Indoor Positioning Provided by Real-Time RSSI Values in Unmodified WLAN Networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, pp. 821–831, Oct. 2009.

[6] Ubisense Ltd., *The Ubisense Precise Real-time Location System - Series 7000 Sensor*, 2011.

[7] D. Titterton and J. Weston, *Strapdown Inertial Navigation Technology*. The American Institute of Aeronautics and Astronautics, second ed., 2004.

[8] F. Zampella, A. Jimenez, F. Seco, J. Prieto, and J. Guevara, "Simulation of foot-mounted IMU signals for the evaluation of PDR algorithms," in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*, pp. 1 –7, sept. 2011.

[9] E. M. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *Computer Graphics and Applications, IEEE*, vol. 25, pp. 38–46, Nov.-Dec. 2005.

[10] A. Jimenez, F. Seco, J. Prieto, and J. Guevara, "A comparison of Pedestrian Dead-Reckoning algorithms using a low-cost MEMS IMU," in *2009 IEEE International Symposium on Intelligent Signal Processing*, pp. 37–42, Ieee, Aug. 2009.

[11] V. Renaudin and B. Merminod, "Optimal data fusion for pedestrian navigation based on UWB and MEMS," in *Position Location And Navigation Symposium*, pp. 341–349, 2008.

[12] A. Jimenez Ruiz, F. Seco Granja, J. Prieto Honorato, and J. Guevara Rosas, "Accurate pedestrian indoor navigation by tightly coupling foot-mounted imu and rfid measurements," *Instrumentation and Measurement, IEEE Transactions on*, vol. 61, pp. 178 –189, jan. 2012.

[13] D. Inserra, A. Tonello, and N. Moret, "Positioning based on 2-d angle of arrival estimation," in *Vehicular Technology Conference (VTC Spring), 2011 IEEE 73rd*, pp. 1 –5, may 2011.

[14] A. Jiménez, F. Seco, J. Prieto, and J. Guevara, "Indoor pedestrian navigation using an INS/EKF framework for yaw drift reduction and a foot-mounted IMU," in *Positioning Navigation and Communication (WPNC), 2010 7th Workshop on*, pp. 135 –143, march 2010.

[15] I. Skog, P. Handel, J. Nilsson, and J. Rantakokko, "Zero-velocity detection - an algorithm evaluation," *Biomedical Engineering, IEEE Transactions on*, vol. 57, pp. 2657 –2666, nov. 2010.

[16] F. Zampella, A. Bahillo, P. J., A. Jiménez Ruiz, and F. Seco Granja, "Pedestrian Navigation fusing Inertial and RSS/TOF measurements with Adaptive Movement/Measurement Models: Experimental Evaluation and Theoretical Limits," *Sensors and Actuators: A*, vol. ., p. accepted, 2013.

[17] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Intelligent Robotics and Autonomous Agents, MIT Press, 2005.

[18] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," *Proceedings of the 10th international conference on Ubiquitous computing - UbiComp '08*, p. 114, 2008.

[19] F. Zampella, M. Khider, P. Robertson, and A. Jimenez, "Unscented Kalman filter and Magnetic Angular Rate Update (MARU) for an improved Pedestrian Dead-Reckoning," in *Position Location and Navigation Symposium (PLANS), 2012 IEEE/ION*, pp. 129 –139, april 2012.

[20] V. Renaudin, M. Afzal, and G, "New method for magnetometers based orientation estimation," in *Position Location And Navigation Symposium*, p. 9, 2010.