# NAVIGATION SYSTEM FOR ELDERLY CARE APPLICATIONS BASED ON WIRELESS SENSOR NETWORKS

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## ABSTRACT

The work presents the development of a navigation system based on wireless sensor networks specially designed for elderly care applications. The main constraints of the application scenario are analysed and the tracking algorithm is designed following the application constraints. The tracking is done by the fusion of RSSI measurements using the weighted centroid algorithm to compute the position and inertial sensors to compute the heading and speed by means of a step detection. The measurement information is processed using an Extended Kalman Filter.

***Index Terms—*** Tracking, Inertial Systems, Elderly care applications

## 1. INTRODUCTION

The development of digital electronics in the last years has made it possible to obtain low-cost, small size and low-power devices, with the capability to communicate wirelessly. Now, it is possible to manufacture wireless sensor networks (WSN) with an affordable cost. Therefore, it can help to increase our standard of living. One of this areas of applications based on WSN is the elderly care. Nowadays, with the progressive increment of the life expectancy, research efforts should be focused in enhancing quality of live. In that context, elderly care applications perfectly match this idea. One of the most common reluctance of old people who need continuous health care is that they want to remain at home. At this point, wireless sensor technology is mature enough to act as an invisible caregiver.

The large amount of existing sensors allow us to control the most common dangerous situations at home, as fires, gas leaks or water leaks among others. Furthermore, the vital signs of people can also be sensed and therefore, it is possible to monitor the health state of a person. As important as this is to known the position of the person in order to monitor strange patterns of movement, as for example, a circular movement during a long time. The information of all the sensors and the position of the person, at every moment, is the basis to create a complete health care system.

The scope of this paper is the design of an indoor localization system for elderly care applications. During the design process some special characteristics have to be taken into account. One of them is the total cost of the system, which has to be as low as possible in order to be affordable for lots of people. The energy consumption is another important issue, as the network has to be working for long periods of time. Another constraint is the size and weight of the mobile node as far as it has to be wearable by the person. The position of the mobile node in the body is also a special consideration in order to assure the comfort of the user.

The localization methods typically used in WSNs are based on measurements of the distance between the unknown position node and the neighbouring nodes with known position, also known as anchor nodes. The distance between nodes is usually calculated using ToA(Time of Arrival), AoA(Angle of Arrival) or RSSI(Received Signal Strength Indicator) [1, 2]. ToA and AoA present more accurate estimations of distance but they need additional hardware in order to obtain an accurate estimation, with the consequent increment in the total system cost. For this reason, RSSI based localization methods are the most widely used algorithms for obtaining the position of a node in WSNs. The main disadvantage of using RSSI measurements is the poor performance due to the variability of the wireless channel, especially in indoor environments.

Current localization algorithms may not achieve the accuracy that is necessary for person tracking. One possible solution in order to increase the performance of the localization algorithms, is the inclusion of new measurements. Recently, several authors have proposed to employ inertial sensors in order to overcome the position accuracy problem. However, the proposed algorithms do not fulfil the constrains above (low-cost, low-size, energy efficient and user comfortability) and are not applicable in our scenario. In this paper, we propose a new tracking system based on RSSI measurements and inertial sensors that fulfils the above constraints and still provides

This work is supported by the Spanish Government under project TEC2011-28219 and the Catalan Government under grant 2009 SGR 298.

enough accuracy to track the movements of a person at home.

The remainder of this paper is organized as follows: Section 2 present the state of the art of tracking using inertial sensors in WSN. Section 3 detail the proposed tracking algorithm while Section 4 presents the experimental results. Finally, conclusions and future work are presented in Section 5.

## 2. RELATED WORK

This section is an overview of the literature of tracking algorithms, in WSNs, based on inertial sensors. The following algorithms are based on RSSI measurements, which are the most widely used to estimate the distance between nodes, due to its easy implementation. The standards of communications used in WSN typically include the RSSI measurement as a field in the radio packets. The distance is estimated using a propagation model. Commonly, the log-distance path-loss model is employed [3]:

$$PL = P + 10n\log_{10}\left(\frac{d}{d_0}\right) + N_G \tag{1}$$

where $PL$ is the measured path-loss, $d$ the distance, $P$ a reference measurement of the received power at distance $d_0$, $n$ the path-loss coefficient and $N_G$ a normally distributed noise term. The parameters of the model ($P$,$n$,$N_G$) have to be experimentally determined for each scenario through a calibration process. In a house environment the effect of walls and furniture has to be considered and therefore, the calibration process is a hard work that requires time, thence system implementation time is increased, which at the end affects to the total system cost. We propose to avoid the calibration process by using a modification of the centroid algorithm [2].

The Inertial Measurement Units(IMU) are usually composed by accelerometers, magnetometers and gyroscopes. Typically IMU sensors used in aerospace applications employ gimballed sensors or laser based gyroscopes providing very accurate measurements. However, they are bulky and heavy devices, hence unwearable by a person. Therefore, low size and weight sensors have to be used as the ones based on integrated chips. The performance of inertial sensor depends linearly on the size and consequently the integrated inertial sensors have a significant bias [4].

The position of the IMU on the body determines how the information of the inertial sensors is obtained. There are some authors that mount the IMU on the foot. The main advantage of using this method is that the errors of the inertial sensors can be corrected using the Zero-Velocity-Update strategy (ZUPT) every time the foot is on the floor [4]. However, although the measurements of the foot-mounted IMU are very accurate, the idea of wearing an electronic device on the foot does not seem comfortable to the user. As a solution, some other authors propose to wear the IMU device on the hip. One disadvantage of this method is that it is not possible to correct the inertial drifts using ZUPT [3]. Moreover, even if the idea of a hip mounted IMU seems more comfortable than the foot-mounted one, older adults will not feel comfortable with an electronic device near their hip. Instead of this, we propose to use an IMU sensor in a button size electronic device mounted on the chest, that is, a necklace or a brooch. Furthermore, once the position of the IMU on the chest is fixed, it is not longer necessary to use a 9 degrees of freedom (DoF) IMU. Consequently the total cost of the system is also decreased. We propose to use a 6 DoF IMU that contains a 3-axial accelerometer, a 2-axial magnetometer and a 1-axial gyroscope.

In the literature, inertial sensors are usually employed to obtain the attitude of the mobile object. The estimation of this attitude is done by means of a Kalman Filter (KF) or one of its extensions, as the Extended Kalman Filter (EKF) (see [5]) or the Unscented Kalman Filter (UKF) (see [6]). However, the complexity of those filtering methods requires an additional processor to compute the attitude, typically a DSP is employed [5, 7]. The use of an extra processor does not fulfil our energy consumption constraint and instead of estimating the attitude and velocity of the mobile node, we rely on heading and step detection estimations, which require low complexity algorithms and no additional processors.

Once the measurements of the inertial sensors are obtained and the position of the node is computed using RSSI, this information is used by a tracking algorithm in order to obtain an accurate estimation of the position. A review on tracking algorithms can be found in [8]. For example in [3] the authors use and EKF combining the velocity measurements extracted from the inertial sensor with the distance measurements obtained from the RSSI measurements. Other authors [9, 7] use a Particle Filter (PF) combined with map information. The inclusion of the map information improves the accuracy of the positioning system. However, the computational complexity of a PF is assumed to be high for the typical MCU used in WSN [3]. Moreover, the elaboration of a map of the house requires a long time. In this paper an EKF is used to track the mobile node. Even that an EKF is a complex algorithm, it is considered that can be processed in a typical MCU used in WSN. Note that, it is avoided to use an additional KF substituting the attitude estimation by step detection and heading estimation, which require lower computational resources.

## 3. SYSTEM DESIGN

In this section we design a navigation system especially developed for elderly care applications taking into account the following system constraints: low-cost, energy efficiency, reduced size and weight and user comfortability.

The navigation system designed is based on an EKF that combines the information of RSSI measurements and inertial sensors . The information is preprocessed in order to give to the EKF measures of position, heading and speed. The position measurements are computed using the RSSI measures while the heading and the speed of the mobile node are obtained using a chest-mounted IMU.

This section explains the algorithms used by the navigation system. First, it is explained how the measurements are preprocessed and then the EKF is detailed.

### 3.1. RSSI Measurements

It is well known that power decays with distance, therefore, using a propagation model as the log-distance path-loss model (see equation 1) the distance can be computed. However, the channel impairments (multipath fading, diffraction, ...) produce large errors in the estimated distance.

The RSSI measurements have been extensively studied and to obtain good measurements large calibrations procedures or high complex models have to be used in order to minimize the channel-induced errors. In this work it is considered that the increment in the accuracy that can be obtained using a typical WSN processor does not compensate the additional energy consumption and therefore, for the sake of low complexity, one of the simplest localization methods have been chosen. That is, the Weighted Centroid Localization (WCL) algorithm.

The WCL algorithm computes the position of the mobile node as a weighted average of the position of the anchor nodes. The main advantage of this method is that as it does not compute the distance between nodes, it is not necessary to use a propagation model and consequently the calibration process is avoided. However, the precision of the algorithm is strongly influenced by the position of the anchor nodes, as it always returns a position measurement inside the area determined by the received anchor nodes.

In this case we have chosen the weights $w_i$ in order to be proportional to the received power.

$$w_i = P_i/P_T \tag{2}$$

where $P_i$ is the received power of the $i$-th node and $P_T$ is the total power received from all the nodes.

$$\hat{\mathbf{x}}_j = \sum_{i \neq j}^{N} w_i \mathbf{x}_i \tag{3}$$

where $\mathbf{x}_i$ is the position of $i$-th node and $\hat{\mathbf{x}}_j$ the estimated position of $j$-th node.

### 3.2. Step Detection

Since typical IMU contain accelerometers, the speed of the node can be computed by the integration of the acceleration. However, the inherent systematic errors present in integrated accelerometers tend to accumulate during time producing large errors in the estimation [10]. Furthermore, the earth gravity is sensed by the accelerometers and therefore it has to be removed in order to obtain the real acceleration of the mobile node. If there is a misalignment between the system axis and the sensor axis the gravity will not be totally removed and therefore the measured acceleration will contain an error. Note that the gravity of the earth $9.8m/s^2$ is much bigger than the usual acceleration of a person, so the error produced by this effect is not negligible.

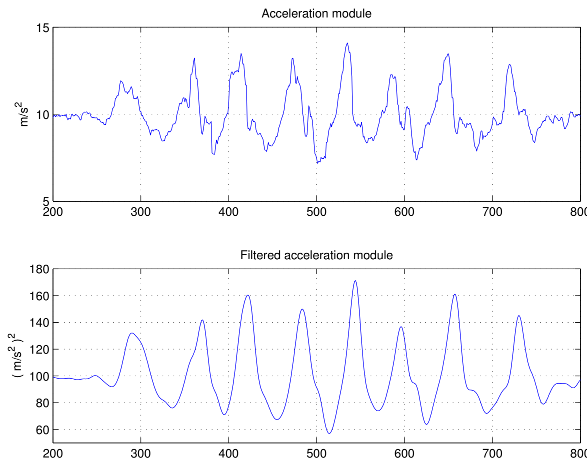


**Fig. 1**. Original and Filtered acceleration signal.

An alternative is to use the accelerometer signal to detect the steps of the pedestrian hence, compute the velocity using a mean step length. More information about step detection algorithms can be found in [3, 6, 10].

In this case we will use a step detection algorithm based on the module of the acceleration. Note that using the module of the acceleration the problem of misalignment is avoided. In order to obtain the step estimator, we compute the module of the acceleration vector measured and then its convolution with a low pass linear-phase FIR (Finite Impulse Response) filter of order 20 and cut-off frequency of 3Hz [10]. Finally the square of the filtered signal is computed and the number of steps is known by detecting the number of peaks bigger than a certain threshold defined for each user. In Figure 1 it is shown the original acceleration module signal and the filtered one, where the number of steps can be easily identified.

### 3.3. Heading

In order to work with full velocity information is interesting to known the heading of the mobile node. The heading measure can be obtained from the gyroscope and the magnetometer. A magnetometer gives a vector information of the main magnetic field, which usually is earth magnetic field. Using a 2-axis magnetometer aligned with the XY plane (see Figure 2), it is possible to obtain the angle between the magnetic field and the sensor. Hence, using the initial angle measurement as a reference, the orientation of the sensor at each mo-

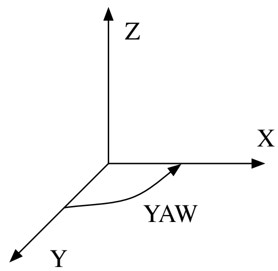


**Fig. 2**. System axis.

ment is obtained, as a comparison of the actual measurement and the reference. The main advantage of magnetometers is the long term stability of the sensors. However, it is common that home appliances became a magnetic source producing alterations in the main magnetic field. This produces errors in the measurements when the sensor is near those magnetic sources. Fortunately, the errors can be compensated with a gyroscope. Gyroscopes measure the angular acceleration and therefore the heading can be obtained by integration of the yaw angular speed (see Figure 2). Although the error of the gyroscope will grow with time, a short term stability is verified. Consequently the combination of gyroscopes and magnetometers solve the problems of both kind of sensors when they are independently used. The combination is done using the following equation [7]:

$$h_k = (1 - W)\left(h_{k-1} + \omega_k dt\right) + W h_{mag,k} \tag{4}$$

where $h_k$ is the heading estimation at time $k$, $W$ the weighing factor, $\omega_k$ the gyroscope measurement and $h_{mag,k}$ the heading obtained using the magnetometer [7].

### 3.4. Extended Kalman Filter

Once the information of the sensors is processed, a filtering method is used to fusion all the information with a kinematic model and to obtain a more accurate estimation of the position of the mobile node. In this case, we use an EKF with the following state vector **x**:

$$\mathbf{x} = \begin{bmatrix} x & y & V & \theta \end{bmatrix} \tag{5}$$

where $x, y$ are the respectively, $x, y$ coordinates, $V$ is the speed modulus and $\theta$ the speed direction. Among the huge amount of kinematic models [8] we have choose a simple constant velocity model, which can be defined as:

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & T\cos\theta & 0 \\ 0 & 1 & T\sin\theta & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

where $T$ is the time period between measurements. Note that the kinematic model is defined to use the velocity in polar coordinates instead of using cartesian coordinates. The reason of choosing Polar coordinates is that the speed measurements obtained from the inertial sensors are in Polar coordinates.The step detection algorithm gives a measurement of the speed module while the speed direction measurement is given by the heading algorithm. This differentiation makes the speed module and speed direction independent measurements and therefore can be separately treated in the EKF (see equation 13). The EKF algorithm is divided in two steps: the prediction step and the correction step. In the prediction step a priori estimation of the state vector $\hat{\mathbf{x}}^-(k+1)$ and the state covariance $\mathbf{P}^-(k+1)$ are updated using the kinematic model.

$$\hat{\mathbf{x}}^-(k+1) = \mathbf{F}(k)\hat{\mathbf{x}}(k) \tag{7}$$

$$\mathbf{P}^-(k+1) = \mathbf{A}(k)\mathbf{P}(k)\mathbf{A}^T(k) \tag{8}$$

where $\mathbf{A}(k)$ is the Jacobian matrix of the model, which is defined as:

$$\mathbf{A}(k) = \begin{bmatrix} 1 & 0 & T\cos\theta & -T\sin(\theta)V \\ 0 & 1 & T\sin\theta & T\cos(\theta)V \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Then using the information of the measurements, in our case position and speed, the a priori estimations are updated in the correction step.

$$\mathbf{K}(k+1) = \mathbf{P}^-(k+1)\mathbf{H}^T(\mathbf{H}\mathbf{P}^-(k+1)\mathbf{H}^T + \mathbf{R})^{-1} \tag{10}$$

$$\hat{\mathbf{x}}(k+1) = \hat{\mathbf{x}}^-(k+1) + \mathbf{K}(k+1)(\mathbf{z}(k+1) - \mathbf{H}\hat{\mathbf{x}}^-(k+1)) \tag{11}$$

$$\mathbf{P}(k+1) = (\mathbf{I} - \mathbf{K}(k+1)\mathbf{H})\mathbf{P}^-(k+1) \tag{12}$$

where $\mathbf{K}(k+1)$ is the so-called Kalman gain, **H** is the measurement matrix, **R** is the covariance matrix of the measurement noise and **z** the measurement vector [8]. As each component of the state vector has its correspondent measurement, the measurement matrix is the identity matrix. The covariance matrix of the measurement noise is defined as a diagonal matrix with the correspondent variance of each measurement.

$$\mathbf{R} = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 \\ 0 & 0 & \sigma_V^2 & 0 \\ 0 & 0 & 0 & \sigma_\theta^2 \end{bmatrix} \tag{13}$$

## 4. EXPERIMENTAL VALIDATION

The hardware platform we use for the deployed WSN is the Iris mote which uses an ATM1281 processor and an RF230 radio chip module. The IMU board contains an ADXL345 accelerometer, an HMC5843 magnetometer and a ITG-3200 gyroscope. Although the IMU used is a 9 DoF IMU, we use only 6 axis as defined in Section 3.

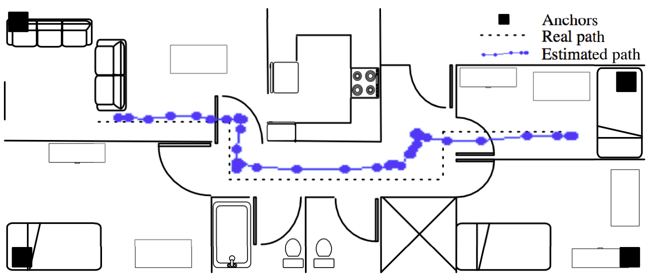


**Fig. 3**. Real and estimated trajectories in a 6x14 m house.

We have tested our solution in a 6x14 meters house. Four motes have been used as anchor nodes to cover the whole area and another one (with the IMU connected to it) as the mobile node. The accelerometer is sampled with a rate of 100 Hz and the gyroscope and the magnetometer with a rate of 5 Hz. The anchor nodes transmit at a rate of 1 Hz. Once per second, the step detection, heading and WC algorithms compute the measurements and the EKF solution provides a processed position. Several trajectories have been tested obtaining a mean RMSE (Root Mean Square Error) of $2.2m$ with a variance of $0.9m^2$. In Figure 3 we plot a representative part of one of those trajectories. The anchors nodes are represented as black squares, the dash line is the real trajectory and the blue circle line is the estimated trajectory.

## 5. CONCLUSIONS

In this work we proposed a navigation system for elderly care applications based on WSNs. The WSN monitors the house to detect dangerous situations and the navigation system adds functionalities in order to obtain a full health care system that can increase the user standard of life. For the elderly care applications four constraints are considered: low-cost, energy efficiency, reduced size and weight and user comfortability.

The navigation system is based on two kind of measurements. On the one hand, the position measurements are computed using a WCL based on RSSI. On the other hand, the speed and heading of the module is obtained using step detection and heading algorithms. Finally the information of the measurements is processed using an EKF. The system is designed minimizing the inclusion of new hardware to the WSN. Note that, the unique additional hardware is the IMU and this kind of device is widely used and has a low cost. Moreover, the low complexity of proposed algorithms fulfils the energy efficiency constraint. The validity of the system is confirmed by the experimental results. The presented navigation system allows to track the position of a person with enough accuracy to monitor the person at his home. Moreover, it requires low computational efforts and is energy efficient therefore, it can be used in elderly care applications.

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