Analysis of a Kalman Approach for a Pedestrian Positioning System in Indoor Environments

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Abstract. In this work we present the design principles of a wearable positioning system for users in unprepared indoor environments. We describe the most suitable technology for our application and we model the dynamics of a walking user. The system uses inertial sensors and a location system based on ultrawideband (UWB). Data fusion is carried out with a Kalman filter. The user position is estimated from data provided by the UWB location system. To update the position and direction of the user we use a dead reckoning algorithm. The use of redundant sensors and the data fusion technique minimises the presence of shadow zones in the environment. We show the advantages of combining different sensors systems.

1 Introduction

The precise determination of the position of users or objects in an environment is a crucial task for many applications. The task was inaccessible a decade ago, for precision location in mobile systems, due to the lack of technology. The development of micro-electromechanical systems (MEMS) has allowed the design of sensors based on the principles of the location systems found in boats or airplanes. We now find on the market several low cost, miniature gyroscopes or accelerometers. This evolution has facilitated the development of applications that use the position of the user, often known as Location Based Services.

There are a great number of applications that need to know the position of a user. Among them we can mention access and security control in enterprises or institutions, civil defense and rescue tasks, or the guidance of users in facilities such as museums or monuments. In the implementation of Location Based Services, the efficiency of the service depends strongly of the location system used.

Present technology allows the design of location systems precise enough for most applications. Systems able to operate in prepared indoor environments have been described. Optical, acoustic and magnetic technologies allow the precise location of a user in indoor environments. Their main disadvantage is that they require complex, expensive infrastructures. On the other side, vision based systems are imprecise, and also require previous preparation of the environment, usually placing markers - fiducials - that assist the recognition process.

In this work we present the design principles of a system for locating users in ad hoc (unprepared) indoor environments. The system uses inertial sensors and specific data fusion techniques. We describe the most suitable technology for our application and we model the dynamics of a walking user. The user's position is estimated from data provided by the system based on UWB. The update of the position and direction of the user is done with dead reckoning algorithm. The use of redundant sensors and the data fusion technique minimises the presence of shadow zones in the environment.

2 Background

Over the past decade research in ubiquitous computing has been impelled by the demand of mobile applications. A fundamental component in mobile systems is the location system. The design of a location system implies the integration of different disciplines and technologies as needed for the application. In this work we propose the design of a location system suitable for unprepared indoor environments. We seek to avoid the use of complex infrastructures while preserving the reliability and robustness of the system.

At the moment, the most widely used technique to determine the position of a user is the combination of different technologies such as optic, acoustic or inertial technologies. There are other technologies, such as those used by cellular telephones (time delay) or the triangulation methods based on wireless networks. We did not consider these technologies because they are not precise enough for most applications. None of them is able to detect with exactitude the position of a user in a room. The main disadvantages of optical or acoustic technologies are that they require complex and expensive infrastructures that usually are not practical. Additionally, the presence of smoke, echoes or other phenomena that affect the transmission or reception of the signal, introduces errors. A direct line-of-sight between the receiver and the transmitter must exist.

Recently the High Sensitivity GPS technology (HSGPS) has been developed for the location of users in indoor environments. The technology solves the problems that conventional GPS reception presents in zones where its signal is obstructed or where there are multi-path effects. Nevertheless, the works of Lachapelle [11], Mezentsev et al, and Mezentsev and Lachapelle, [12], [13], show that HSGPS technology does not work as a stand-alone system, but rather it requires additional technologies for the precise location of users.

2.1 Related Work

The design of location systems based on the fusion of data estimated by different sensors has been described in many investigations. Golding et al.[2] present a system based on machine-learning techniques and multi-sensor data fusion.

They use accelerometers, magnetometers, temperature sensors and light sensors. They show that measuring the characteristics of the environment can help to determine the position of the user, using statistically significant information. The complexity of the method prevents its application in systems that operate in real time.

Gabaglio et al. [4] propose a navigation system based on a Kalman filter. It uses the information provided by magnetic compass, gyroscope, accelerometers and a GPS. Although the system complements GPS when the signal is blocked, the accuracy is lower for particular applications. Kourogi and Kurata [7] propose a location system for Augmented Reality (AR) applications. The user carries a system composed of self-contained sensors (accelerometers, gyroscopes, magnetometers and inclinometers) and a camera. They obtain the data needed to estimate the displacement, register images and fuse the information by means of a Kalman filter. The use of computer vision techniques requires a very large database that is also dependent on the application environment.

Stirling et al. [8] and Foxlin [9] propose location systems based on Inertial Measurement Units (UMI) installed on the feet of the users. The system detects the steps of the user to incrementally calculate its present position. Both works conclude that the system cannot work correctly as a stand-alone system. However, the work is a first step in the search of an integral solution.

3 System description

In this work we propose a location system based on inertial sensors and an ultra-wideband (UWB) location system. In this section we will describe the hardware used to implement the system, the mechanisms of data gathering and fusion, and the dynamic model proposed for a walking user.

3.1 Hardware

Our goal was to design a system that returns the position *(X, Y)* and orientation (roll, pitch, azimuth) of human users in indoor environments. In order to select the most suitable sensors for our application we considered characteristics such as the precision, autonomy or the availability of the sensor. Based on these parameters, the following sensors have been selected:

1. **Ubisense**: a location system based on ultrawideband (UWB). It uses a network of sensors installed at well-known positions and a set of tags located in the moving users or objects of the environment. The system uses an Ethernet network for the communication between the different elements. This system can be very useful in large environments. However, it is not suited for environments where larger flat metallic surfaces exist which can cause reflections and therefore affect the transmission and reception of the sensor's signals. We use this system to estimate the positions *(X, Y)* of the elements to be located.

2. **InertiaCube2**: an Inertial Measurement Unit (IMU), which determines the direction of a user as three Euler angles (*roll, pitch, azimuth*). It has a static accuracy of 1° rms and a dynamic accuarcy of 3° rms, communication through USB or serial port and its dimensions are suited for mobile applications. In our system, we use this sensor to detect the orientation of the user's head. The sensor rests on a helmet that is worn by the user. See Figure 1.
3. **Xsense**: It is an Inertial Measurement Unit (IMU), which determines the direction like the InertiaCube2. It has a static accuracy less than 0.5° for roll and pitch and 1° for azimuth, and a dynamic accuracy of 2° rms. In our system, we use this sensor to estimate the values of linear acceleration and azimuth of the user. The sensor rests in a belt that is worn by the user. See Figure 1.

The information provided by the sensors is processed in a Tablet PC, as shown in Figure 1.

(a) User wears the system. (b) Sensors.

Fig. 1. Prototype of wearable System

3.2 Data Reception and Fusion

To gather data from the sensors we use OpenTracker, an open source software package developed at the Vienna University of Technology and the Graz University of Technology. OpenTracker[3] can be used in real time applications and collects data with a timestamp. Opentracker defines the interface with sensors by means of modules implemented in C++. The different modules used are called from parameters defined by an XML configuration file, to gather the data from each sensor. After this data gathering process, the final result is obtained by means of a data fusion process.

Data fusion is a multidisciplinary field that considers all aspects from the modeling of the physical system to the final estimation techniques. Its main goal is to obtain an optimal estimation of a state vector, or vector of variables that

[3] More details are in [1]

allows predicting the behavior of the system. The selected estimation technique is the *Kalman Filter (KF)*. This filter has demonstrated its reliability in navigation systems (Brown and Hwang [6]). The Kalman filter inputs are the measured values of a set of parameters. These parameters define the observed state of the dynamic system and are stored in a vector. The filter uses the vector of observed parameters to make a prediction of the state in the next time step . In our work the dynamic system is a user walking around an environment.

3.3 Dynamic Model

The estimation of position is more difficult for a walking user than for vehicles or robots. The added difficulty is due to the unpredictable nature of its trajectory. In order to model the characteristics of the movement of a walking user we must use methods such as *Dead Reckoning* algorithms. In this class of algorithms we consider two fundamental parameters of the walking movement: *the length of the step* of the user and its *azimuth*. The estimation of the length of the step is made from acceleration patterns (Ladetto et al. [5]). Figure 2 shows the behavior of the vertical acceleration, where the peaks of the curve correspond with the foot strike.

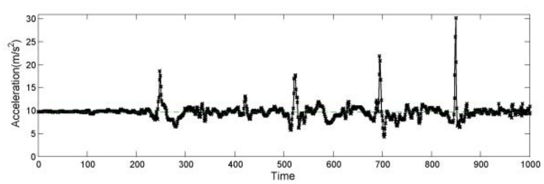

Fig. 2. Acceleration signal from Xsense, when a user walks.

The next set of equations model the movement of a walking user. If we use another type of displacement (for example to jump or to slide) it becomes necessary to define another specific dynamic model. Since our system follows a 2D-navigation dynamic scheme, the equations are as follows:

$$\begin{aligned} X_k &= X_{k-1} + s_k Cos\left(\psi_k\right) \\ Y_k &= Y_{k-1} + s_k Sin\left(\psi_k\right) \end{aligned} \tag{1}$$

where, X_k and Y_k are the information of position provided by the Ubisense, s_k is the length of the step and ψ is the *azimuth* or *heading*.

3.4 Kalman Filter

The data obtained from the Ubisense and the IMUs are integrated with a Kalman filter. The KF requires a model of the system to be defined. In other words, it must implement two models: *state model* and *observation model*.

State Model The state equation of a Kalman filter is (Brown and Hwang [6]):

$$x_k = f * x_{k-1} + b * u_k + w_{k-1} \tag{2}$$

where, x_k is the state vector, f is the transition matrix that relates the state of a previous time to the current time, b relates the input control u_k and w_k represents the noise state vector.

The state vector in our system is $x_k = [X_k \; Y_k \; \theta_k \; \alpha_k \; \psi_k \; \phi_k \; \beta_k \; \gamma_k]$, the transition matrix $f = I_{8x8}$, $b = [Cos\,(\psi_k)\,Sin\,(\; psi_k) \;\; 0\;0\;0\;0\;0\;0]^T$, the vector u_k represents the length of the step (Kourogi and Kurata [7]). $\theta_k \; \alpha_k \; \psi_k$, are the angles *roll, pitch, heading* from the waist's user respectively; $\phi_k \; \beta_k \; \gamma_k$ are the angles *roll, pitch, heading* from the head's user. Although we don't know the value of the noise at each state, we can approximate the state model as:

$$x_k = f * x_{k-1} + b * u_k \tag{3}$$

Observation Model This model is defined according to the information provided by the sensors. Its general form is:

$$z_k = H_k * x_k + v_k \tag{4}$$

where, z_k, is the observation vector, H relates the observation and state vector, and v_k is the observation error vector.

The observation vector is $z_k = \left[\tilde{X}_k \; \tilde{Y}_k \; \tilde{\theta}_k \; \tilde{\alpha}_k \; \tilde{\psi}_k \; \tilde{\phi}_k \; \tilde{\beta}_k \; \tilde{\gamma}_k\right]^T$, $H = I_{8x8}$. In the equations (2) and (4), w_k and v_k, are the state noise and the observation noise. These noises are non-correlated, gaussian noises:

$$\begin{array}{c} p(w) \; N\,(0, Q) \\ p(v) \; N\,(0, R) \end{array} \tag{5}$$

where, Q represents the *state noise covariance* and R represents the *observation noise covariance*.

The KF works in two phases: *the prediction* and *the correction*. In the first phase the filter update the state vector and the error covariance matrix P. The usual equation to calculate P is $P_k = f_k * P_{k-1} f_k^T + Q_{k-1}$. In the correction phase the state is updated by $\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - H * \hat{x}_k^-\right)$, where K is the Kalman gain obtained by: $K = P_k^- H_k^T \left(H P_k^- H^T + R\right)^{-1}$. The update of the error covariances takes place with the equation in the Joseph form $P_k = (I - K_k H_k)\, P_k^- \,(I - KH) + KRK^T$.

It is known that the EK provides bad results by factors as an incorrect definition of the system model or the values of the covariances matrices Q or R. We are interested in forcing the filter to converge in spite of having not an exact definition of the model or the right values for Q or R.

We carry out this task keeping in mind the following considerations:

1. In a KF the residual of the measurement or innovation Z, should fulfill:

$$Z_{k+1}^T * P_{k+1}^{-1} * Z_{k+1} \leq K \tag{6}$$

where:

$$Z_{k+1} = z_{k+1} - \hat{z}_{k+1} \tag{7}$$

with

$$\hat{z}_{k+1} = z_k - H * \hat{x}_k^- \tag{8}$$

In the equation (7) z_{k+1}, is the measurement and $\hat{z}_{k+1}$ is the *estimate measurement*. The result of the equation (6) is called *evaluation coefficient* denoted by ec and K is a scalar value defined with the chi-square distribution.
2. We associated an ec for each component of the state vector. This is done with the goal to eliminate only the wrong values. In other words, if a measurement of any of the variables is wrong this is ignored for the fusion, but the rest are fused.
3. According to the observations R is a factor that can be tuned up to force to the convergence of the filter, that is,
   – if $ec \leq K$, R does not change.
   – if $ec \geq K$, R is decremented and the associated measurement is not taken into account for the fusion. K is chosen based on the chi-square distribution with a confidence limit of 95%.

4 Results and Discussion

We made preliminary tests in a small room 4x7 m^2 where we have installed the Ubisense system. We wanted to observe the system in this space because there are more critical situations to localize an user. The data were gathered and post processed with Matlab. To test the system, (1) the user remained still at a position during a short period of time - at different positions throughout the room, (2) walked a predefined path and (3) walked around the room.

In (1) the filter was evaluated without keeping in mind the distances travelled, while in (2) and (3) already existing movement is considered, specifically the length of a step. An approximation of 50 cm has been used. Nevertheless this can be determined in a more sophisticate way that has not been implemented yet.

The functionality of the system can be observed especially in figure 3. The results are more reliable if using criteria evaluation of the residuals than the pure Kalman filter. If the data are processed with the criteria mentioned, wrong data are ignored and the signals are smoothed. On the other hand, the results for a fixed position are very good. After processing the signal filter the algorithm smoothed the signal ignoring the outliers. Sometimes the multi-path phenomenon is responsible for outliers. The results showed the standard deviation in X decreased when using the criteria evaluation from 4 cm (Kalman filter) to

2 cm. In Y direction the decrease of standard deviation was from 6cm (Kalman) to 2 cm (criteria evaluation).

In the experiments, we observed the influence of Q. In the figure 4, we present the results if Q is varied. We decrement Q if the residuals are not between $\pm\sigma$(standard deviation). While the covariance matrix R causes convergence of the KF, Q helps to smooth the signal.

5 Conclusions and Future Work

We have presented a robust location system for users in indoor environments. The implemented algorithms and the sensors used guarantee an acceptable system performance. The sensors are not affected by typical signals in the environment as magnetism, sounds or changes in the lighting conditions. We can detect if our sensors fail by evaluating the convergence of the Kalman Filter.

With the proposed combination of sensors our system increases the functionality of a portable system. It can work in wide indoor environments and it does not need a previous knowledge of the environment (magnetic disturbances) or big databases as vision based systems.

Although the Ubisense sensor shows problems in environments with metallic surfaces where multi-path phenomena can appear, it is still useful if we do not want to install complex infrastructures. These infrastructures are needed in acoustic or optic technologies. One disadvantage of the Ubisense sytem are multipath effects (reflections) that occur frequently. Nevertheless, we show that our criteria evaluation filter helps to improve this situation considerably. When implementing the filter it is very important to tune the parameters in order to get more suitable results and better performance.

Within the future work we plan the evaluation of the latest HSGPS systems that are on the market, because this may affect the future of the different existing indoor technologies. Also the integration with other kind of sensors as magnetic sensors, for instance.

Acknowledgments.

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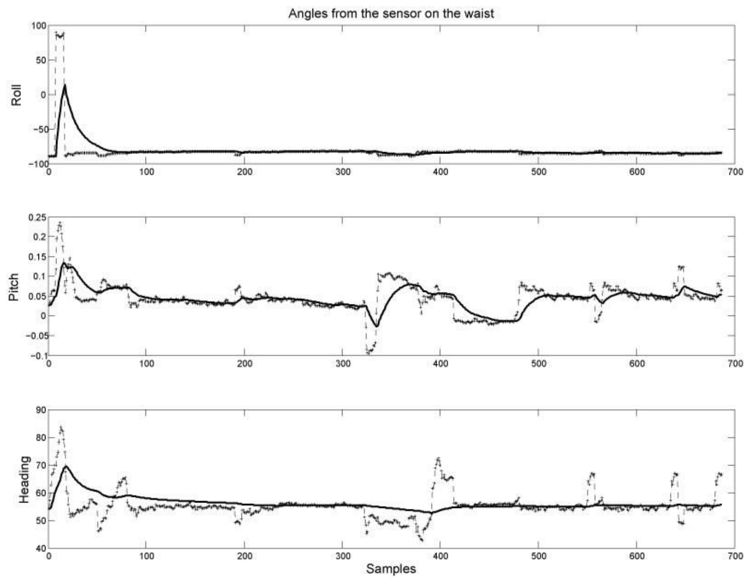
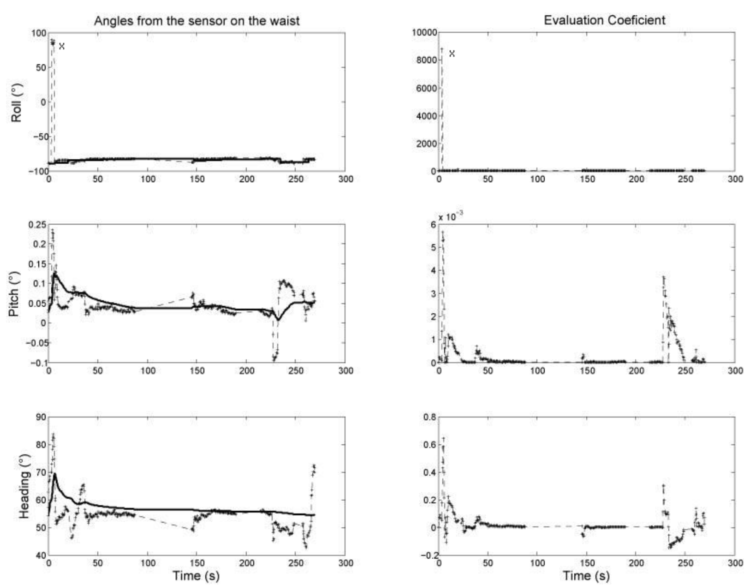
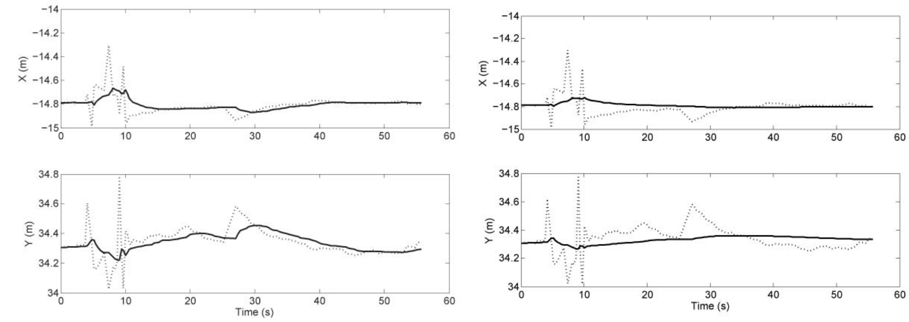


(a) Angles determined by KF



(b) Angles determined using the evaluation criteria

Fig. 3. Example of the elimination of wrong measurements, for the angles provided by Xsense unit.



(a) Using the classical KF. (b) Using the criteria evaluation.

Fig. 4. Results for position (X, Y).

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