Assessment of Step Determination in a GPS/Compass/IMU System for Personal Positioning

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BIOGRAPHY

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ABSTRACT

Nowadays, there have been great advances in the location technology, even though the user's location indoor, outdoor is still a challenge. The personal positioning offers a very interesting field of research because the user walking has an unpredictable behaviour and it is difficult to assume predefined routes or to take into account other implemented location techniques for vehicles or robots.

The combination of GPS with sensors like accelerometers, gyroscopes or magnetometers is often used. The data fusion from these sensors is very important because we have to know the position and orientation constantly.

In this research we are interested in analyzing the system behaviour when the signal GPS is unavailable as when the signal is blocked or in indoor environments. The analysis will be carried out through the assessment of a Dead Reckoning algorithm to improve the position information. The system was tested both indoor and outdoor of the faculty building. The personal positioning system is made up of: a receiver GPS, an electronic compass, and an IMU.

The Dead Reckoning algorithm for pedestrians has two parameters: *the travelled distance* and *the heading*. The travelled distance is obtained by means of knowledge of *the step length* user. The pattern acceleration (forward and vertical) is analysed to determine when a user takes a step; once the step is detected the step length is calculated by a simply neuronal network. All that information is needed to obtain the relative position.

The implemented technique estimated was the Kalman filtering. According to it, the results of the position estimation can be improved if the filtering innovations are evaluated.

We presented the bases of an evaluation mechanism to observe divergences and make the corrections to obtain better results.

INTRODUCTION

User location is an emerging research subject of large-scale due to the high demand of its functionality in mobile applications, i.e., Location-based Services (LBS).

Several research works on user positioning have been done both indoors and outdoors (Gabaglio et al. (2001), Kourogi et al, (2003)). Many have proposed the multisensor fusion, as a result of the problem complexity and to the absence of a unique device (one-ship) to obtain the position and orientation user.

Table 1. Technologies for Personal Positioning

Technology	Indoor	Outdoor	Accuracy	Availability	Coverage
GPS	-	X	Medium	Medium	High
HSGPS	X	X	Low	Medium	High
Inertial	X	X	Medium	High	High
Vision	X	X	Medium	Medium	Low
Optical	X	-	High	Medium	Low
Magnetic	X	-	High	Medium	Medium
UWB	X	-	Medium	Medium	Medium

In the location systems, the absolute position in the outdoor environment is provided by GPS receivers whose accuracy range is in meters. The GPS system does not provide appropriate information in the case of signal obstruction. Recently, the HSGPS system (High Sensitivity GPS) has been designed to solve this problem. Nonetheless, according to the research by Mezentsev et al. (2004), it does not work very well as stand- alone and its range of accuracy is not high

Therefore all of these systems need to be augmented with other systems in order to reach acceptable accuracy, availability, reliability and coverage.

In this work an algorithm for user positioning system is presented based on multisensor fusion. The multisensor fusion allows to obtain the position and direction at all times.

In the system presented the *GPS* functionality is increased in outdoor environments by means of the combination with an *electronic compass* and an *inertial measurement unit (IMU)*. In the case of an unavailable GPS signal the information provided for the compass or the IMU is processed on a *Dead Reckoning (DR)* algorithm. Finally, the data are fused by *Kalman filtering* and the results are assessed with a evaluation mechanism based on the *chi-square test*.

Here, a comparative analysis of the system performance is carried out when it is imperative to apply a Dead Reckoning algorithm for indoor and outdoor.

SYSTEM DESCRIPTION

Accuracy, ergonomics, availability, among others, are characteristics that must be considered to define the components of a personal wearable system. There is no a unique sensor that fulfils these characteristics. However there are several technologies that combine them increment the usefulness of the systems.

Each technology offers advantages and disadvantages which depend of factors like surroundings or the application, among others. In Table 1, we present a summary of some relevant characteristics of technologies.

For instance, the optical technology is highly accurate, nonetheless it cannot be considered for this work due to the complicated infrastructure that it requires. On the other hand in virtual and augmented reality systems, it is very appreciated thanks to its higher accuracy.

To analyze the dynamic in personal positioning, a system was configured with the following sensors:

- GPS: it is a low-power consumption A1025 receiver by Tyco Electronics with serial communication, a frequency of 1Hz and an accuracy of 3m. The information provided by this sensor is in the NMEA format and the following parameters are obtained: *time, speed, longitude and latitude*.
- Electronic Compass: it is a low-power consumption card by Aositilt with serial communication. It is made up of a 3-axes magnetometer to obtain azimuth and two inclinometers to obtain the roll and pitch angles. It has an accuracy of 0.5 degrees in azimuth, with a maximum frequency of 4Hz.
- Xsense: it is the inertial measurement unit (IMU) that provides 3D direction data (roll, pitch and azimuth), 3D linear acceleration, 3D angular velocity and the 3D magnetic field. It has an accuracy which is less than 0.5º in roll and pitch, and less than 1º in azimuth, with a frequency of 100 Hz.

The set-up of the sensors was carried out as shown in the Figure 1. In the bag there is a GPS receiver and all connections.

DYNAMIC MODELS

In outdoor environments, the dynamic model for user walking is defined as a 2D low dynamic system of movement, with the following equations:

$$X_k = X_{k-1} + V_k \cos(\psi_k) * \Delta t_k \quad (1)$$

$$Y_k = Y_{k-1} + V_k \sin(\psi_k) * \Delta t_k \quad (2)$$

where, X, Y, V, Δt are the parameters of *longitude*, *latitude*, *speed* and *time interval* provided by the GPS. ψ is the azimuth provided by the electronic compass or the IMU.

Figure1. Setup of the personal positioning system.

As observed in Equations (1) and (2), the system basically depends on the availability of the GPS signal. Nevertheless, the signal is not always available, which obliges us to use another system which guarantees a continuity of user position information.

Therefore, when this situation occurs, the system switches to the DR mode, which is also implemented for the indoor component.

To modelling a user walking in the DR mode, the following considerations are taken into account:

- The user's walking trajectory is unpredictable, which complicates modelling.
- Two parameters are fundamental for the DR mode: *the travelled distance* and *azimuth.* The travelled distance is calculated trough the knowledge of *the step length*.
- It is a 2D system.

According to what has been previously stated, the equations are as follows:

$$X_{DR_k} = X_{DR_{k-1}} + s_k * \cos(\psi_{DR_k}) \quad (3)$$

Where: X_{DR}, is the relative position, s is the step length, and, ψ is the.

When a user walks has a cyclic movement. This cycle can be observed through the acceleration pattern. In the experiments we observed the pattern in both forward and vertical acceleration. In order to compute the step length, first the occurrence of a complete walking cycle has to be detected.

For this reason, a step detection mechanism has to be implemented; here, a similar algorithm proposed by Kourogi et al. (2003) is applied.

Before the detection of mechanism starts, it should be known the threshold of the period and also of the negative peak of the vertical acceleration. Those thresholds were obtained after doing many tests off-line.

Observing the Figure 2, the procedure to detect a step is:

1. Colleting samples of forward acceleration and vertical acceleration.
2. Filtering the acceleration signals with low pass filters.
3. Detection of a positive peak of the forward acceleration.
4. Detection of a positive peak of the vertical acceleration.
5. Detection of a negative peak of the forward acceleration.
6. Detection of a negative peak of the vertical acceleration.
7. Evaluation of the threshold of the negative peak of the vertical acceleration.
8. Evaluation of the period.
9. Detect Step.

In spite of the fact that this is not the usual methodology to detect a step, we observed that the step detection is efficient and the step count error is very low.

The step length is affected by the frequency (Lewi et al (1999)) and the covariance of the acceleration (Ladetto (2000)) and one of the techniques proposed to calculate it is linear regression. However, other techniques could be interested in solving that problem. Here, we propose a simply neural network. The neural network is considered a good tool when the modeling physics is difficult to determine.

It was designed a Feed-Forward Network with 4 neurons and a Log-Sigmoid transfer function. The inputs for the network were the *frequency* and the *convariances*, several tests were carried out, to training it. The outputs and the errors of the net are shown in the Figure 3 and Figure 4.

DATA PROCESSING

The data was fused with a Kalman filter. The system adopted two means to work: the equations (1) and (2) represent the state model; (1) when the GPS is available and (2) when the GPS is not available the system proceeds to determine the position by the DR, in this case it is necessary to implement a Discrete Kalman filter

(KF), since the systems starts to determine the position according to the occurrence of user's steps.

In the framework of the Kalman filtering the state model is defined as:

$$x_k = f(x_{k-1}, u_k, w_{k-1}) \tag{6}$$

f is the non-linear function that relates the previous state to the current state, u is the optional control input, w is the noise of the state and x is the state vector defined as:

$$x = [X\ Y\ V\ \psi] \tag{7}$$

where: X, Y represent the position, V represents the speed and ψ, is the azimuth.

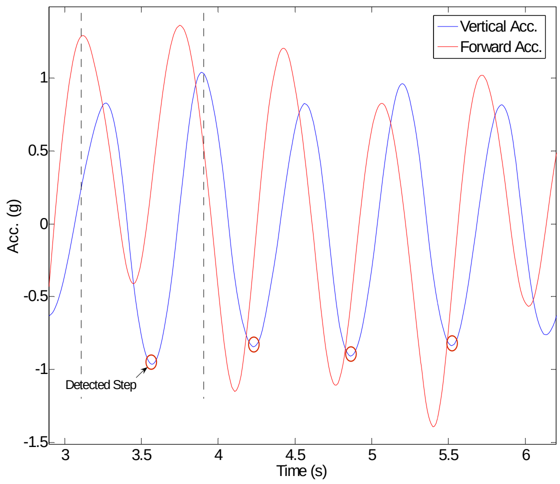


Figure 2. Pattern Acceleration.

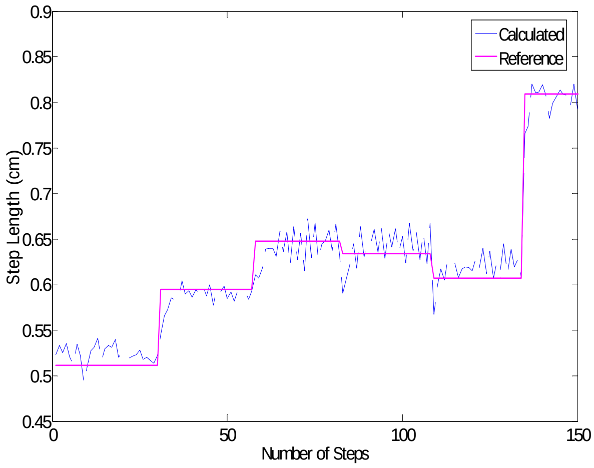


Figure 3. Results of the Neural Network.

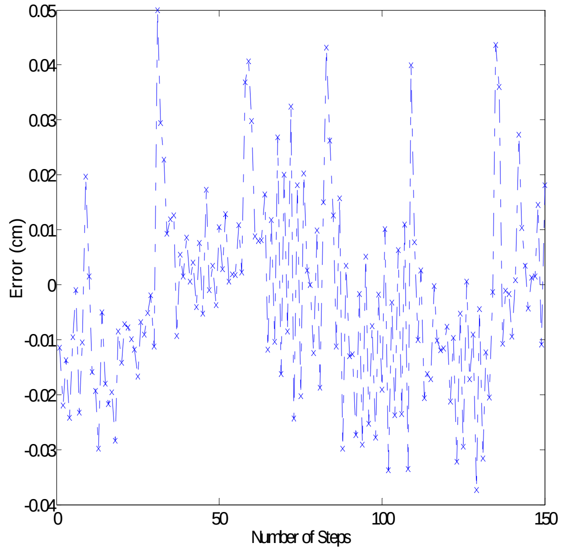


Figure 4. Errors of the Neural Network.

When the GPS is not available, the system starts to calculate the relative position with the starting point as the last GPS available measurement. The position is updated according with the step length as in the equation (3).

The Kalman filter in the DR mode, used the step length like the unit control u. The state vector is: $x = [X\ Y\ s\ \psi]$, but u is $[\cos(\psi_k)\ \sin(\psi_k)\ 0\ 0]^T$, while the transition matrix is the identity matrix $[I]_{4X4}$.

The measurement vector is $z = [\tilde{X}\ \tilde{Y}\ \tilde{V}\ \tilde{\psi}]$, or each component represents the measurement provided by the sensors correspondent to the state vector components.

The state error covariance matrix Q, is initialized with $10^{-4} * I_{4X4}$ and the measurement error covariance matrix R is initialized according with the sensor datasheet.
The Kalman filter has problems and tend to diverge especially when the sate model is not clearly known or, R and Q matrix have unsuitable values. In any of these cases the filter is not consistent anymore.

The consistent of the filter could be observed trough the innovations or measurement residuals performance . The innovation is defined as:

$$r_{k+1} = z_{k+1} - \tilde{z}_{k+1} \tag{8}$$

where, z_{k+1} is the measurement in $k+1$, while $\tilde{z}_{k+1} = H_k \tilde{x}_k^-$, is the measurement estimation according with the previous estimation of x. The innovation has a covariance defined as:

$$I_{k+1} = R_{k+1} + H_{k+1}\tilde{P}_k^- H_{k+1}^T \qquad (9)$$

Then the consistent of the filter could be observed with:

$$r_k^T I_k^{-1} r_k \leq \delta \qquad (10)$$

δ, has a chi-square distribution with n degrees of freedom which value depend of the dimension of z. It can evaluated all variables together and get just one δ and according with that eliminated all information in that instant to fuse and get the next samples. However, many times no all variables are wrong and it could be eliminating right values. To avoid this, each variable is evaluated with δ_i, i, represents the variable (X, Y, V, s, ψ) and δ_i has one degree of freedom.

The Q and R matrices have a very strong influence in the performance of the filter. It's possible to observe that through residuals performance and δ_i performance.

Therefore, when a variable doesn't fulfill the condition (10), it is not used for the fusion and the covariance of the variable in R has to be modified. On the other hand, the residuals have to be near to zero, when become to be larger Q has to be modified, usually decremented.

EXPERIMENTS AND RESULTS

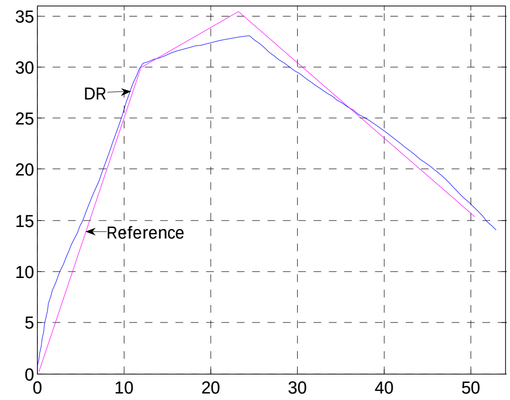
The experiments were carried out in both indoor and outdoor environments. The data collected was post-processed in Matlab.

1. Indoor Tests

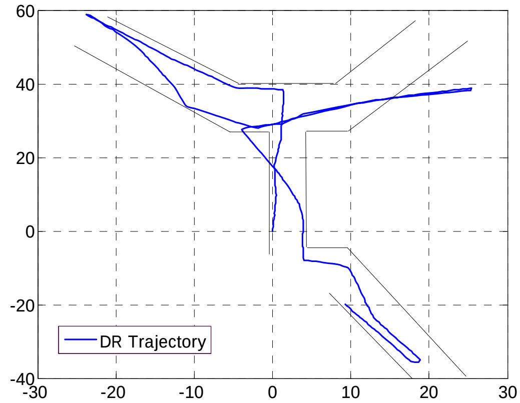
The indoor experiments were carried out inside of the faculty building (Jaume I University). In this case it was used the IMU and the electronic compass. Determining the orientation is a very sensitive issue in this kind of systems, since the sensors are magnetic, hence they are remarkably affected by the magnetic disturbances of the surroundings. Therefore it was made a soft iron calibration for the electronic compass.

In order to determine the relative position, the neural network determines the length of the step, and the IMU provides the heading as mentioned in previous sections. After the Kalman filter was executed; X_{DR} is calculated accumulatively, to obtain the traveled distance.

In the Figure 5 the results are presented. When the sensors met disturbances the results were strongly affected.



(a)



(b)

Figure 5. Results of the Dead Reckoning algorithm in indoor environment.

However, when there is no disturbance the system recovers an acceptable position. In this particular case, the focus is the error in the step length; therefore sophisticated techniques were not applied to correct the heading.

In the Figure 5 (a), the user walked along the halls where she found metallic doors and environment without metal stuff. In the Figure (b) the route was shorter to check the detection algorithm. The summary is presented in the table 2.

Table 2. Results for Indoor Tests

Item	Test (a)	Test (b)
Counted Step	109	485
Steps Detected	109	486
Error Travelled Distance	3.1219%	2.13%

2. Outdoor Tests

The experiments were carried out in a parking lot of the university, where the user walked around. For this case all sensors were used (GPS, IMU and electronic compass). As in the previous section a soft iron calibration must be performed so that the compass can perceive the surroundings.

In the Figure 6 the results are shown for the dead reckoning algorithm; also the GPS signals without applying the Kalman filter.

The user walked with the system and we collected the information, however the GPs signal was not correlated with the real trajectory. This could be because the tests were carried out next to the building. For that reason it is quite difficult to correct the information provided by the GPS which provided data with a high error. We tried to illustrate this situation in the Figure 7.

For this especial case, the determination of the relative position is acceptable for a medium accuracy. The error in the step counted was of 1.6%. and the error for the travelled distance was 1.1393%.

Finally, the Figure 7 shows the impact of the wrong values of the values for R and Q in the performance of the Kalman filter, this is an extreme case but when it is not possible to know the right value for R and Q , it is good to evaluate the performance of the Kalman filter. The advantage is that it could be carry out online.

CONCLUSION

Although the absolute position relies on the GPS sensors, in pedestrian positioning it is not the most suitable system. We could know the rough position user but we had to augment the GPS with additional sensors and techniques

The Dead Reckoning algorithm is very robust if the frequency of the vertical acceleration is high. In the experiments the acceleration data was collected at 10 Hz and 100Hz. According to our observations it is not possible to apply the detection algorithm proposed if the frequency of the acceleration is low. The vertical acceleration had not the same pattern for both frequencies. On the other hand, the forward acceleration had a similar pattern for both frequencies (high and lower). Therefore if the frequency is slow the forward acceleration is considered good enough to detect a step. The algorithm proposed here is more robust, but it has not been assess the computational cost.

The determination of the threshold is very sensitive issue because it depends of the characteristics of the user. It is necessary to find robust ways to solve this problem to avoid mistaken detections.

The determination of the step length with the neural network was efficient. The method require plenty of offline work, but it's worth because the results are good, also the traveled distance has low error.

The big problem was the heading under very noisy environment. That implies to recalibrate the system constantly. On the other hand when the environment was clean the results of the dead reckoning algorithm were good.

ACKNOWLEDGMENTS

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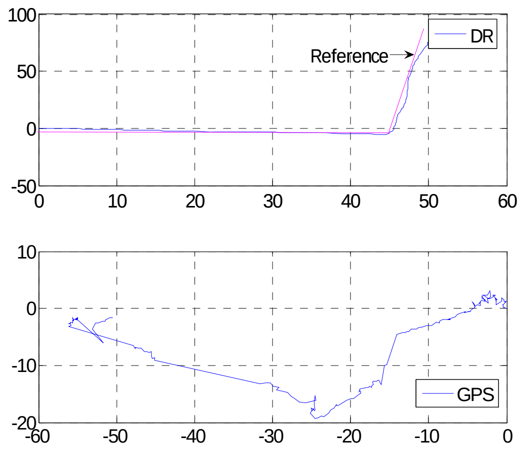
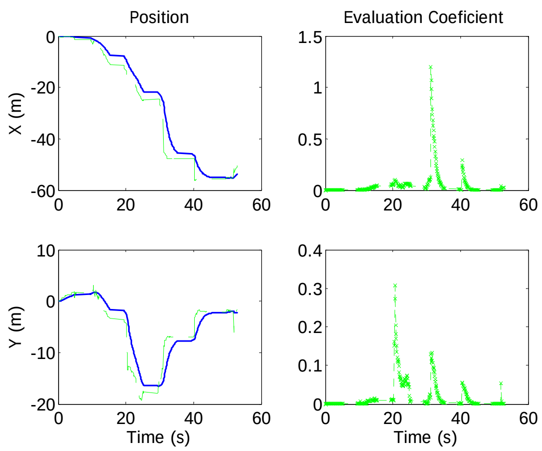
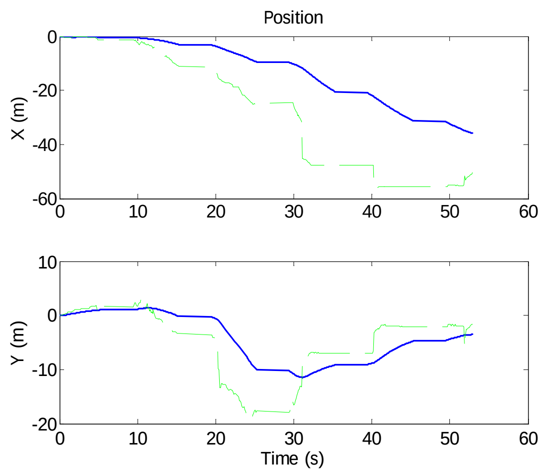


Figure 6. Dead Reckoning results for an outdoor environment and data provided by the GPS.



(a)



(b)

Figure 7. (a) Results of the Kalman filter to position. (b) Example of the effect of wrong values for R and Q in the performance of the Kalman filter.