Kalman Filter Approach for Augmented GPS Pedestrian Navigation

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BIOGRAPHY

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ABSTRACT

The key component in 2D navigation are the azimuth and the distance travelled. The devices used to obtain such information vary significantly with the application. In pedestrian navigation, the limitations on weight, size and ergonomics of the devices play important roles that make the classical inertial or GPS-aided inertial approach unsuitable. To overcome these constraints, other concepts have been investigated that integrate a digital magnetic compass and/or gyroscopes, bi-axial or tri-axial accelerometers, and altimeter with a single-frequency GPS receiver. The distance travelled is computed by merging the accelerometer signal with a physiological model whose parameters are calibrated on-line by GPS data.

This paper presents the centralised Kalman filter approach developed for pedestrian navigation, as well as real-time considerations about the azimuth processing. Experience shows that the main source of error in position comes from the errors in the azimuth determination. Two different approaches to determine the azimuth are compared. One using a magnetic compass, and the other using gyroscopes.

1. INTRODUCTION

The increasing demand in positioning people for medical applications, geographic data acquisition, fire rescue or military purposes requires adapted technologies. New miniaturised low power Inertial Measurement Units (IMUs) coupled with satellite receivers can provide accurate position in indoor and outdoor situations.

According to the needs and specificity of pedestrian navigation, the classical GPS/INS approach used for vehicle navigation is not suitable. Limitations apply to the weight, size and ergonomy of the device. The system must be able to determine the trajectory of a person in both presence and absence of GPS measurements. The main challenge is to maintain a good accuracy of the position even when no satellite data are available.

The Geodetic Engineering Laboratory is currently developing two different systems for pedestrians that combine GPS with other navigation sensors. The first one combines a GPS receiver, three accelerometers and a magnetic compass (Ladetto, 2000). The second system comprises of a GPS receiver, two accelerometers and a gyroscope (Gabaglio and Merminod, 1999). In the domain of pedestrian navigation, majority of the available commercial products (Judd, 1997) and prototypes in development (Legat and Lechner, 2000, Jirawimut et al. 2000) utilise a magnetic compass. Other groups have conducted tests with a full INS/GPS system containing accurate ring laser and compasses (Soehren and Keyes 2000) or fibre optic gyros.

2. SYSTEM DESCRIPTION

The core of the first system is the Leica Digital Magnetic Compass (DMC-SX) that combines three micro-electromechanical (MEMs) accelerometers and three magnetoresistive (MR) field sensors. Compare to flux-gate sensors that were more common in electronic compasses up to now, MR technology offers a much more cost effective solution. Due to their higher sensitivity, MR sensors are also superior to Hall elements in this application field. For absolute positioning and calibration of the different dead reckoning (DR) algorithms, the system uses the output of a mono frequency GPS receiver produced by μ-blox AG.

The hardware components of the second system comprises of a gyroscope, two accelerometers and a mono frequency GPS receiver. The gyroscope and the accelerometers are components of the Crossbow DMU. This motion unit measures specific forces along three orthogonal axes as well as rotation rate about these axes. The gyros consist of vibrating ceramic plates that utilise Coriolis forces to output angular rate (Lawrence, 1998). This device is not suitable for further miniaturisation but offers good capabilities for investigations when selecting the useful sensors and using the accelerometers and the gyroscope. The GPS receiver is manufactured by BAE systems (formerly Canadian Marconi): the Allstar providing absolute positions at 2 Hz using carrier-smoothed code (Hatch, 1982).

While the selection of the used sensors is important in the pedestrian navigation, the critical part is their placement on the person (Bouten et al. 1997). Indeed, the response of the sensors can be completely different if they are placed on the limbs (arm, legs), on the trunk (back or thorax) or on the head. The location of the sensor of the first system has been chosen at the lower back, which can be considered as relatively stable while walking. The second one utilises sensors fastened to the thorax. This choice allows the system to use the same sensors also for an automatic fall detection system (FDSS) developed by the CSEM (Centre Suisse d'Electronique et de Microtechnique, Neuchâtel).

The first accelerometer is placed vertically (along the thorax), the second one is mounted perpendicular to the first and oriented along the walk direction (anterio-posterior). The third accelerometer, used only in the first system, is placed laterally. It is mainly used to detect special kind of movements such as side-stepping. The gyro measures the angular rate about the axis of the first accelerometer and the magnetic compass senses the azimuth of the anterio-posterior accelerometer.

The first system is fully integrated. All sensors are connected to a single processor placed on a box that contains also a PCMCIA card for data logging as well as the batteries required for the whole system. In the second proposed system, the sensors are connected to a pen computer through a serial port. The computer acts as a data logger, accomplishes the data synchronisation and runs some pre-processing algorithms.

3. DEAD RECKONING ALGORITHM

The travelled distance is the first component to be determined by a Dead-Reckoning (DR) algorithm. In classical GPS/INS integration, the signals of the accelerometers are integrated twice to provide distance information. This methodology is not applicable for pedestrian navigation using low cost sensors. The velocity and then the distance are computed directly from the acceleration pattern. The techniques are presented in Ladetto et al. (2000) and Gabaglio et al. (2000)

The proposed model reaches its limitation when the slope becomes greater than about 7%. This slope limit corresponds to the change in the personal "walking strategy" (Perrin et al. 2000, Herren et al. 1999) that makes the model invalid. Another limitation is the speed range. If the pedestrian's velocity is greater than 2.0m/s then the person is running and another model must be chosen. The on-line calibration allows to adapt the model when those circumstances appear. Of course this is only possible when GPS signals are available.

The second component of a DR algorithm is the orientation. As mentioned in the introduction, the digital magnetic compass is widely used in pedestrian navigation. It offers a good solution because it observes directly the azimuth. But the terrestrial magnetic field can often be perturbed by soft and hard magnetic disturbances (Gnepf 1999) that introduce unknown biases into the system. These magnetic perturbations are the main reasons to conduct investigations with a gyroscope.

Of course gyroscopes have their own disadvantages. Firstly they provide only relative information (angular rate) and need an initial orientation. Secondly the raw data are affected with a bias that is not constant in time; especially for low cost gyros. A comparison between gyros and magnetic compass for pedestrian navigation is presented in Ladetto et al. (2001).

The raw signal of a gyro fastened to the thorax has been logged (f_s: 30 Hz) during a realistic test (illustrated in Figure 3). It is decomposed with a symlets wavelet (sym8) that is suitable for this type of signals. The use of a Meyer wavelet is also adapted. The decomposition is done up to level 5. Figure 1 illustrates the raw signal at its approximation level. The detail levels are not shown.

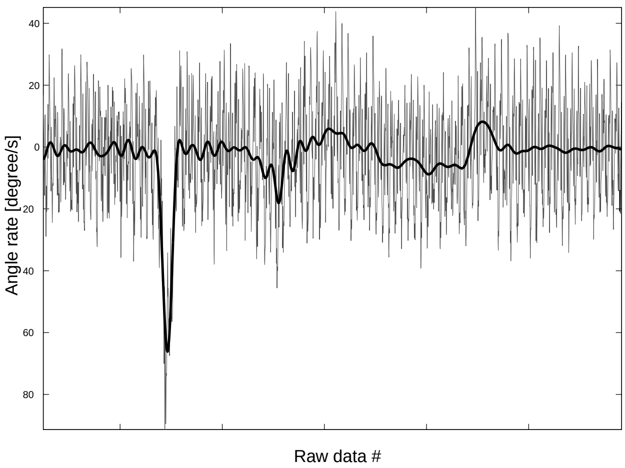

Figure 1: Gyro output signal (grey) and approximation (bold) at level 5 (symlets, 8). The raw signal show clearly the effect of the oscillation of the trunk during the walk.

The orientation determined by the gyroscope is modelled in the following.

$$\phi_k = \phi_{k-1} + dt \cdot (\lambda \cdot \omega + b) \qquad (1)$$

ϕ_k : is the orientation at time k

if k=0, ϕ_o is the initial orientation

λ : is the scale factor

b : is the bias

ω : is the measured angular rate

Scale factor, bias and initial orientation are the parameters to be estimated.

The azimuth determined by the magnetic compass is filtered and processed in a different way because of its different nature and because it depends on position rather than on time (Figure 2).

$$\phi_k = az_k + fct(bias) + \delta \qquad (2)$$

az_k : is the measured azimuth at time k

$bias$: local magnetic disturbance

δ : magnetic declination

Once the magnetic declination is corrected, the bias can be considered as the effect of the soft and hard magnetic disturbances. In the absence of synchronised GPS and/or gyroscope data, such influence is not detectable in the raw compass signal. The function of the bias takes into account the distance instead of the time elapsed since the last bias determination.

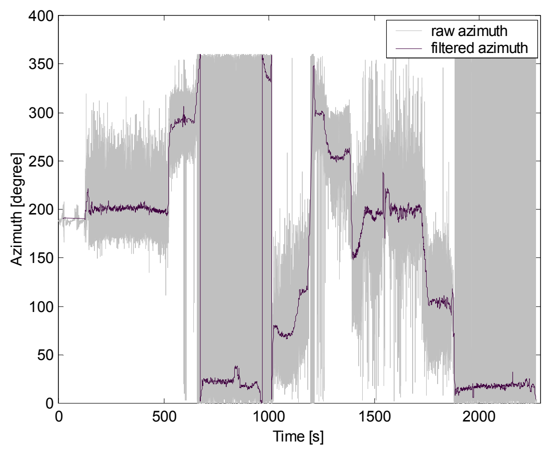

Figure 2: raw and filtered azimuth. The variation of the signal is mainly caused by the physiological movement of the waist while walking.

The two elements of a DR approaches have been presented. The folding process of those elements is done in the following mechanisation, that furnishes the navigation parameters:

$$N_k = N_{k-1} + dist_k \cdot \cos(\phi_k) \qquad (3)$$

$$E_k = E_{k-1} + dist_k \cdot \sin(\phi_k) \qquad (4)$$

where

N , E are the North and East coordinates

ϕ_k is the azimuth

$dist_k = s\ dt$ is the travelled distance

s is the speed computed with the acceleration pattern

dt is the time interval over which a distance and an azimuth are computed.

4. VARIANCE PROPAGATION

The error analysis of the DR algorithm provides the information to compute the precision of such a system. The error propagation in the model is computed in the following.

For the orientation computed with a gyroscope, we have the following linear form:

$$d\phi_k = \frac{\partial \phi_k}{\partial \phi_{k-1}} \cdot d\phi_{k-1} + \frac{\partial \phi_k}{\partial b} \cdot db + \frac{\partial \phi_k}{\partial \lambda} \cdot d\lambda \qquad (5)$$

$$d\phi_k = 1 \cdot d\phi_{k-1} + dt \cdot db + dt \cdot \omega \cdot d\lambda \qquad (6)$$

where

$d\phi_k$ is the error on the orientation induced by an error db in the bias , $d\lambda$ in the scale factor and $d\phi_{k-1}$ in the orientation at time k.

The propagation of the error on distance and orientation into the North and East coordinates is:

$$dN_k = \frac{\partial N_k}{\partial N_{k-1}} \cdot dN_{k-1} + \frac{\partial N_k}{\partial \phi_k} \cdot d\phi_k + \frac{\partial N_k}{\partial dist} \cdot ddist_k \qquad (7)$$

where $d\phi_k$ is replaced by formula (6), $ddist_k$ is the distance error and dN_{k-1} is the error for the previous computed coordinate.

For North and East we have:

$$\begin{cases} dN_k = dN_{k-1} - dist \cdot \sin(\phi_k) \cdot d\phi_k + \cos(\phi_k) \cdot ddist_k \\ dE_k = dE_{k-1} + dist \cdot \cos(\phi_k) \cdot d\phi_k + \sin(\phi_k) \cdot ddist_k \end{cases} \qquad (8)$$

In matrix notation we obtain:

$$\begin{bmatrix} dN_k \\ dE_k \end{bmatrix} = F_{DR} \cdot \left[dN_{k-1} \;\; dE_{k-1} \;\; d\phi_k \;\; ddist_k \right]^T \qquad (9a)$$

where $$F_{DR} = \begin{bmatrix} 1 & 0 & -dist \cdot \sin(\phi_k) & \cos(\phi_k) \\ 0 & 1 & dist \cdot \cos(\phi_k) & \sin(\phi_k) \end{bmatrix} \qquad (9b)$$

Finally, the variance propagation is computed with the following equation that provides the covariance matrix C_{DR} of the parameter N, E:

$$C_{DR} = F_{DR} \cdot C_{xx} \cdot F_{DR}^T \qquad (10)$$

where C_{xx} is the covariance matrix of position, azimuth, distance and sensor parameters (b, λ and those for $dist$).

5. CENTRALIZED KALMAN FILTER

The Kalman filter (KF) is the optimal combination, in term of minimisation of variance, between the prediction of parameters from a previous time instant and external observations at the present instant (Brown and Hwang, 1997). KF is build around two independent models: the kinematic model and the observation model. Each one has a functional part and a stochastic part.

Kinematic model

The functional part of the kinematic model represents the prediction of the parameters. The parameters considered in the GPS-gyro-accelerometer system form the following vector:

$$x^T = [E \;\; N \;\; \phi \;\; b \;\; \lambda \;\; A \;\; B] \tag{11}$$

where A and B are the parameters of the distance model.

Unlike other navigation applications, the trajectory of a pedestrian is difficult to predict. Changes in speed and orientation are sudden and can be of great amplitude. Therefore it is preferable for the prediction of the parameter to consider only the DR mechanisation. No other navigation parameters, such as speed or acceleration, are introduced in the state vector. Then the functional part of the kinematic model is the DR mechanisation.

Considering the increments of the parameters, the state vector is:

$$dx^T = [dE \;\; dN \;\; d\phi \;\; db \;\; d\lambda \;\; dA \;\; dB] \tag{12}$$

Then the functional part of the model is:

$$d\tilde{x}_k = \Phi_k \cdot d\tilde{x}_{k-1} + w \tag{13}$$

where the matrix Φ is the transition matrix. The system noise w is assumed to have mean zero and no correlation with the components of dx.

The three first lines of the Φ matrix (concerning the first derivative of dE, dN and $d\phi$) are the equations (6) and (8) developed for the DR mechanisation and error propagation.

Concerning the lines 4 and 5 of the matrix, the parameters of the sensors db, $d\lambda$ are modelled as Gauss-Markov processes. The system noise of db is greater than the one of the scale factor. Regarding the lines 7 and 8 of the matrix, dA and dB are modelled as random walk processes. The choice of the system noise of the parameter dA and dB is critical. Over the flat areas the pre-calibrated parameters can be taken into account and the two driving noises are low. When there is a slope larger than about 7% then it's better to re-estimate these parameters and to adapt the driving noise. This situation can be resolved through an adaptive Kalman filter, where the driving noise on dA and dB can be controlled by the slope angle determined for example with a barometer or by GPS. The slope can also be detected by analysing the signal itself, as proposed in Herren et al. (1999). However implementing such detection in real-time is still to be resolved.

During the mechanisation phase, the stochastic part of the model is obtained via variance propagation:

$$C_{\tilde{x}\tilde{x}k} = \Phi_k \cdot C_{\tilde{x}\tilde{x}k-1} \cdot \Phi_k^T + C_{ww} \tag{14}$$

The $C_{\tilde{x}\tilde{x}k}$ matrix contains the variance of the predicted parameters at time k and the C_{ww} is the covariance matrix of the process noise.

Observation model

The considered external observations are the GPS position (ℓ_E and ℓ_N) and the GPS azimuth (ℓ_ϕ). They form the observation vector ℓ_k. In fact they are indirect observations computed from the GPS code and phase rate measurement. This is taken in account through the variance and correlation included in the covariance matrix of the observations $C_{\ell\ell}$.

Each observation is function of the parameters:

$$\ell_k - v = f(x) \tag{15}$$

where v is the vector of residuals of the observations.

Working with the increase in the parameters, equation (15) becomes by linearization around the mechanised values:

$$\tilde{v}_k - v = H \cdot dx \tag{16}$$

where

$\tilde{v}_k = \ell_k - f(\tilde{x}_k)$	is the vector of predicted residuals (observed minus computed term);	(17)
$\tilde{x}_k$	is the vector of the mechanised parameters at the observation time t_k;	
H	is the design matrix.	

In the equation (17) $\tilde{v}_k$ represents the difference between the GPS position and azimuth and the DR output after mechanisation. This vector can be used as a first reliability indicator. Large discrepancies could indicate a fault in the GPS measurements or in a DR sensor.

Update

The update phase is a combination of the two models presented above. It is an estimation that minimizes the variance of both the observations and the mechanisation. The update phase is performed when the following conditions are fulfilled:

- GPS is available
- The variance of the three navigation parameters (position and azimuth) reach a predefined level.
- The GPS position and azimuth are reliable.

The reliability is controlled through the $\tilde{v}_k$ computation and with consideration regarding the changes in the GPS azimuth compared with the gyro raw data.

The updated parameters are given by:

$$d\hat{x}_k = K_k \cdot \tilde{v}_k \tag{18}$$

$$\hat{x}_k = \tilde{x}_k + K_k \cdot \tilde{v}_k \tag{19}$$

where $\tilde{x}_k$ denotes the mechanised parameters at time t_k. The "hat" denotes an estimate and the "tilda" indicates the mechanised value.

K_k is the gain matrix and can be written as:
$$K_k = C_{\tilde{x}\tilde{x}k} \cdot H^T \cdot [H \cdot C_{\tilde{x}\tilde{x}k} \cdot H^T + C_{\ell\ell}]^{-1} \tag{20}$$

The covariance matrix of the updated parameters is computed for stability reasons (Merminod, 1989) in the Joseph Form:

$$C_{\hat{x}\hat{x}k} = [I-K_k \cdot H] \cdot C_{\tilde{x}\tilde{x}k} \cdot [I-K_k \cdot H]^T + K_k \cdot C_{\ell\ell} \cdot K_k^T \tag{21}$$

The equation (18) can be considered as a distribution of the differences between GPS and DR into the increments of the parameters. The gain matrix K, that is a function of both covariance matrices, drives the distribution.

6. TEST AND RESULT

Several tests have been conducted in different environment. The test presented below consists in following a track around a building on the University campus (Figure 3) with strong iron concentration and electrical currents.

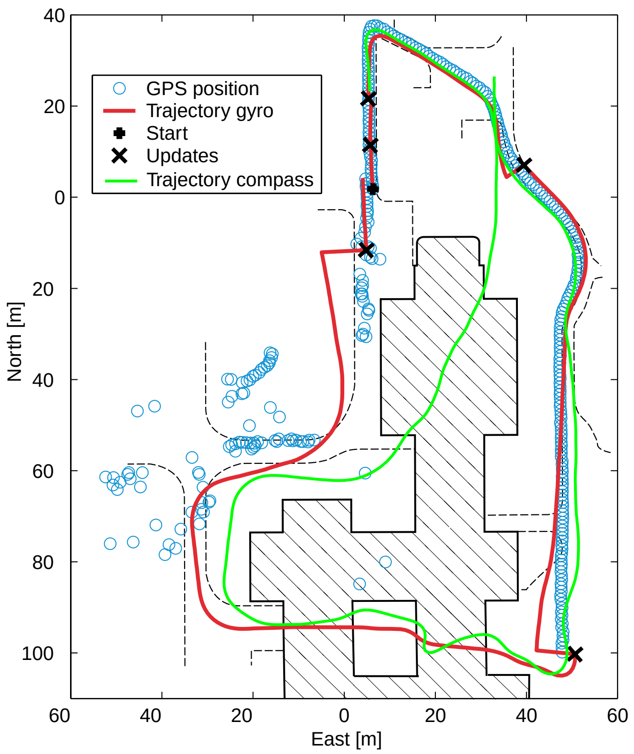

Figure 3: trajectory around the DGR building at EPFL. The bold trajectory is the result of the KF using a gyroscope to measure changes in the azimuth. The light grey line represents the trajectory using the magnetic compass only.

The pedestrian walks about 400m at the average speed of 1.6 m/s on flat area. He follows a track situated between the dashed lines of the figure 3 and passes under the building. GPS signals from at least 4 satellites are available for the first part of the track. They provide an initial orientation to the gyroscope and allow to perform the first update, which is essential for the bias calibration. The interruption of the GPS signals is caused by the building. When the GPS signals reappear they are perturbed by multi-path. The next and last update is done when the conditions presented in Section 5 are fulfilled. Local perturbations of the compass appear very clearly, affecting the trajectory. It can be stressed that once the magnetically disturbed zone is passed, the computed azimuth returns to its previous, undisturbed value.

Another test took place in a residential area where it was possible to experience the loss of some satellite signals as well as "normal" magnetic disturbances (Figure 4). The total length of the trajectory, measured by carrier phase differential GPS, is 1840 m. The variation of altitude during the run is 31 m. The maximal slope is 13%.

The maximal error between the computed trajectory and the true one is 5.2m for the GPS-DMC system and 25 m for the GPS-gyro module.

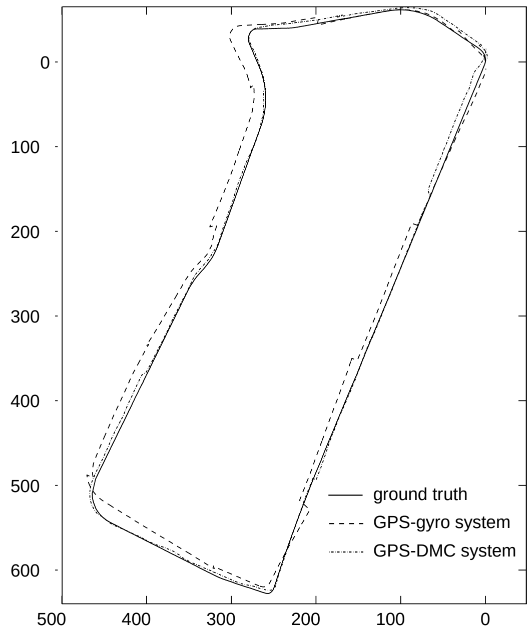

Figure 4: Comparison of the GPS–DMC/gyro integration on a path in a residential area.

These different tests conducted in parallel with the two sensor systems show clearly that the weaknesses of one system are the advantages of the other one. According to this remark, an optimal and more reliable system is obtained by coupling the gyroscopes with the magnetic compass.

	Advantages	Disadvantages
Magnetic compass	- absolute azimuth - long term accuracy - repeatability	- unpredictable - external disturbance
Gyroscopes	- no external disturbance - short term accuracy	- drift - relative azimuth

Table 1 : comparison between compass and gyro

The gyroscope provides a useful indication to identify magnetic disturbances, while the compass is useful to determine the bias of the gyros and the initial orientation, even when no GPS is available.

7. CONCLUSIONS

The presented research demonstrates that combining a single gyroscope or/and a magnetic compass together with accelerometers can complement GPS in pedestrian navigation when the satellite signal becomes masked by obstructions. The main drawback is that the gyro needs frequent updates (about every 2 minutes) to maintain a position accuracy of 15 meters. Using gyro of higher accuracy could augment the DR bridging. The other option under investigation is to use a digital compass that offers the possibility to control the gyro bias when necessary. Furthermore, even a low cost gyro is able to detect whether a change in azimuth measured by the compass is due to a real turn or to hard and soft magnetic disturbances.

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