DGPS/INS data fusion for land navigation

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Abstract - *The interest for land navigation has increased for the recent years. With the advent of the Global Position System (GPS) we have now the ability to determine the absolute position anywhere on the globe. The problem is that the GPS systems work well only in open environments with no overhead obstructions and they are subject to large unavoidable errors when the reception from some of the satellites is blocked. This occurs frequently in urban environments, forests and tunnels. GPS systems require at least four "visible" satellites to maintain a good position fix. In many situations in which higher level of accuracy is required, the navigation cannot be achieved by GPS alone. This paper discusses the design of a reliable multisensor fusion algorithm using GPS and Inertial Navigation System in order to decrease the implementation cost of such systems on land vehicles.*

Keywords: Data fusion, inertial navigation system (INS), GPS system, Kalman filter, informational filter.

1 Introduction

Land navigation has led to the creation of many research projects and platforms like TRAVEL and OPSYDE, which are part of the AUTORIS project (Automatics for an Intelligent and Safe Road).The purpose of this project is the development of land navigation techniques to increase the security of highway transports. The TRAVEL platform considers the creation of an autonomous convoy of vehicles while the OPSYDE project consists of data fusion techniques to solve the problem of multisensor navigation in order to increase the accuracy and reliability. The test platform installed is composed of ROBUCAR electric vehicles and their on-board sensors where the most important are GPS and attitude sensors. These sensors are known for their use as standalone navigation systems. However, to achieve sufficient accuracy, the cost of such sensors would be prohibitive. Nevertheless, their fusion permits us to use low-end sensors without losing the accuracy of position, attitude and velocity estimates. There are various multisensor data fusion approaches of which the fusion using Kalman filtering is one of the most significant. However, this "classical" approach has several flaws; the most significant is that the implementation is simple only in the case of two sensor fusion (discussed in section 3.3). The subject of this paper is to develop a reliable navigation system based on informational data fusion techniques. The main attribute is the possibility to add multiple sensors without changing the structure of the data fusion algorithm. In order to evaluate the proposed method, the informational filter is compared to the classical Kalman filter. To test filter performance, seven sets of GPS and INS data from field tests (provided by CADDEN Company) are used. The results of the simulations are presented and discussed also.

2 Inertial navigation

The purpose of a navigation system is to provide the user with position estimates. We distinguish two kinds of sensors [1][4]:

- Absolute sensors (GPS, camera…) which acquire information from the exterior of the vehicle and give absolute position estimate.
- Dead-reckoning sensors (gyroscopes, accelerometers…) which acquire information from the vehicle itself and give relative estimate.

Table 1: Sensor characteristics

Sensor type	Absolute	Dead-reckoning
Localisation	Absolute	Relative
Acquisition frequency	Low	High
Long-term accuracy	Very good	Bad
Short-term accuracy	Medium	Very good

Unfortunately, no ideal single sensor can give us accurate measurements in real time situations. These sensors are complementary and well suited for data fusion. An intuitive solution is the use of an absolute sensor to fix the data provided by a dead-reckoning sensor [6].

In this paper, we propose:

- Absolute position measurements issued from a DGPS (Differential GPS) system. The GPS [3][5] is a satellite-based radio-navigation system providing absolute position estimate in ECEF (Earth Centred, Earth Fixed) frame. Four or more satellites are required to compute GPS position. This constraints the use of GPS system to uncovered and open areas. The DGPS system is the SAGITTA system from THALES Navigation. The accuracy is +/-20cm and the acquisition frequency is 10 Hz.

- Dead-reckoning rate measurements issued from an Inertial Navigation System (INS): The inertial sensor provides us with rotation rate (gyroscopes) and acceleration (accelerometers). Generally, it integrates three gyroscopes. The used sensor is a fibre-optic strap-down INS [1] [2], the "OCTANS" from THALES Navigation. The accuracy is 500 µg for the accelerometers and 0.01° for the gyroscopes. The acquisition frequency is 100Hz.

- Vehicle model which role is to relate rate information (acceleration and rotation rates) to position information through a model of vehicle motion. Acceleration data are converted from the body frame (vehicle frame) to the navigation frame (North East Down frame [3]) and integrated two times to obtain the position estimate. The conversion is made using DCM [2] (Direction Cosine Matrix). DCM elements are updated from gyroscopes as shown in Fig. 1.

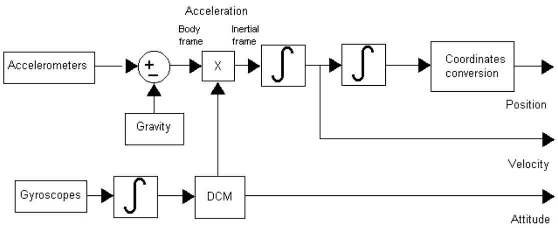

Fig. 1: Navigation model

The vehicle position is estimated in terms of longitude, latitude and height, in order to apply GPS position fix. The gravity is considered constant (test field area is 8x8 km) and the effects of Coriolis acceleration are neglected. The results are shown in Fig. 2.

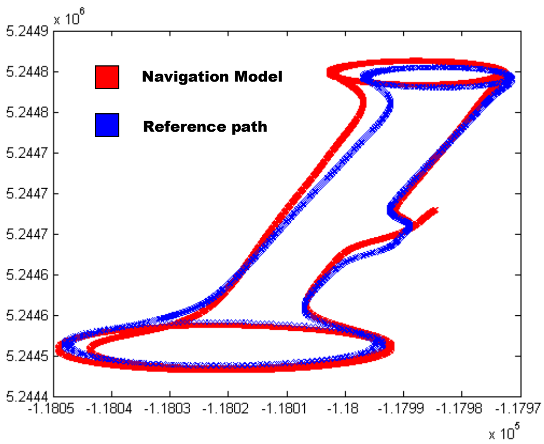

Fig. 2: Navigation model results compared to reference

3 Informational approach of data fusion

Estimation problems inherently deal with uncertainty of states, observations and actions. Uncertainty in these quantities is described in terms of probability distribution. It is essential to provide a measure of the informativeness of the probability distributions associated with the data fusion task. Two definitions of information exist: Shannon information (or entropy) and Fisher information. They evaluate the information contained in a probability distribution in terms of its compactness. We propose the use of an informational filter for data fusion.

3.1 Entropy-based information

The entropy *H(x)* associated with a probability distribution *N(x)* and defined on a continuous-valued random variable *x* is given by:

$$H(x) = -\mathrm{E}\left[\log N(x)\right] = -\int N(x).\log N(x).dx \qquad (1)$$

Entropy-based information [8] is given by

$$i(x) = -H(x) \qquad (2)$$

Entropy is the only coherent definition of informativeness and thus it is an appropriate evaluation criterion of probabilistic modelled information sources.

In the case of an *n*-dimensional state *x* modelled by a Gaussian distribution of mean $\overline{x}$ and covariance *P*, entropy-based information is given by:

$$i(x) = -H(x) = -\frac{1}{2}\log\left((2\Pi e)^n.|P|\right) \qquad (3)$$

3.2 Fisher information

Fisher information [7] is defined on continuous distributions. *Y(x)* is defined as the second derivative of the log-likelihood:

$$Y(x) = \frac{d^2}{dx^2}\log N(x) \qquad (4)$$

In the case of a Gaussian probability distribution *Y(x)* is equal to P^{-1}. Fisher information is the inverse covariance of *x*. The relationship between Fisher information and entropic information measurements appears through the determinant of *P*:

$$i(x) = -\frac{1}{2}\log\left((2\Pi e)^n.|P|\right)$$

$$= \frac{1}{2}\log\left((2\Pi e)^n.\left|Y(x)\right|\right) \quad (5)$$

3.3 Information filter

Information filter is mathematically equivalent to Kalman filter. It is an informational form of Kalman filter obtained by replacing the representation of the state estimate and covariance with information state $\hat{y}$ and Fisher information Y [3] [7].

Consider:

$$x(k) = F(k).x(k-1) + B(k).u(k) + G(k).v(k) \quad (6)$$

$$z(k) = H(k).x(k) + w(k) \quad (7)$$

Where *v(k)* and *w(k)* are blank Gaussian noises with covariance *Q* and *R*.

The information matrix is defined by:

$$Y(k/k) = P^{-1}(k/k) \quad (8)$$

And the information state by:

$$\hat{y}(k/k) = Y(k/k).\hat{x}(k/k) \quad (9)$$

The information contribution of the observation *z(k)* to the information state is evaluated by *i(k)* and to the Fisher information by *I(k)*:

$$i(k) = H^T(k)R^{-1}(k).z(k) \quad (10)$$

$$I(k) = H^T(k).R^{-1}(k).H(k) \quad (11)$$

The predicted information state is evaluated using:

$$\hat{y}(k/k-1) = \left[Y(k-1/k-1)F(k)Y^{-1}(k-1/k-1)\right]$$

$$.\hat{y}(k-1/k-1) + B(k).u(k) \quad (12)$$

And the corresponding information matrix by:

$$Y(k/k-1) = \left[F(k).Y^{-1}(k-1/k-1).F^T(k) + Q(k)\right]^{-1} \quad (13)$$

Note that the computation in the prediction stage is more complex in comparison with the Kalman filter [9][10]. However, this complexity is compensated by the very simple computation in the update stage:

$$\hat{y}(k/k) = \hat{y}(k/k-1) + i(k) \quad (14)$$

$$Y(k/k) = Y(k/k-1) + I(k) \quad (15)$$

In the case of multiple (parallel) observations the expressions remain simple, information contribution is summed and added to the predicted state:

$$\hat{y}(k/k) = \hat{y}(k/k-1) + \sum i_j(k) \quad (16)$$

$$Y(k/k) = Y(k/k-1) + \sum I_j(k) \quad (17)$$

This cannot be done with Kalman filtering because:

$$\hat{x}(k/k) \neq \hat{x}(k/k-1) +$$

$$+ \sum Ki(k).\left[z_i(k) - H_i(k)x.(k/k-1)\right] \quad (18)$$

The simple additive nature of the update stage makes the informational filter very attractive for multisensor decentralised estimation. One can imagine a structure with multiple nodes; each one representing a sensor and an informational filter generating local estimates $\tilde{y}_i(k/k)$. The innovation is transmitted to the other nodes *via* the network and the global information is updated with the local estimate by simple addition. Thus, the process of fusing information from different sensors is greatly simplified. Note that in a mono-sensor system the performance of the information and the Kalman filters are identical.

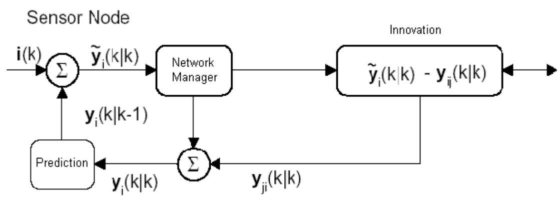

Fig. 3: Decentralised filter

4 INS/GPS Data fusion

Two fusion techniques are compared, the classical approach (based on Kalman filtering) and the proposed informational approach:

4.1 The classical approach

4.1.1 Principle

Direct feedback filter [1] is realised (Fig. 4) to be compared with the informational data fusion method introduced in section 4.2.

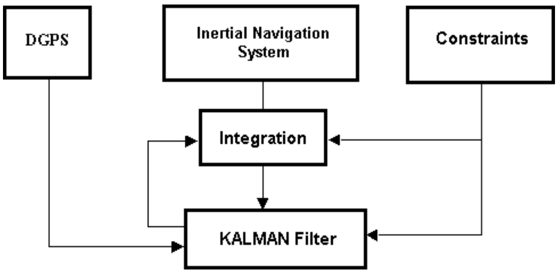

Fig. 4: Direct feedback structure

The filter is fed with data from the INS sensor. The DGPS block provides the observation data to the filter while the constraints block is used to fix irrelevant estimations (the vehicle is considered always moving along its longitudinal axe, so V_y and V_z are nil).

$$V_{nav}^{+} = C_b^n \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} C_b^{n\,T} V_{nav}^{-} \tag{19}$$

INS data is transformed from the inertial frame to the ECEF frame (19).

4.1.2 Modelling

The state vector is composed by position, velocity and acceleration errors [1].

$$x = \begin{bmatrix} \delta p & \delta v & \delta a \end{bmatrix}^T \tag{20}$$

The process is modelled by:

$$\begin{cases} \delta\dot{p} = \delta v \\ \delta\dot{v} = \tilde{fe}.\delta a + C_b^n \delta fb \end{cases} \tag{21}$$

The state transition matrix is:

$$F = \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & A \\ 0 & 0 & 0 \end{bmatrix} \tag{22}$$

With

$$A = \begin{bmatrix} 0 & -f_d & f_e \\ f_d & 0 & -f_n \\ -f_e & f_n & 0 \end{bmatrix} \tag{23}$$

The acceleration data are fed directly in the process model through A, so there is no control vector ($u=0$). F elements are considered as constants during the sampling interval ΔT . F is obtained by:

$$F_k = e^{F\Delta T} \tag{24}$$

Discretisation uses only the first term of Taylor series decomposition (and neglecting others):

$$F_k = I + F\Delta T + \theta(\Delta T) \tag{25}$$

And state transition is given by:

$$\hat{x}(k/k-1) = F_k \hat{x}(k-1/k-1) \tag{26}$$

The implementation of this model is linear and independent from vehicle dynamics.

We suppose that there is no initial error $x(1/0)=0$. The system noise covariance is evaluated using:

$$Q_k = \frac{1}{2}\left[F_k G_k Qc_k G_k^T F_k^T + G_k Qc_k G_k^T\right]\Delta T \tag{27}$$

And

$$Qc_k = \begin{bmatrix} \delta\tilde{p} & 0 & 0 \\ 0 & \delta\tilde{fb} & 0 \\ 0 & 0 & \delta wb \end{bmatrix} \tag{28}$$

$\delta\tilde{p}$ is the noise in the position error evaluation and it depends on the uncertainty of velocity estimation (*via* integration). Other errors are considered as sensor errors and taken from manufacturer's datasheets. G_k is:

$$G_k = \begin{bmatrix} I & 0 & 0 \\ 0 & C_b^n & 0 \\ 0 & 0 & -C_b^n \end{bmatrix} \tag{29}$$

The observation is given by:

$$z_{pk} = z_{pk}^{inertial} - z_{pk}^{others} \tag{30}$$

And the constraint corrected observation by:

$$z_{vk} = z_{vk}^{inertial} - z_{vk}^{correct} \tag{31}$$

The observation matrix is given by:

$$H^{INS} = \begin{bmatrix} 0 & I & 0 \end{bmatrix} \tag{32}$$

And the observation noise covariance matrix is:

$$R^{INS} = \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_z^2 \end{bmatrix} \tag{33}$$

Given that the velocity vector is transformed from the mobile frame to the navigation frame, the same transformation must be done with R^{INS}:

$$\overline{R}^{INS} = C_b^n R^{INS} C_b^{n\,T} \quad (34)$$

For the GPS sensor, the observation is:

$$z_k = \begin{bmatrix} z_{pk}^{inertial} - z_{pk}^{GPS} \\ z_{vk}^{inertial} - z_{vk}^{GPS} \end{bmatrix} \quad (35)$$

The observation matrix is given by:

$$H^{GPS} = \begin{bmatrix} I & 0 & 0 \\ 0 & I & 0 \end{bmatrix} \quad (36)$$

And the noise covariance matrix by:

$$R^{GPS} = \begin{bmatrix} I_{3x3}.\sigma_p^{\ 2} & 0_{3x3} \\ 0_{3x3} & I_{3x3}.\sigma_v^{\ 2} \end{bmatrix} \quad (37)$$

4.2 Informational approach

4.2.1 Principle

Reliable inertial navigation supposes constant correction of the inertial data. This is the role of the GPS sensor. The problem is that the GPS relies on the environment, so in many cases (urban or forest environment), the sensor receives reflected satellite signals (multipath error) and in tunnels, the position estimate is not available at all, due to the lack of satellite signal. The classical method cannot handle this aspect.

We are going to define an information criterion to reject the erroneous measures. The justification is intuitive: we are looking for the measures which maximise the information and minimise the estimation error [7].

4.2.2 Modelling [5]

The state vector is composed by position, velocity and acceleration in the navigation frame:

$$x = \begin{bmatrix} p & v & a \end{bmatrix}^T \quad (38)$$

The process model is:

$$x_{k+1} = \begin{bmatrix} I & \Delta T & \Delta T^2 \\ 0 & I & \Delta T \\ 0 & 0 & I \end{bmatrix} . x_k + \gamma \begin{bmatrix} \frac{\Delta T^3}{6} \\ \frac{\Delta T}{2} \\ \Delta T \end{bmatrix} \quad (39)$$

ΔT is the sampling interval. The observation matrix corresponding to the GPS and the INS sensors are:

$$H^{GPS} = \begin{bmatrix} I & 0 & 0 \end{bmatrix} \quad (40)$$

$$H^{INS} = \begin{bmatrix} 0 & 0 & I \end{bmatrix} \quad (41)$$

And the information obtained from the two sensors is:

$$I^{GPS} = H^{GPS\,T} R^{GPS\,-1} H^{GPS} \quad (42)$$

$$I^{INS} = H^{INS\,T} R^{INS\,-1} H^{INS} \quad (43)$$

4.2.3 Decentralised data fusion [7]

Data from each sensor are filtered with a dedicated information filter. The global information vector and the information matrix take this form:

$$\hat{y}_i(k/k) = \begin{bmatrix} \hat{y}_{i,1}(k/k) \\ \hat{y}_{i,2}(k/k) \end{bmatrix} \quad (44)$$

$$Y_i(k/k) = \begin{bmatrix} Y_{i,1}(k/k) & 0 \\ 0 & Y_{i,2}(k/k) \end{bmatrix} \quad (45)$$

The corresponding entropy is obtained by (3.1, 3.2):

$$i_i(k) = \frac{1}{2}\log\left[(2\Pi e)^{18} \left|Y_i(k/k)\right|\right] \quad (46)$$

In our system, using two sensors, we obtain three modes:

1. GPS alone
2. INS alone
3. INS + GPS

The information gain corresponding to each mode is computed for every iteration:

$$I_i(k) = H_i^{\ T} R_i^{-1} H_i \quad (47)$$

The mutual information is computed as follows:

$$\Gamma_i(k) = \frac{1}{2}\log\left[\frac{\left|\mathrm{Y_i(k/k-1) + I_i(k)}\right|}{\left|\mathrm{Y_i(k/k-1)}\right|}\right] \quad (48)$$

And the utility is given by:

$$U(a,k) = \sum \Gamma_{i,a_i}(k) \quad (49)$$

With a representing the selected mode (*a=1, 2, 3*). The optimal mode must maximise *U.*

5 Experimentations

The discussed filters are fed by data from field tests made by CADDEN. GPS provides data in ECEF frame with 10Hz rate. OCTANS INS provides the roll, pitch, yaw and heading angles, the corresponding angular velocities and the accelerations on the three body axes. The measures are done at 100Hz.

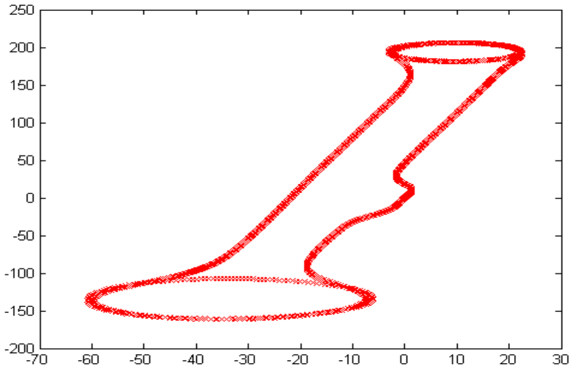

Fig. 5: GPS path

The two approaches are implemented using Matlab®. Noise is added to the data corresponding to the path on the Fig. 5. An error of +/- 15 meters is added to GPS data (Figs. 6, 7). The evaluation of the two methods is done by comparison between reference and filtered position estimates.

5.1 Classical approach

Using classical approach (based on Kalman filtering), we obtain 50% accuracy improvement (Fig. 8).

In the case where the GPS position is not available, position estimates are biased as a consequence of the non-observability of the process.

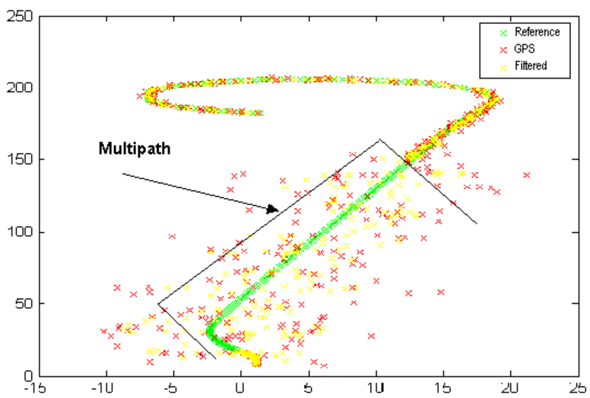

Fig. 6: Multipath

The multipath problem is not handled by this approach (Fig. 9).

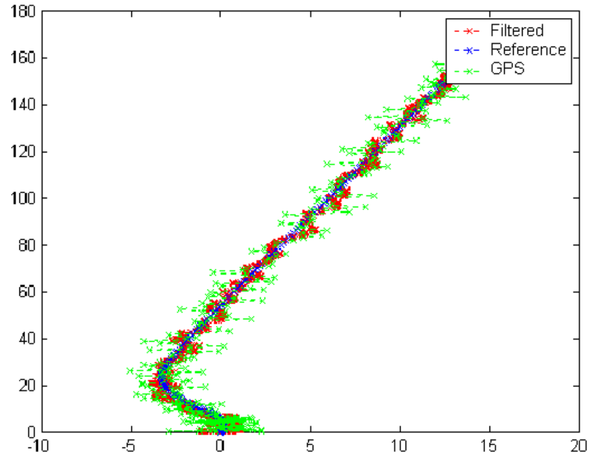

Fig. 7: Kalman Filtering

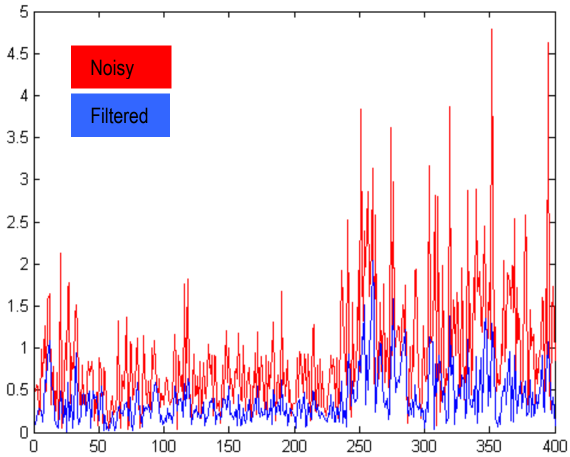

Fig. 8: Position estimate error

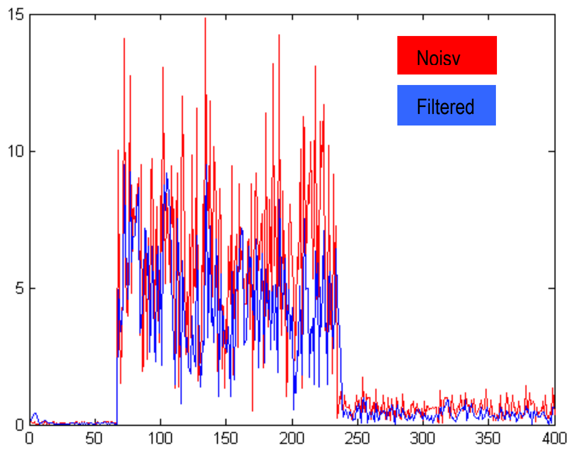

Fig. 9: Multipath error

5.2 Informational approach

With the information filter, accuracy improves up to 30% (Fig. 11). This is a bad result considering the classical approach results. At the same time the information criterion failed to reject erroneous measures in multipath conditions.

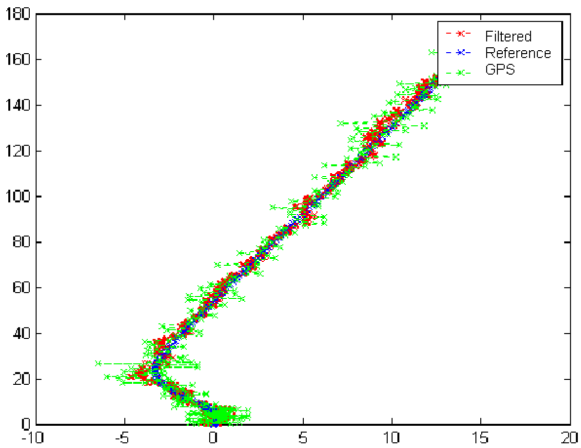

Fig. 10: Informational approach

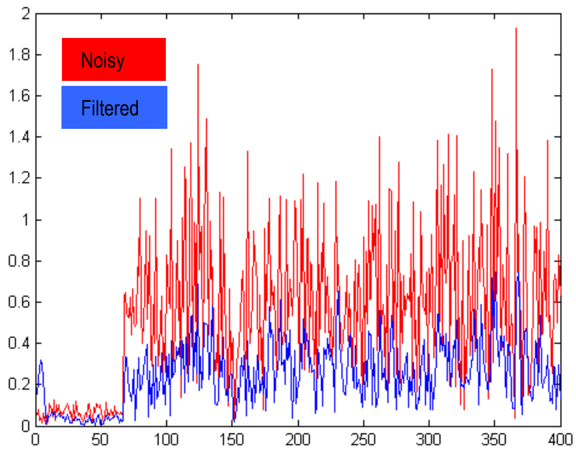

Fig. 11: Estimation error in the case of the informational approach

5.3 Comparison

Classical approach gives expected results. It is not the case of the informational approach, especially in the rejection of the multipath errors. This is due to the difficulty in the choice of an utility function which reflects the information gain in the case of a system based on two sensors. This fact limits the use of such systems to a multisensor (n>2) platform.

6 Conclusion

This paper presented an aided inertial navigation system capable to be a reference system for driving applications. An inertial navigation model was defined. Two approaches were compared:

- A classical one, based on Kalman filtering on a direct feedback structure.
- A decentralised data fusion, a promising new approach which requires careful modelling and a sufficient number of sensors. The results obtained are essentially due to a small number of sensors and the lack of raw data from GPS.

However, the work is still in progress, and improvements of the informational filter can be achieved by integrating GPS raw data in the utility criterion and increasing the accuracy of GPS and INS, in order to find the most cost-efficient sensors to use in the TRAVEL platform by artificially decreasing the accuracy of GPS and INS sensors.

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