IMPROVING THE RELIABILITY OF A GPS/INS NAVIGATION SOLUTION FOR MM VEHICLES BY PHOTOGRAMMETRY

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ABSTRACT:

Integration of INS and GPS is necessary for continuous georeferencing in Mobile Mapping (MM); improved mathematical models, such as tightly coupled solutions, make very efficient use of the available information, especially with poor GPS solutions. However, experience shows trajectory errors still arise. If data from the two system components do not agree for whatever reason, deciding which data is wrong may not be easy and depends on filter implementation. The availability of data from other sensors can help to identify the erroneous data source. In this paper, use of photogrammetry to verify the consistency of GPS/INS data is proposed.
First, the GPS-aided inertial navigation solution implemented is introduced, discussing its extension to photogrammetry-aided solution. Some reliability tests are reviewed. Finally, the concept and implementation details of an automatic procedure providing a photogrammetric check of the GPS/INS data is described. In short, the idea is rather simple: to compare the image locations of a set of object points, computed from the stereo pair at time t_i, with those of the same points projected on the images at t_{i+1}, based on the exterior orientation computed by the navigation solution at time t_{i+1}.
Although no test of the method has been made yet, experience shows that tracking points on the road surface in MM image sequences is feasible; implementation details take care of redundancy as well as of speed of computation: in principle the check can be applied to every consecutive pair of the sequence.

1. INTRODUCTION

1.1 Mobile Mapping Vehicles

Mobile Mapping Vehicles (MMVs) are used to georeference data acquired by different sensors along roads and their surroundings.
The survey missions of MMVs fall in two main areas of application, to a large extent overlapping. The first is data collection for the population or the updating of a road cadaster database or a urban GIS; in this case geometric and attribute data about the road infrastructure but also about its surroundings area of interest are collected. The second, normally of interest to road and traffic departments which are responsible for road maintenance and road safety, concentrates more on the state of the road surface (frequency and severity of potholes, cracks, degree of surface roughness). Other issues concerning safety (such as driving comfort, visibility distances), as well as the impact on the environment (pollution and noise level due to traffic on nearby buildings, etc.) can be also relevant to a survey mission.

From a functional standpoint, a MMV hosts a Positioning and Orientation System (POS), which provides navigation data, and a Data Acquisition System, which manages the on-board sensors; both have their storage and power requirements and must be synchronized to allow for data georeferencing.
Today's MMVs are designed to acquire data at operating speed around 50–80 km/h; data georeferencing is achieved with an on–board POS, typically composed by an INS and one or more GPS receivers, providing the position of the body system with respect to a mapping reference system and its orientation with respect to a local level system at high frequency (100–200 Hz). Geodetic–like antennas with optical gyroscopes and vibrating accelerometers are actually the most used configuration. In most cases, a Distance Measuring Instrument (DMI) is also integrated in the POS, either as a support to navigation as well as to provide a coarse georeferencing in terms of linear distances along the road, useful for operational purposes.

Active on–board sensors depend on the task; normally they include one or several digital cameras; laser scanners with different speed, operating range and accuracy are also increasingly used. Image data are mostly collected to retrieve geometric information by photogrammetry; careful design of image resolution, frame rate, focal lengths, placement and orientation of cameras should ensure stereo coverage of the corridor of interest of the survey. Besides, other cameras may be mounted for specific purposes, such as crack detection. Image processing techniques can also be used to automate, at least to some extent, some of the tasks (e.g. to measure the lane width, recognize road signs, detect cracks, etc). Laser scanners were installed at first mainly to measure road surface parameters (e.g. the International Roughness Index) by along– track profiling with mm level accuracy) or the extent of rutting on the lane by cross profiling; today they also provide other information, such as the clearance under bridges and overpasses; besides, the distance to nearby buildings or a detailed DSM of the corridor may be generated to study traffic noise propagation or as support for 3D city model generation.

Depending on the mission purpose, on the georeferencing accuracy required and on the sensor characteristics, time synchronization and offsets as well as misalignments between the body system and the sensor systems must be taken into account with an accurate calibration and monitored for stability over time. For instance, image georeferencing is obtained by interpolation of the navigation data at the exposure time, accounting for the offset and misalignment of the camera reference frames with respect to the body frame.

1.2 Aided inertial navigation

The integration of GPS and INS data benefits many aspects of the navigation solution and the overall survey quality, because of the improved accuracy and reliability of an integrated system respect to the separate ones. Improvements in the mathematical modelling and software implementation such as tightly coupled solutions make very efficient use of the available information, especially with poor GPS solutions. However, experience shows that use of these sensors and algorithms is not always sufficient to guarantee a fault tolerant system. Sometimes, error caused by outliers or residual model errors even in only one of these sensors can lead to incorrect estimates of position or attitude. This is particularly true in case of GPS outages or changes in GPS constellation which often result in sudden shifts in the trajectories. If the two system components (GPS and INS) do not agree, at least weights should be adjusted in the filter to minimize the contribution of erroneous data. With only two data sources available, deciding which data are wrong may not be feasible. Due to the error characteristics of the IMU, however, the system often relies primarily on GPS data; the relative weighting of IMU and GPS data therefore favour the latter as long as their quality is believed to be accurate.

If GPS outages are long and severe, drift errors of the IMU become too large and the accuracy of the POS data decreases. This may happen for instance in city centres, where operating speed is sometimes slow because of traffic (so outages last longer), along narrow streets where buildings are very close to the road, along boulevards or countryside roads bordered by dense tree rows, in road sections through forests, tunnels, etc. In such cases, we may turn to a purely photogrammetric approach to recover the image orientation parameters and proceed with restitution, possibly keeping human interaction to a minimum. Automatic image sequence orientation to support an IMU/GPS system to overcome GPS outages was proposed in (Chaplin and Chapman, 1998 and 2001; Tao et al, 1999; Roncella and Forlani, 2005).

There are however cases where the GPS solution can lead to errors, if unchecked. It is not uncommon indeed to have trajectory jumps (up to tens of cm and more) even with more than 5-6 satellites continuously available: this can be the case for instance when a new satellite rise or one being tracked is masked if this causes a significant change in the geometry of the solution, that might be reflected in a PDOP change. The trajectory shift may last for some time and finally vanish with a new jump, back on the correct position. In our experience as GPS users, these sudden shifts in the OTF solution are often very hard to correlate to any degradation of the user-available quality parameter of the GPS kinematic solution (RMS of trajectory coordinates, number of satellites tracked and PDOP). In other words, it's difficult to find out if and what went wrong, unless you have an independent check (the projection of the trajectory on the map being a poorly accurate but at least an always available one). With GPS and IMU integration, we did not expect these problem to arise; but in a series of runs over the same road section with a MMV equipped with a commercial GPS/INS system, we found that problems with the GPS solution resulted, rather than in a sudden shift, in a slow drift to a wrongly shifted trajectory (about 40 cm in height). This example highlights the need for greater reliability in the navigation solution, especially from a user standpoint. As for GPS outages, we believe that photogrammetry may provide an aid in the identification of problems in the navigation solution.
In the past years we have been working to the development of an aided inertial navigation algorithm, where photogrammetry may also be used as aid to the IMU, should the GPS outage last too long. Although work is still in progress, we believe that photogrammetry can be successfully applied to check extensively (i.e., all along the trajectory) the navigation solution, providing much needed reliability.
In the following, the navigation solution is first addressed, briefly describing the characteristics of our implementation, including photogrammetrically aided inertial navigation; some proposals for a reliability theory are then reviewed. Finally, we present how the cross-check of the IMU and GPS solution by photogrammetry can be implemented efficiently so that it can be performed all over the image sequence.

2. NAVIGATION SOLUTION

Integration of INS and GPS is usually accomplished using a Kalman filter for recursive estimation, although this is not the only feasible way. The advantage of this method is the supply of a real time result which allows the user to get a first idea about the quality of the solution during the survey; moreover, it carries out a recursive estimation of the parameters of interest with a modest numerical effort.

2.1 Kalman filter

Let $\mathbf{x}_k$ be the *m*–dimensional system state at time *k*. This is a vector of parameters which are supposed to describe completely the system. Suppose that this system is a time–varying discrete dynamic system, evolving in time with a linear model of the type:

$$\mathbf{x}_k = \mathbf{F}_{k,k-1}\mathbf{x}_{k-1} + \boldsymbol{\varepsilon}_k \tag{1}$$

$\mathbf{F}_{k,k-1}$ is the state transition matrix from time k–1 to k and $\boldsymbol{\varepsilon}_k$ is a noise which takes into account model errors and non–deterministic components which affect the system evolution. Such an error is hypothesized with zero mean, normally distributed, time independent and with known covariance matrix $\mathbf{C}_{\boldsymbol{\varepsilon\varepsilon}}$, so

$$E[\boldsymbol{\varepsilon}_k] = 0 \quad \forall k$$

$$\mathbf{C}_{\boldsymbol{\varepsilon}_k\boldsymbol{\varepsilon}_j} = \delta_{kj}\boldsymbol{\Sigma}_k^{\boldsymbol{\varepsilon}}$$

Equation (1) is the *steady–state equation* and represents the mathematical model.
It is necessary to initialise the system state, defining

$$\mathbf{x}_{k=t_o} = \mathbf{x}_0$$

under the hypotheses that $\mathbf{x}_0$ is normally distributed and uncorrelated with $\boldsymbol{\varepsilon}$

$$\mathbf{x}_0 \sim N(\boldsymbol{\mu}_0, \mathbf{C}_0)$$

$$\mathbf{C}_{\mathbf{x}_0\boldsymbol{\varepsilon}_k} = 0$$

Let $\mathbf{y}_1, \mathbf{y}_2 \ldots \mathbf{y}_{n_k}$ be n_k measurements**,** related by a linear relation with some of the parameters which characterise our dynamic system:

$$\mathbf{y}_k = \mathbf{A}_{k,k-1}\mathbf{x}_k + \mathbf{e}_k \quad (2)$$

$\mathbf{A}_{k,k-1}$ is the design matrix; $\mathbf{e}_k$ is the measurement error, which is hypothesized with zero mean, Gaussian distributed and with known covariance matrix $\mathbf{C}_{\mathbf{ee}}$. This is the *measurement equation*. Also in this case we suppose that the errors $\mathbf{e}$ are independent from $\boldsymbol{\varepsilon}$:

$$E[\mathbf{e}_k] = 0 \quad \forall k$$

$$\mathbf{C}_{\mathbf{e}_k\mathbf{e}_j} = \delta_{kj}\boldsymbol{\Sigma}_k^{\mathbf{e}}$$

$$\mathbf{C}_{\mathbf{x}_0\mathbf{e}_k} = 0$$

$$\mathbf{C}_{\boldsymbol{\varepsilon}_k\mathbf{e}_j} = 0$$

The Kalman filter allows to determine the optimal linear estimate of the system state $\mathbf{x}_k$ $\forall k$, in a Wiener – Kolmogorov sense, by means of a two step procedure: the *Kalman filtering*, typically used for real time purpose, and the *Kalman smoothing*, which follows it and is employed usually in post–processed applications like mobile mapping surveying. The first step is also composed by two stages: the *prediction* and the *update*.
The prediction supplie the estimated value of parameters at time k , given their values estimated at time k–1 and their precision:

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_{k,k-1}\hat{\mathbf{x}}_{k-1|k-1}$$

$$\mathbf{C}_{k|k-1} = \mathbf{F}_{k,k-1}\mathbf{C}_{k-1|k-1}\mathbf{F}_{k,k-1}^T + \mathbf{C}_{\boldsymbol{\varepsilon},k}$$

While the update equations give the estimated value of the state at time k given the measurements at the same time:

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{y}_k - \mathbf{A}_{k,k-1}\hat{\mathbf{x}}_{k|k-1})$$

$$\mathbf{C}_{k|k} = (\mathbf{I} - \mathbf{K}_k\mathbf{A}_k)\mathbf{C}_{k|k-1}$$

where $\mathbf{K}_k$ is the *Kalman gain matrix*,

$$\mathbf{K}_k = \mathbf{C}_{k|k-1}\mathbf{A}_{k,k-1}\left(\mathbf{A}_{k,k-1}\mathbf{C}_{k|k-1}\mathbf{A}_{k,k-1}^T + \mathbf{C}_{\mathbf{e},k}\right)^{-1}$$

The smoothing stage allows to determine the optimal linear estimation of the system state at time k, taking into account not only the measurements obtained up to this epoch, but also of all the measures collected during the successive instants k+1, k+2,… T, where T is the last epoch of the survey. That procedure is performed with reverse time scale: one start from the last epoch of measurement and updates sequentially all the estimates of the states, from the T–1 epoch to the initial instant.
The relations involved are the following:

$$\mathbf{B}_k = \mathbf{C}_{k|k}\mathbf{F}_k^T\mathbf{C}_{k+1|k}^{-1}$$

$$\hat{\mathbf{x}}_{k|T} = \hat{\mathbf{x}}_{k|k} + \mathbf{B}_k\left(\hat{\mathbf{x}}_{k+1|T} - \hat{\mathbf{x}}_{k+1|k}\right)$$

$$\mathbf{C}_{k|T} = \mathbf{C}_{k|k} + \mathbf{B}_k\left(\mathbf{C}_{k+1|T} - \mathbf{C}_{k+1|k}\right)\mathbf{B}_k^T$$

In this way one obtains $\hat{\mathbf{x}}_{k|T}$ and its covariance $\mathbf{C}_{k|T}$ $\forall k$.

These Kalman filter estimators are optimal in the Wiener – Kolmogorov sense, have minimum variance and are normally distributed. Optimality, however, is assured only as long as the assumptions of mathematical and statistical models of the filter are correct. This is not always the case, for instance when reduced order model of the real navigation system is employed. To guarantee Kalman filter stability it is requested merely that observability and controllability conditions are suited.

2.2 The implemented navigation solution

We developed an integrated solution which uses GPS positions of three antennas and IMU data. Usually, classical equations of the INS errors are used as a system model, while differences between the INS and GPS positions and velocities are used as measurements. This kind of integration scheme is referred to as cascaded approach. In our case, instead, we use a unique filter for GPS positions and IMU corrected data, in a loosely coupled fashion. The system model has been developed in an earth-fixed frame, with cartesian coordinates, and the navigation equations have been solved analytically. The analytic approach allows to eliminate some approximations made in many numerical solutions. This method of integration is simple and universal for different kind of inertial systems and GPS receivers. On the other hands, it suffers from two limitations in its current implementation: at least four satellites are needed to provide a GPS solution, which is fed to the integrated filter; for the time being, it needs three antennas on the vehicle. Besides the presence of both the GPS–only solution and the integrated solution simplifies fault detection if a failure occurs in either systems.

2.3 Photogrammetry–aided inertial navigation

As already pointed out, during long GPS outages the IMU solution must be strengthened by other means. Photogrammetry may be up to the job. It has been shown in previous papers (Roncella and Forlani, 2005) that tie points can be automatically extracted along a small sequence (e.g. 200-300 m), to provide a consistency of the EO parameters irrespective of the IMU and GPS solution.
To this aim, a stereo sequence is processed, consisting of two overlapping strips, with known orientation parameters at both ends, i.e. at the last image pair where the POS solution is still reliable (the beginning of the sequence) and at the first image pair (the end of the sequence) where the POS solution is again reliable. Tie points may be tracked with Structure and Motion techniques (Fitzgibbon and Zissermann, 1998; Pollefeys et al, 1998) on a large number of images. Because of the very small base compared to scene depth, the inner stability of the block is very low. Constraints such as epipolar geometry through the fundamental matrix (Longuet–Higgins, 1981) and the geometry of three cameras through the trifocal tensor (Shashua,1994) can be added to reject outliers. The solution will soon or later drift, due to the poor control applied; since the relative orientation of the on–board cameras is known by calibration, this can be enforced in the strip adjustment, effectively improving the stability over time of the solution.
During GPS outages, a cooperation of the position and orientation data of a low–grade IMU with the Structure and motion (S&M) reconstruction is possible and has been proposed in (Horemuz and Gajdamowicz, 2005). Because of the characteristics of our Kalman filter implementation, orientation data from photogrammetry can be straighforwardly incorporated. In fact, the measurement equations can be easily reconfigured to accept attitude parameters from photogrammetry, only changing the covariance matrix respect to that of GPS attitude information. At the moment, though, the system has not yet been tested, so we have no experimental evidence of the benefits of combining both techniques, each with its drift behaviour.

3. RELIABILITY OF THE SOLUTION

In a mobile mapping survey, identification of outliers, failures or variation in the mathematical model, in real time or in post–processing, is of extreme importance. These situations can be generated by a wide variety of problems like, for instance, sensor bias shifts in INS or variation of the noise level, but also in jump or drift in the GPS solution which can affect the results.
Redundancy is often used as a means of providing a check against failures. However a single redundant instrument may be used to detect a failure, but not isolate to a particular system and this redundancy methods are costly due to power weight and value of redundant systems. An alternative methodology is the use of dissimilar instrumentation to provide integrity of operation, decreasing the overall cost of the instrumentation system. Usually are installed DMIs, but also compasses, magnetometers and other instruments can be used. But there are other sensors which are yet present onboard and can possibly used to aid navigation solution and reliability: the cameras. A test has been performed by (Horemuz and Gajdamowicz, 2005), obtaining interesting results.
In the case of recursive algorithms, it is possible to use statistical tests test which can identify the failure in real time, or in near real time.

3.1 Reliability theory

Let us define *innovation*, or *predicted residual*, the difference between the actual real measurements and the measures predicted on the basis of the predicted state:

$$\mathbf{v}_k = \mathbf{y}_k - \mathbf{A}_{k,k-1}\hat{\mathbf{x}}_{k|k-1}$$

Innovation represents the new information introduced by the last observation. In fact, the filtered state is a linear combination of the predicted state and the innovation.
If the mathematical or statistical model has been defined correctly, the innovations are independent and Gaussian distributed

$$\mathbf{v}_k \sim N\left(0, \mathbf{C}_{\mathbf{v}_k}\right)$$

with known covariance matrix:

$$\mathbf{C}_{\mathbf{v}_k} = \mathbf{C}_{\mathbf{y}_k} + \mathbf{A}_k \mathbf{C}_{k|k} \mathbf{A}_k^T$$

Knowledge of the distribution of the innovation can be used for integrity monitoring. In fact the parameters forming the innovations are based on all past and present measurements with a model of the system. Hence this parameter contains all the information needed to detect changes in the mean of the Gaussian sequence.

3.1.1 Output separability: It is possible during design to know if the system is able, and the critical situations in which it is not, to detect and isolate the faults. One can have two possible failures: a failure in the system model and a failure in the measurements.
In case of a system failure, equation (1) can be rewritten as

$$\mathbf{x}_k = \mathbf{F}_{k,k-1}\mathbf{x}_{k-1} + \mathbf{B}_{k,k-1}\boldsymbol{\mu}_{k-1} + \boldsymbol{\varepsilon}_k \qquad (3)$$

where $\mathbf{B}_{k,k-1}$ is the direction matrix and $\boldsymbol{\mu}_{k-1}$ is the unknown fault to be detected. In this case no hypothesis has been introduced about the particular kind of failure.
In case of a failures in measurements, in a similar manner, equation (2) can be rewritten as

$$\mathbf{y}_k = \mathbf{A}_{k,k-1}\mathbf{x}_k + \mathbf{D}_{k,k-1}\mathbf{m}_k + \mathbf{e}_k \qquad (4)$$

where $\mathbf{m}_k$ is a fault whit a known direction $\mathbf{D}_{k,k-1}$.
It can demonstrated (Williamson et al., 2005) that a fault in the measurement model can be rewritten like a system fault, and therefore the equation (4) can be rewritten in an equivalent form of (3). So the problem of a measurement fault identification is equivalent to a system fault identification.
For a given fault direction $\mathbf{B}_{k,k-1}$, if $\left(\mathbf{A}_{k,k-1}\mathbf{F}_{k,k-1}^{\delta}\mathbf{B}_{k,k-1}\right)$ is full rank for any choice of δ, then the fault direction is identifiable. If we have more than one possible failure, it is sufficient to perform this test for any hypothesised failure.
This simple test can be performed before the system implementation, so one can carefully design mobile mapping system.

3.1.2 Chi–square test: It is possible to identify the presence of a blunder in the observations by means of a local test (Teunissen and Saltzmann, 1989) which analyze all the observations at each epoch. If we want to verify the following alternative hypotheses:

$$H_{0,k} : \mathbf{v}_k \sim N\left(0, \mathbf{C}_{\mathbf{v}k}\right)$$
$$H_{A,k} : \mathbf{v}_k \sim N\left(\overline{\mathbf{v}}_k, \mathbf{C}_{\mathbf{v}k}\right)$$

The appropriate statistics is

$$T_k = \mathbf{v}_k^T \mathbf{C}_{\mathbf{v}_k}^{-1} \mathbf{v}_k$$

so

$$H_{0,k,i} : T_k \sim \chi_n^2$$
$$H_{A,k,i} : T_k \sim \chi_n'^2(\lambda)$$

where λ is the non–centrality parameter of a non–central chi–squared distribution and n the degrees of freedom.
The null hypothesis is rejected at a significance level α, if

$$T_k \geq \chi_{n_k,\alpha}^2 .$$

This test, named *local overall test*, has the great advantage that it is particularly simple to be implemented, does not imply an increment of computational load during the filtering stage, because innovations and their covariance are still present at each step of update, and allows fault detection in real time.

If, between the observations, we want to identify the erroneous measure, it is possible to use the *local slippage test*

$$t_{k,i} = \frac{\left(\mathbf{c}_i^T \mathbf{C}_{\mathbf{v}_k}^{-1} \mathbf{v}_k\right)^2}{\left(\mathbf{C}_{\mathbf{v}_k}^{-1}\right)_{ii}}$$

with

$$\mathbf{c}_i = \begin{pmatrix} 0 & \cdots & 1 & \cdots & 0 \end{pmatrix}^T$$
$$\begin{matrix} 1 & & i & & n_k \end{matrix}$$

for $i = 1, \ldots, n_k$.
The null hypothesis is rejected for

$$t_{k,i} \geq \chi_{1,\alpha}^2 .$$

This test presents the same advantages of the previous one and, if we have the necessary observability and separability, allows the identification of the failing sensor.

Local tests sometimes are not able to identify non modelled trends and little jumps in bias. So it is useful to implement a global test on the innovations estimated from time *l* to instant *k*. This can be done simply extending the previous tests in the following mean, for the overall test:

$$T_{l,k} = \sum_{j=l}^{k} \mathbf{v}_i^T \mathbf{C}_{\mathbf{v}_j}^{-1} \mathbf{v}_j$$

and the null hypothesis is rejected when

$$T_{l,k} \geq \chi^2_{N,\alpha}$$

where

$$N = \sum_{i=l}^{k} n_k$$

This test is named *global overall test*.

For the slippage test

$$t_{l,k,i} = \frac{\left(\sum_{j=l}^{k} \mathbf{c}_i^T \mathbf{C}_{\mathbf{v}_j}^{-1} \mathbf{v}_j \right)^2}{\sum_{j=l}^{k} \mathbf{c}_i^T \mathbf{C}_{\mathbf{v}_j}^{-1} \mathbf{c}_j}$$

In this case the H_0 hypothesis is rejected if

$$t_{l,k,i} \geq \chi^2_{1,\alpha} .$$

The global tests need a greater complexity of implementation than the local ones, as the need of a moving window, and because the identification of the failure instant requires to come back to this time and start a new solution strategy. Obtaining this can be tricky for an automatic algorithm.

3.2 Isolation of navigation data anomalies

Modelling of a fault, increasing the number of states in steady state equations or augmenting the terms in the measurements equations with error models, can results in an accurate error estimates which are used for error compensation through the proper use of the available process and measurement information. However, excessive complication of a system model degrades the estimation accuracy of the state vector components. For many purposes, it can be sufficient to use a not augmented filter which supposes a no–fail condition, then to estimate the innovations and successively to test them with a global or slippage test, and finally to remove or correct, only if necessary, with appropriate modelling of the errors. Thus, the filter size is kept to a minimum without a loss of generality. On the other hand, problems arise from the use of these tests when we have a not completely correct mathematical or statistical model, for instance when we have a non–white noise of measure or an approximation of steady–state equations, like due to linearization. In such cases we can get many false alarms, which may increase the elaboration time. It can be useful to model at least the noises, for instance as simple first-order Markov processes.

In such a scheme, the inertial sensor outputs and GPS estimates are integrated in the Kalman filter. The inertial data are compensated before by the bias estimates. Innovations for each sensor are then evaluated by using the filter's estimate for the output of the sensors. As previously stated, if the measurement noises are zero mean, white and Gaussian, the innovation sequence, in absence of sensor failures, is approximately (exactly in the linear case) a zero mean, white, Gaussian sequence of random vectors. Detectors, which implement the statistic tests, operate over a window of the predicted residuals. The start of the window is the hypothesized time of failure, and the length of the window is based on the sensor type, the expected failure level, the probability of false alarms and the desired detection speed. In the case of single sensor failures, the total number of detectors is equal to the number of measurements.

If a failure is declared, with only GPS and an IMU, we are generally unable to identify the failed sensor. In this case, photogrammetric information becomes useful. With this information it is possible to identify the problematic sensor. Two possibilities now face the designer. First, if possible, one can model the failures, for instance as bias jumps in the measurements equations. In the linear case this type of sensor failures manifest themselves in an additive fashion with respect to the residuals. In this way we need to estimate the intensity of the failure in the associated sensor output (which is hypothesized to occur at the beginning of the corresponding window) and the effects of the hypothesized sensor failure are removed from the filter innovation by processing the estimated sensor failure level. Distinguishing between normal operating sensor errors and sensor failures, in particular with biases, can be difficult, because most analytic fault tolerant system techniques model failures as bias jumps in sensor outputs. If modelling is not feasible, or the sensor measurements are completely absent, like in case of GPS outages, the sensor must be removed from the analysis and the Kalman filter must be reconfigured to take into account its absence.

4. THE IMPLEMENTATION CONCEPT

As already underlined in the introduction, for the time being we have just defined the flow chart combining the different sensors data to check the reliability of the navigation solution. Since the photogrammetric check is the novel contribution to the problem, in the following we will concentrate on the implementation details of the procedure.

4.1 Overview of the photogrammetric check

To be valuable and feasible, the contribution of photogrammetric observations to the reliability check must be sufficiently accurate and computationally affordable.

We have therefore devised a simple procedure satisfying both requirements. In a nutshell, the idea is just to compare the image locations (pixel positions) of a set of object points, computed from the stereo pair at time t_i, with those of the same points projected on the images at t_{i+1}, based on the exterior orientation (EO) computed by the navigation solution at time t_{i+1}.

If the computed and predicted image locations are within the accuracy of the forward-backward projection, then we expect the chi-square test to be satisfied; otherwise a fault will be highlighted in the data at time t_{i+1}. Calculating the difference between computed and predicted image information allows to increase innovation dimensions (adding them to those obtained from GPS and IMU observations) and to identify the failed sensor. As far as IMU and GPS data are concerned, the underlying assumption is that orientation data at time t_i are correct. Therefore the check can be either performed at every shooting time or just if the test between IMU and GPS fails. In the former case, navigation data must be routinely interpolated to the shooting time to provide the orientation data of the stereo sequence. In the latter, the comparison may be performed at a different rate (e.g. at the data rate of the GPS observations) to spot inconsistencies: if any is found, then interpolation at nearby exposure times is performed. Since the method relies on the correctness of data at time t_i, when a system failure is declared, it is safer to start the photogrammetric check some frames before the time of GPS and IMU data disagree.

4.2 Selection of a region of interest in object space

To address the accuracy and computational requirements, the number, distribution and location of the object points should be considered. Since the aim of the procedure is not the orientation of the stereo pair at time t_{i+1}, but just to assess if measured and predicted EO agree, the object points to be used in the check need not to be well distributed over the whole stereoscopic area, to ensure good accuracy for the EO elements: a smaller one should be enough, provided it is visible in both images and it ensures good conditions for the identification of homologous points. To this aim, the nearest strip of the road surface, say 3-4 m deep and 6 m wide, visible in both image pairs can be used. This ensures that the image resolution is the best in both images and that every consecutive stereo pair can be checked. Moreover, using the areas nearest to the vehicle, should grant that even small discrepancies between estimated and real OE paramaters can be detected. Adding a larger area might bring in some cases well defined points, but also possibility of occlusions. In order for the method to be feasible, the distance between consecutive image pairs should not be too long (3-5 m) to avoid the perspective to reduce too much the resolution in the image pair farthest from the strip.

To select the same strip in object space in consecutive stereo pairs we take advantage from the fact that the vehicle runs on a smooth surface. For our purpose the road surface can be well approximated by a plane, therefore the relationship (homography) between the image plane of each camera and the road surface plane is constant (or anyway stable enough for the task) and can be computed just once. Besides, in most cases is the DMI that commands the exposure, so the distance between image pairs is constant, irrespective of speed changes (should the image acquisition run on a fixed time rate instead, again the limits can be easily computed, because both OE elements at time t_i, and t_{i+1}, are known). To avoid an extensive search over the whole strip, a set of locations can be arranged in object space within the strip (e.g. in a grid-like fashion) and projected (only once) in image space.

4.3 Selection and computation of reference object points

To select image points, interest operators or other feature extraction techniques should be applied to the template image (say, the left image at time t_i) in a window around each location of the set; the Harris operator (Harris and Stephens, 1987) has been used successfully. Being the epipolar geometry of the stereo pair known from calibration and given the fairly constant relationship between cameras and road surface plane, the search for the homologous points in the slave image is bounded along the epipolar line.

In a previous paper (Forlani et al, 2005) the Harris operator proved successful in selecting and finding homologous points as far as rotations and perspective differences were not too big. In such cases, the Lowe operator (Lowe, 1999) and the Lowe descriptor (Lowe, 2004) may be more robust in finding and matching features. Using feature matching in our case, nevertheless, may not be the best option. Based on previous work on road marking extraction and following (Roncella and Forlani, 2006), a different technique is used.

To reduce the effect of perspective differences in image space, both images are rectified to the road surface plane, based on the already computed homography: using look-up tables, this does not affect computing time.

The templates are selected using the Harris operator on the rectified template image. To find the homologous in the slave image, since both images after being rectified doesn't show critic perspective changes, simple normalized cross-correlation is used (rather than least squares matching), being faster and still up to the task. Once the set of homologous points for the image pair at time t_i has been found, their object coordinates are computed by forward intersection.

4.4 Compatibility check between consecutive image pairs

To check the compatibility of GPS and IMU data with photogrammetry, the object points computed from the t_i stereo pair are projected on the stereo pair t_{i+1}. Since the projection on the left and on the right should give the same information (occlusions should not be expected and the relative geometry camera-point is the same for the two images), it is unnecessary to reproject on both. The rectified image for the (say) left image at time t_{i+1} is generated. Once the ideal position (i.e. the position without errors in EO) is available, the limits of the search area for the homologous point are computed by error propagation of the intersection-resection and of the EO covariance matrix from the Kalman filter. Afterwards, exhaustive simple correlation search is carried out on the rectified image picking as template the image around the point location selected at time t_i. If there is at least a match with correlation coefficient larger than a threshold (say, 70%) the point is accepted as homologous. Ideally, it should be a yes-no test: if one match is passed, all should be; in practice, even if some do, others will not due to several reasons (noise, sensor response, illumination changes, gray values changes due to change in the angle sensor-object-sun, occlusions, etc.). From a probabilistic standpoint, there is no need to verify all points: as soon as a clear majority emerges in probabilistic terms, the chi-square procedure may stop.

5. CONCLUSIONS

The reliability issue on navigation data from MMV has been discussed and a procedure has been devised to extensively add to the navigation solution from GPS/INS an automatic photogrammetric check. Although no testing has yet been performed, the implementation details based on previous experiences with MM data ensures that it is computationally feasible. The question of how sensitive it is to errors in the GPS/IMU data could not be addressed yet, however, and will be the primary goal of ongoing work.

Other issues of practical relevance, such as what to do once an inconsistency has been highlighted, has not yet been addressed either, but will involve switching to photogrammetrically-aided inertial navigation, at least during GPS outages. Input data from INS will also be used to support search for correspondences along the sequence.

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