Intelligent Vehicles Symposium 2006, June 13-15, 2006, Tokyo, Japan
15-3

A Novel Design of a High Integrity Low Cost Navigation Unit for Road Vehicle Applications

Rafael Toledo-Moreo
Department of Information and Communication Engineering
University of Murcia
Computer Science Faculty 30071
Campus de Espinardo, Murcia, Spain
Email: toledo@um.es

Miguel A. Zamora-Izquierdo
Department of Information and Communication Engineering
University of Murcia
Computer Science Faculty 30071
Campus de Espinardo, Murcia, Spain
Email: mzamora@um.es

Antonio F. Gómez-Skarmeta
Department of Information and Communication Engineering
University of Murcia
Computer Science Faculty 30071
Campus de Espinardo, Murcia, Spain
Email: skarmeta@dif.um.es

Abstract— **Actual solutions for new Intelligent Transport System (ITS) applications cannot fulfill current user requirements. Road applications such as traveller information, route guidance, automatic emergency calls, freight management or electronic fee collection require a road side equipment (RSE) capable to offer a high available accurate position with low price, even in unfriendly environments with low satellite visibility, such as built-up areas or tunnels. Users demand from the RSEs not only accurate continuous positioning, but also integrity information of the reliability of this position. Specifically in life critical applications, high integrity monitored positioning is absolutely required. This paper presents a solution based on the fusion of GNSS and inertial sensors (a GNSS/INS integrated system), running an Extended Kalman Filter combined with an Interactive Multi-Model method (EKF-IMM). The solution developed in this work supplies not only continuous positioning at a reasonable price, but also a meaningful trust level of the given solution.**

I. Introduction and State of the Art

Most of the current low cost RSEs (Road Side Equipments) for land vehicles are based on a single GNSS (Global Navigation Satellite System) solution. However, GNSS devices cannot guarantee high integrity positioning, specially in unfriendly environments. Low cost, including easy installation and maintenance, continuous precise positioning, even during the outages of the GNSS signals, fault detection, and continuous monitored integrity are the main features of a solution suitable for mass market applications. The main objective of this work is the development of a high integrity navigation system for road vehicles in real driving conditions, including hostile environments. Since the solution developed must suit the requirements of mass market applications to location based services, cost considerations must be done.

According to the actual literature, the most reliable solution to the problem of terrestrial vehicle localization implements a positioning system based on the integration of a GNSS and some other aiding positioning systems. Different approaches are being studied in order to guarantee the proper position quality. All of them rely on an accurate GNSS position, either as the leading positioning information input, or as an assistance system, to determine vehicle movements along roads. A few examples can be found in [1]–[3]. For this reason, a complete study of a single GNSS solution viability has been done and the Satellite Based Augmentation Systems (SBAS) have been also studied.

Regarding the fusion of the American Global Positioning System (GPS) with inertial sensors, the research group of the University of Sydney has very interesting works in the field of robotics. In [4], a low cost navigation system based on inertial sensors is presented. The navigation system employs medium price GPS receivers and inertial units based on MEM (Micro-Electro-Mechanical) technology. MEM sensors are much cheaper than other inertial sensors based on traditional technologies, at the expense of lower levels of performance. In [5], the inertial sensors are presented as a real alternative approach for robot applications. In the same paper, data fusion filters are widely developed. Error models for low cost inertial sensors are also described. Durrant-Whyte in [6], describes a Kalman filter for GPS navigation systems. Blackman and Popoli, in [7], present different filters and architectures for navigation and tracking systems. The most usual algorithms for data fusion can be found in this interesting book. Grewal, Weill and Andrews [8] introduce basics of inertial navigation and mathematical models, paying special attention to its integration with GPS.

II. The System Description

The solution proposed in this paper is based on a GNSS/SBAS/INS integrated system. On one hand, the use of combined GNSS/SBAS, as compared with a single GPS solution, provides noticeable improvements, but nevertheless, they cannot fulfill the requirements of high integrity demanding applications, specially in city environments. On the other hand, the INS (Inertial Navigation System) units supply accelerations and rates of turn relative to the three Cartesian axis of the sensor body frame. Although these measurements complement the GNSS/SBAS lacks and provide positioning during the outages of the satellite signal, the double integration process required to obtain position from the acceleration is the main source of error for the INS units. In order to avoid excessive drifts, often updates must be performed by a global system. In addition, only low cost inertial units, based on MEM technology, are affordable considering a real mass market RSE. Unfortunately, these sensors present bad noise features and drifts and the implementation of error models is advisable. In order to diminish the drifts during the GNSS outages, odometry measurements coming from the ABS (Anti-Blocking System) encoders of the vehicle are also considered in our system. The ABS system provides non precise velocity information, with a very low increase of the final cost, since no further installations or sensors are needed. Apart from the precision problem due to the low level of performance of the ABS encoders, typical odometry problems, such as glides, unequal wheel diameters or effective wheel diameter uncertainty are also presented.

To obtain the proper inputs to the data fusion filter from the raw measurements coming from the sensors, observation models are implemented, and considerations about the sensor performances done.

A. The Multisensor Data Fusion Filter

The data fusion filter developed to combine the information coming from the GNSS, INS and odometry sensors is based on a loosely coupled extended Kalman filter architecture, implementing an interactive multi-model method to employ the vehicle model definition which better describes the current vehicle's behavior.

1) The Kalman Filter: The Kalman filter is a recursive least squares estimator. It produces at time k a minimum mean squared error estimate $\hat{\mathbf{x}}(k|k)$ of a state vector $\mathbf{x}(k)$. This estimate is obtained by fusing a state estimate prediction $\hat{\mathbf{x}}(k|k-1)$ with an observation $\mathbf{z}(k)$ of the state vector $\mathbf{x}(k)$. The estimate $\hat{\mathbf{x}}(k|k)$ is the conditional mean of $\mathbf{x}(k)$ given all observations $\mathbf{Z}^k = [\mathbf{z}(1), \cdots \mathbf{z}(k)]$ up until time k,

$$\hat{\mathbf{x}}(k|k) = \mathbf{E}[\mathbf{x}|\mathbf{Z}^k] \tag{1}$$

where $\mathbf{Z}^k$ is the sequence of all observations up until time k.

2) The Vehicle Models: In order to represent the movements of the vehicle along roads, two models have been developed. Both are based on the rigid solid definition of a four wheel vehicle, the back wheels of which can rotate only about a transversal axis of the vehicle, and the forward wheels turn describing curves centered in their instant rotation center. The straight model (or non-maneuvering model) represents a basic non-maneuvering behavior of the vehicle, being its transition equation defined as:

$$\mathbf{x}(k+1) = f(\mathbf{x}(k)) + G(\mathbf{x}(k))\upsilon(k) \tag{2}$$

where f is the state transition matrix and G the noise matrix, and the state and noise vectors are respectively:

$$\begin{aligned} \mathbf{x}(k) &= [x_c(k)\; y_c(k)\; \theta(k)\; \dot{\theta}(k)\; v_c(k)\; \phi_c(k)\; s_c(k)]^T \\ \upsilon(k) &= [\ddot{\theta}(k)\; \dot{v}_c(k)\; \dot{\phi}_c(k)\; \dot{s}_c(k)]^T \end{aligned} \tag{3}$$

where $x_c(k)$, $y_c(k)$ are the coordinates of the geometrical centre of the vehicle (g.c.), $\theta(k)$ the vehicle orientation,

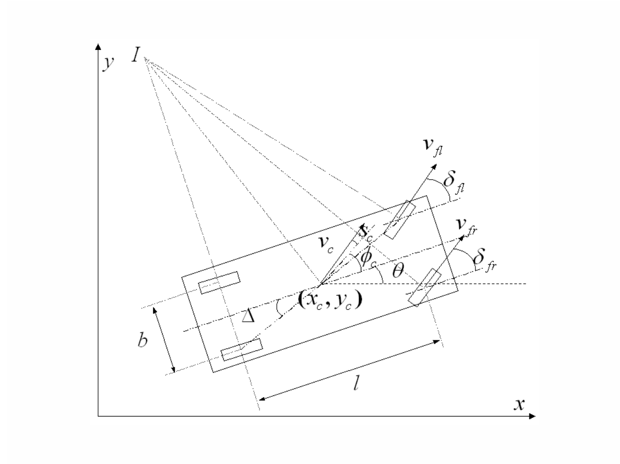

Fig. 1. The kinematical model nomenclature.

$v_c(k)$ the velocity in the g.c., $\phi_c(k)$ is the angle of the velocity $v_c(k)$, and $s_c(k)$ the slide correction angle. In the straight model, $\phi_c(k)$ is modelled by a first order function, so both straight and mild trajectories fulfill the kinematical definition of the model. However, when sharp curves are performed, it is advisable to represent $\phi_c(k)$ by a second order equation. Thus, the state and noise vectors of the curved model (or maneuvering model) are:

$$\begin{aligned} \mathbf{x}(k) &= [x_c(k)\; y_c(k)\; \theta(k)\; \dot{\theta}(k)\; v_c(k)\; \phi_c(k)\; \dot{\phi}_c(k)\; s_c(k)]^T \\ \upsilon(k) &= [\ddot{\theta}(k)\; \dot{v}_c(k)\; \ddot{\phi}_c(k)\; \dot{s}_c(k)]^T \end{aligned} \tag{4}$$

Fig. 1 shows graphically the kinematical model and its nomenclature.

3) The Sensor Models: In order to obtain the filter observations $\mathbf{z}(k)$ at the scan k, different transformations must be done. The observation vector of our system is defined as:

$$\begin{aligned} \mathbf{z}(k) \;=\; & [x_c^G(k)\; y_c^G(k)\; x_c^I(k)\; y_c^I(k) \\ & \theta^I(k)\; \dot{\theta}^O(k)\; v_c^O(k)\; \phi_c^O(k)\; v_c^I(k)]^T \end{aligned} \tag{5}$$

where $x_c^G(k)$, $y_c^G(k)$ and $x_c^I(k)$, $y_c^I(k)$ are the Cartesian coordinates of the g.c. according to the GNSS and the INS measurements respectively, $\theta^I(k)$ and $v_c^I(k)$, obtained from the inertial measurements, define severally the orientation and the velocity of the g.c. of the vehicle and finally, $\dot{\theta}^O(k)$, $v_c^O(k)$ and $\phi_c^O(k)$ are respectively the angular velocity, the linear velocity and its angle in the g.c. observed by the odometry system. Some of these variables can be easily obtained from the sensor measurements. In this Section we present the transformations required to obtain the observations $\dot{\theta}^O(k)$, $v_c^O(k)$, $\phi_c^O(k)$, $x_c^I(k)$, $y_c^I(k)$ and $v_c^I(k)$.

4) The Odometry Observations: Regarding the odometry observations, taking into account the assumption of the vehicle as a rigid solid, the velocity in the g.c. $v_c(k)$ can be calculated as:

$$v_c^O(k) = v_{fl}(k)\frac{\cos(\Delta - \delta_{fl}(k))}{\cos(\Delta - \phi_c(k) - s_c(k))} \tag{6}$$

where $v_{fl}(k)$ and $\delta_{fl}(k)$ are respectively the velocity and the angle of the forward left wheel. The angular velocity can be calculated depending on these variables as:

$$\dot{\theta}^O(k) = v_{fl}(k)\frac{\sin(\delta_{fl}(k))}{l} \tag{7}$$

Finally, to calculate the angle of the velocity in the g.c. (Fig. 1), the geometrical transformations from the angles of the forward wheels to the g.c. are given by:

$$\begin{aligned} d &= \frac{l}{\tan(\delta_{fl})} + \frac{b}{2} \\ \tan(\phi_c(k) + s_c(k)) &= \frac{l/2}{d} \end{aligned} \tag{8}$$

Thus, the angle of the velocity is:

$$\phi_c^O(k) = \arctan\left(\frac{l \cdot \tan(\delta_{fl}(k))}{2l + b \cdot \tan(\delta_{fl}(k))}\right) - s_c(k) \tag{9}$$

5) The Inertial Observations: To obtain the inertial observations four different phases must be performed:

Whereas low cost inertial sensors are used, error models must be considered. The first step must be the implementation of error models for the inertial measurements. The models implemented in our work are based on the Billur Barshan work [5], and can be described by the expression:

$$\varepsilon = C_1\left(1 - e^{\frac{-t}{\tau}}\right) + C_2 \tag{10}$$

where ε represents the error model for the acceleration in the body frame of the sensor and C_1, C_2 and τ are model parameters. Fixing the values $C_1 = -0.0043$, $C_2 = -0.007$ and $\tau = 500$ by using a Nelder-Mead non-restricted non-linear multidimensional method where the minimizing function was the mean squared error, a mean value of -3.2172×10^{-4} and a standard deviation value of 0.0033 were achieved for the compensation of the forward acceleration of the body frame. With these values, in tests where no forces were applied to the sensors (but the Earth gravity) and no external updates were performed, the position drifted 70 cm. after 60 seconds. In the same tests, but without applying any error model, the position drifted up to 55 m.

Secondly, in order to obtain the acceleration vector referenced to the global frame (North-East-Down) (**G**) from the local reference (**S**), the rotation matrix $^{GS}\mathbf{R}$ defined in [9] can be used.

Then, a gravitational model must be applied to compensate the Earth gravity effects. Typically, in terrestrial applications with mobile units, the gravity is assumed to value $-9.81\ \mathrm{m/s}^2$. in the z axis of the global reference frame (local tangent plane).

As a final step, the inertial observations x_c^I and y_c^I can be calculated by applying the equation

$$x_c^I(k+1) = x_c(k) + v_{c_x}(k)T + 0.5 \cdot a_x T^2 \tag{11}$$
$$y_c^I(k+1) = y_c(k) + v_{c_y}(k)T + 0.5 \cdot a_y T^2 \tag{12}$$

where $x_c(k)$ and $y_c(k)$ are the state variables just after the last update, T is the difference between the time stamp of the inertial measurements and the time stamp of the last measurement which updated the state vector, a_x and a_y are the acceleration values in the global reference system, as obtained from the previous step, and the values of the velocities v_{c_x} and v_{c_y} are given by the equations

$$v_{c_x}(k) = v_c(k)\cos\big(\theta(k) + \phi_c(k) + s_c(k)\big) \tag{13}$$
$$v_{c_y}(k) = v_c(k)\sin\big(\theta(k) + \phi_c(k) + s_c(k)\big) \tag{14}$$

The observation v_c^I can be calculated by using the expression

$$v_c^I(k+1) = v_c(k) + a_t^I T \tag{15}$$

where $v_c(k)$ is the state variable just after the last update and a_t^I represents the module of the acceleration tangential to the vehicle's trajectory, calculated according to the inertial measurements. To calculate a_t^I, we will assume that the geometrical and the gravity center of the vehicle coincide in (x_c, y_c). Naming α the angle between the absolute acceleration vector of the vehicle, $\mathbf{a}$, and the x axis, we can affirm that

$$\alpha = \arccos\left(\frac{a_x}{a}\right) \quad , \quad a = \sqrt{a_x^2 + a_y^2} \tag{16}$$

where a_x, a_y are the horizontal components of the vector $\mathbf{a}$ and a its projection on the xy plane. Besides, the module of the tangential acceleration can be calculated as

$$a_t^I = a\cos\big(\alpha - (\theta + \phi_c + s_c)\big) \tag{17}$$

Thus, next expression for the a_t^I value can be obtained

$$a_t^I = \sqrt{a_x^2 + a_y^2} \cdot \cos\left(\arccos\left(\frac{a_x}{a}\right) - \big(\theta(k) + \phi_c(k) + s_c(k)\big)\right) \tag{18}$$

B. The EKF Implementation

The implementation of the EKF is developed in three phases: prediction and observation of the state and its covariance $\hat{\mathbf{x}}(k|k-1)$, $P(k|k-1)$, calculation and validation of the observation innovations coming from the sensors $\nu(k)$, and calculation of the Kalman gain $W(k)$ and update of the state and its covariance $\hat{\mathbf{x}}(k|k)$, $P(k|k)$. More details on the Kalman implementation can be found in [9].

C. The IMM filter

In most of the real driving situations it is not possible to know in advance which kind of maneuvers will be performed, and the idea of selecting routes with only mild maneuvers is not very realistic. Therefore, an interactive multi-model filter has been developed and implemented. The IMM filter calculates the probability of success of each model at every filter execution scan, supplying a realistic combined solution for the vehicle's behavior. These probabilities are calculated according to a Markov model for the transition between maneuver states, as detailed in [9]. The likelihood calculation and the model probability update are performed according to the statistical distance value, given by

$$d^2 = \nu^T S^{-1} \nu \quad (19)$$

Given an IMM approach, there will be a different residual covariance matrix, $S_i(k)$ and distance $d_i^2(k)$ associated with each of the i models, for the update at the scan k. Assuming measurement dimensionality M, and Gaussian statistics, the likelihood function for the observation model given model i is

$$\Lambda_i(k) = \frac{exp[-d_i^2(k)/2]}{\sqrt{(2\Pi)^M |S_i(k)|}} \quad (20)$$

Finally, using Bayes's rule, the updated model probabilities become

$$\mu_i(k) = \Lambda_i(k) C_i(k-1)/C \quad (21)$$

where the normalization constant C and C_i, the probability after interaction that the vehicle is in state i, can be calculated as described in [9].

D. The hardware architecture

The hardware architecture of the RSE is based on a standard single board computer with a 32bit Pentium processor. The vehicle PC interacts with the user via the HMI (Human Machine Interface) by a custom-made monitor, keyboard and mouse. Serial buses communicate the sensors with the PC via RS232. Some other additional communication networks are also available. A BlueTooth wireless link can be used to connect the vehicle PC with a laptop or other mobile devices such as PDAs, PocketPCs, etc. A WLAN connection is available through the PCMCIA slot of the vehicle CPU, facilitating the communication with nearby vehicles. Finally, a GPRS/UMTS link supply Internet connection to the system. The GPRS/UMTS link is used for receiving the EGNOS (European Geostationary Navigation Overlay System) messages via SISNeT (Signal In Space through the interNeT), and can also be used to communicate the vehicle with remote stations (or other vehicles) for remote location based services.

III. Trials and Results

Concerning the road applications of the GNSS sensors, two different scenarios must be distinguished. Despite the fact the objectives and the technologies are the same, the different problems a GNSS sensor has to deal with in urban and wide open environments encourage their study from different points of view [10]. Whereas satellite constellation visibility in wide open environments is not a problem, and main efforts are focused on diminishing the pseudorange errors and increasing the positioning accuracy, in urban environments the signal availability and the multipath propagations, performing spurious GPS positions due to the signal reflection nearby the antenna, are the main problems.

To evaluate the results in closed circuit tests, a custom-made map developed by using the Trimbel GeoXT Pathfinder Office version 3.0. package provides 30 cm. accuracy of the map reference. Next sections explain the results achieved by double constellation, single GPS, and EGNOS capable sensors. Finally, the performance of the GNSS/SBAS/INS solution is discussed.

A. The GNSS/SBAS Trials

1) Double constellation trials: In the tests performed by using the GPS/GLONASS Thales GG24 double constellation sensor the cumulative distribution function (CDF) for the HDOP value was calculated in both urban an wide open areas. In the urban case, assuming HDOP = 3, the signal availability is not much higher than 80% (in the best case), while on highways values of 95% are usual. Same trajectories were logged by using a single GPS sensor and similar values achieved. According to our results, despite the fact there is a slight increase of the position availability by using the double constellation sensor, the main problems, such as the lack of coverage in city environments and multipath errors, remain.

2) The SBAS improvements: Table I summarizes some interesting results obtained in our tests. According to them, EGNOS can increase significantly the accuracy of the single GPS position (64.78%), and the use of SISNeT, the EGNOS corrections via Internet, can raise this increase from 64.78% up to 89.15% (24.37%). Despite of the important improvements, high demanding applications require more than 96% of positioning availability, and aiding positioning systems, specially in city environments where this rate decreases to 60%, are recommended.

B. The GNSS/SBAS/INS performance

The lack of GNSS coverage in some environments is a considerable problem that cannot be solved by a global positioning system. As observed in the previous Section, the use of SISNeT and EGNOS improves the single GPS solution quality, but cannot guarantee the system success during the outages of the GPS signal. Next, the performance of the GNSS/SBAS/INS is presented. Main issues to be analyzed are fault detection capacity, continuous positioning availability and ability to reproduce the vehicle's behavior in different usual driving situations.

1) Fault Detection: In order to achieve a reliable solution, system failures must be detected and the proper actions must be performed. The term fault includes not only hardware and software failures, but also false measurements coming from the sensors. In this Section, we will focus our attention on the problem of the wrong measurements.

Spurious positions are one of the main problem for a high integrity navigation system, specially in city environments. We define as spurious (or false) measurements those outside of the 6σ scaling certainty region centered

TABLE I

GPS/SBAS availability and estimate distance.

Epoch	No Pos.	GPS	EGNOS	SISNeT	Distance
2777	3.78%	7.05%	64.78%	24.37%	20,07 Km.

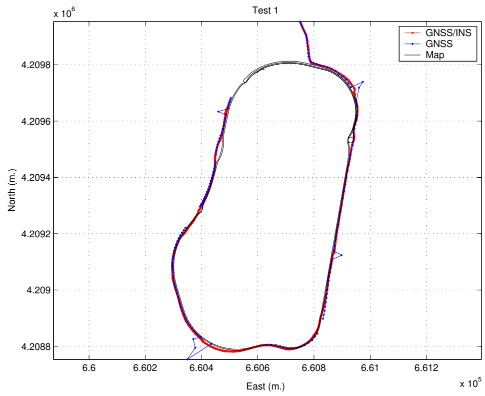

Fig. 2. Trajectory for the GNSS/INS test.

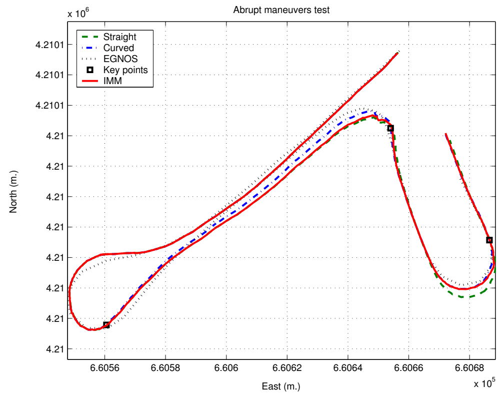

Fig. 3. Trajectory provided by the EKF-IMM filter.

in the real value of the measurement (assuming Gaussian distributions). Unfortunately, no real values are unknown, and some other parameters must be used to categorized a measurement as false. In the case of the satellite sensors, many GNSS receivers provide useful integrity parameters to the user. Usual parameters are GDOP (Geometric Dilution of Precision) values, based on the geometry of the satellite constellation used in the solution, and the $\mathrm{HPL}_{\mathrm{SBAS}}$ parameter (when used SBAS capable sensors), which employs the SBAS corrections for the pseudorange measurements and considers multipath propagations. Unfortunately, these parameters cannot be used as realtime indicators for rejecting false GNSS measurements. Thanks to the redundant information coming from the INS sensor, spurious measurements can be removed most efficiently from the solution. Apart from the own sensor validation processes, a Nyquist algorithm has been implemented in order to eliminate inadequate observations. The result of applying a validation process can be observed in Fig. 2. As shown, undesirable multipath errors are efficiently removed.

Additionally, the inertial units are not susceptible to magnetic noises, providing efficient anti-cheating enforcement against GPS jamming.

2) Continuous Positioning: What most users desire, even more than high accuracy in the positioning, is continuous accurate positioning. Fig. 2 illustrates a typical situation in an urban environment. As observed, outages of the GPS/GEO coverage and multipath problems are usual. The filter developed provides continuous high accurate position, also during the gaps of GPS coverage. In the different tests performed, the position reliability was guaranteed during short time GNSS outages, usual in built-up areas. For longer SIS outages, the position drifted up to 5 meters after 30 seconds, and remained below 40 meters during 5 minutes and 2.5 km. losses.

3) Trials with Abrupt Maneuvers: In most of the usual situations for in which a road vehicle is involved, a model representing a straight trajectory as presented in this paper works correctly. However, when sharp turns and abrupt maneuvers are performed, this model cannot represent properly the vehicle's behavior, and the use of curved trajectory models is advisable. Unfortunately, the assumption of every vehicle's movement as a curve, increases the noise considerations of the model, having repercussions on the position quality. The IMM filter implemented runs both filters (straight and curved) in parallel, estimating the probabilities of defining the vehicle's behavior for both models, and offering a unique common solution by mixing both filtering processes according to the movement features at every scan. Since sharp turns and abrupt maneuvers are usually perform in short distance situations, such as urban environments or indoor maneuvering, no GNSS information was supplied to the filter during these tests.

In Fig. 3, a comparison between the trajectory offered by the EKF-IMM filter and both single model solutions in a short distance test is shown. The nature of the Markov transition process generates the switching aspect of the solution, where the periods of dominance of one model correspond to high probability values for this model. Fig. 4 presents the values of the model probabilities during the trajectory. The relation between the model probabilities and the IMM solution can be appreciated. According to this figure, key points for the probability values correspond to scans 220, 450 and 633. The vehicle positions at those scans are marked with a black square in the trajectory image (Fig. 3). As observed, these moments correspond to changes in the state maneuver. Since real trials were performed, no certain values for the vehicle positions are available. Nevertheless, the EGNOS positions serve as the best reference for our tests. distance between the horizontal

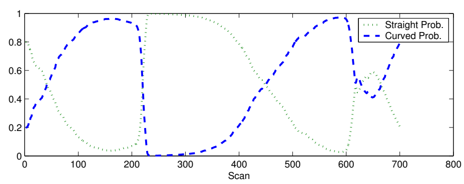

Fig. 4. Model probabilities in the IMM test.

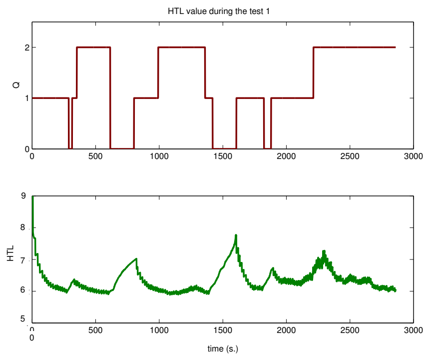

Fig. 5. Coverage and HTL values during the integrity test trajectory.

position supplied by the EKF-IMM filter and the EGNOS reference remained below the CEP value (3 m.), and the suitability of the solution implemented is proved.

C. System Integrity Monitoring

Most of the GNSS sensor manufactures provide extra information relative to the satellite status, type of GNSS solution and its quality. As we have already seen, the GDOP values and the $\mathrm{HPL_{SBAS}}$ parameter supply useful integrity information of the GNSS quality of the solution. However, these parameters only model the GNSS part of the navigation system and the levels of performance of the other sensors employed in the solution are not considered. In addition, these parameters are not available in the periods of GPS absence. A parameter which completely describes the positioning quality, without availability interruptions and considering all the sensors used must be supplied.

The HTL (Horizontal Trust Level) [11] parameter provided by our navigation system, represents the level of reliance on the current position, depending on the sensor variances and the current state. One of the main Kalman filter features is the provision of the vehicle state covariance (matrix P). Since the two first variables of the vector state, x and y, are respectively the North and East coordinates of the vehicle's geometrical center, the submatrix P_{xy}, symmetric and positive definite, represents the two-dimensional quadratic form of the squared position error with 1-sigma scaling, and describes an ellipses. The HTL parameter can be calculated as $\mathrm{HTL} = 6\sqrt{\lambda_{max}}$, being λ_{max} the higher of the two eigenvalues of P_{xy}.

Fig. 2 presents the trajectory selected to test the suitability of the HTL parameter, while Fig. 5 shows the position quality (Q) and the HTL value during this test. In the upper graph, Q = 2 indicates EGNOS quality, Q = 1 single GPS, and Q = 0 no GPS position. No integrity information would be available during the frequent periods of GPS outage. Additionally, the geostationary satellite is often missed, still with enough GPS satellites in view. In the lower image, the HTL value presents significant dependence on the GPS coverage and the filter rejections for avoiding multipath errors. In it also manifest how the reliability on position decreases due to the integration process performed by the filter. When the GEO satellite is visible, the HTL values are close to 6 m. According to the trust levels on the positioning during the whole trajectory, and despite of the often GNSS outages, the system performance may be considered as very high, remaining the HTL value below 7 m the most of the time.

IV. Conclusions and Future Works

A high integrity navigation system suitable for mass market road applications has been presented. According to our investigations, actual GNSS/SBAS system cannot fulfill current road application requirements. Inertial MEM sensors have been proved as useful to guarantee fault detection, and continuous high accurate positioning. Regarding the filter, the implementation of an EKF-IMM solution allows the use of highly dynamic models, avoiding the increase of the noise considerations during non-maneuvering situations. In order to reduce the sensor costs and raise the system performance, future works will be focused on the implementation of tougher coupled architectures.

Acknowledgment

The Authors would like to thank the Spanish Ministerio de Fomento, European Space Agency (ESA) and the C. A. Región de Murcia for sponsoring the research activities under the grants FOM/3595/2003, GIROADS 332599 and ISIS/2I04SU009, respectively.

References

[1] Kaplan, Elliott D. *Understanding GPS. Principles and Applications*. Artech House. 1996.

[2] Ozguner and others. *The OSU DEMO'97 Vehicle*. Procs. of the 1997 IEEE Intl. Conf. on Intelligent Transportation System Detroit, Michigan, USA, September 1995.

[3] RTCA DO-229C. *Minimum Operational Performance Standards for Global Positioning System / Wide Area Augmentation System Airborne Equipment*. The Radio Technical Commission for Aeronautics. November 2001.

[4] S. Sukkarieh. *Low Cost, High Integrity, Aided Inertial Navigation Systems for Autonomous Land Vehicles*. PhD. Thesis. University of Sydney. Sydney, Australia, 2000.

[5] Billur Barshan, Hugh F. Durrant-Whyte. *Inertial Navigation Systems for Mobile Robots*. IEEE Internatinal Transactions on Robotics and Automation. Vol. II NO. 3: 328–342. June 1995.

[6] Simon Cooper, Hugh Durrant-Whyte. *A Kalman Filter Model for GPS Navigation of Land Vehicles*. Intelligent robots and Systems ' 94.' Advanced Robotics Systems and the Real World', IROS' 94. Proceedings of the IEEE/RSJ/GI International Conference on, Vol.1 pp. 157-163. 1994.

[7] S. Blackman, R. Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House. USA, 1999.

[8] Mohinder S. Grewal, Lawrence R. Weill, Angus P. Andrews. *Global Positioning Systems, Inertial Navigation and Integration*. John Willey & Sons. USA, 2001.

[9] R. Toledo. *A High Integrity Navigation System for Vehicles in Unfriendly Environments*. PhD. Thesis. University of Murcia. Murcia, Spain. November 2005.

[10] R. Toledo, M.A. Zamora, B. Úbeda, A.F. Gómez-Skarmeta *An Integrity Navigation System based on GNSS/INS for Remote Services Implementation in Terrestrial Vehicles*. IEEE Intelligent Transportation Systems Conference. pp. 477–480 Washington, D.C., USA. 2004.

[11] P.A. Boysen, H. Zunker. *Low Cost Sensor Hybridisation and Accurancy Estimation for Road Applications*. ESA Conference Navitec 2004. Noordwijk, The Netherlands, December 2004.