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IMM-EKF based Road Vehicle Navigation with Low Cost GPS/INS

Rafael Toledo-Moreo, Miguel A. Zamora-Izquierdo, Antonio F. Gómez-Skarmeta

Abstract— **Actual solutions for the road vehicle navigation problem point to the combination of GPS, odometry and inertial sensors. To combine the information coming from these sensors, most of actual researchers rely on the implementation of variations of the Kalman filter (KF) and the extended Kalman filter (EKF) for non-linear systems. Despite the fact that, in these filters, the definition of the proper vehicle model is of extreme importance, there is not a unique common filter suitable for all the usual situations in which a road vehicle is involved. The diversity of possible maneuvers and the need of realistic noise considerations adjusted to each driving situation encourage the application of IMM (interactive multi-model) techniques in the road navigation. Traditionally applied to the aerial sector, IMM based methods run different models at the same time, selecting that one which better represents the system behavior anytime. For road vehicles, the IMM-EKF solution presented in this paper allows the exploitation of highly dynamic models just when required, avoiding the impoverishment of the solution due to unrealistic noise considerations during straight or mild trajectories. Selected results presented in this paper confirm the improvements obtained by using the IMM-EKF developed, as compared with the single model solution.**

I. INTRODUCTION

ROAD vehicle navigation systems are one of the main fields of interest in the Intelligent Transport System (ITS) world. Road applications such as traveller information, route guidance, automatic emergency calls, freight management, advanced driver assistance or electronic fee collection require a Road Side Equipment (RSE) capable to offer a high available accurate position at low price [1]. For this purpose, many current researches are focused on the combination of odometry, low cost inertial units and satellite navigation [1], [6], [7], [2], [4], [3], [5]. The simplest approach of fusing GPS with odometry information (either coming from the ABS system or odometers installed in the vehicle), as developed in [2], [3] presents the main disadvantage of the lack of precision in the heading. To increase the accuracy of the heading estimate, some authors propose a combination of a gyro, odometers and GPS receivers [1], [4], [5]. More precise systems such as [6], [7] employ GPS/INS systems, at the expense of higher costs. However, further investigations must be performed to maintain the quality of the performance of these systems at lower prices.

In this work, the navigation system is integrated by a SBAS (Satellite Based Augmentation System) capable GPS sensors, low cost inertial accelerometers and gyros and the odometry information coming from the ABS system of the vehicle. The use of SBAS capable GPS sensors (EGNOS and SISNeT in Europe) provides higher levels of performance in the satellite positioning and useful integrity parameters, such as the HPL_{SBAS} (a.k.a. HPL_{WAAS}) parameter [8]. These European SBAS systems increase the positioning accuracy thanks to the GPS corrections sent via the geostationary satellite (EGNOS) and Internet (SISNeT). In order to employ inertial units in mass market applications, only low cost inertial units based on Micro-Electro-Mechanical (MEM) technology are affordable [9]. MEM based inertial sensors are much cheaper than other inertial sensors based on traditional technologies, but they offer much lower levels of performance. On the other hand, the use of the odometry information coming from the ABS system of the vehicle supplies low quality velocity information without any additional cost.

To fuse the information coming from the sensors different approaches can be found in the actual literature. Many of them rely on the implementation of an extended Kalman filter (EKF) [1], [2], [3], [5], [10]. The performance of the EKF is reliable in many practical situations, but the non-linear state equations may lead to instability problems. Other filtering methods can be found in the literature, such as the unscented Kalman filter [11] and particle-based solution [2]. Of special interest in the implementation of the filter is the selection of the proper model for the road vehicle. Actual interesting kinetic models can be found in [7], [4], [5]. These models offer good solutions under certain movement restrictions. However, the problem of a model capable to represent the vehicle movements along roads in usual driving situations, independently of the maneuvering state, traffic conditions, etc., has not been solved yet.

This paper presents an Interactive Multi-Model (IMM) based method applied to the fusion filtering of inertial, odometry and satellite data. The implementation of IMM based methods allows the possibility of using highly dynamic models just when required, diminishing unrealistic noise considerations in non maneuvering situations and the computational charge of the system. The idea of defining different models according to the situation in which the vehicle is involved is not new, and it has been applied to the aerial navigation field in the last years [12], [13]. Lately, some authors have considered its application into the navigation systems of road vehicles. In [14] an IMM method is applied to the problem of object tracking with a video system in a car. The authors in [15] develop an IMM algorithm to detect lane change maneuvers, based on laser, radar and vision data.

In our approach, the use of a IMM method allows exploiting the benefits of high dynamic models in the problem of a road vehicle positioning, while avoiding their disadvantages regarding computational charge and unrealistic noise con-

R. Toledo, M.A. Zamora and A.F. Skarmeta are with Dept. of Information and Communication Engineering, Computer Science Faculty, University of Murcia, 30071 Espinardo, Murcia, Spain toledo@um.es, mzamora@um.es, skarmeta@dif.um.es

siderations. Two models of the vehicle have been defined to reproduce its movements along roads. The straight (or non-maneuvering) model reproduces properly straight and mild trajectories of the vehicle. The curved (or maneuvering) model considers sharp turns and brusque accelerations in the vehicle state, at the expense of higher noise considerations. The IMM-EKF filter developed calculates the probability of success of each model at every filter execution scan, supplying a realistic combined solution for the behavior of the vehicle. These probabilities are calculated according to a Markovian model for the transition between maneuver states.

II. THE SYSTEM DESCRIPTION

The solution presented in this paper is based on a GNSS/SBAS/INS integrated system. On one hand, the use of combined GNSS/SBAS systems, 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 measurements 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.

In order 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,

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

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:

$$\begin{aligned}
x_c(k+1) &= x_c(k)+Tv_c(k)\cos(\theta(k)+\phi_c(k)+s_c(k)) \\
&\quad +0.5T^2\dot{v}_c(k)\cos(\theta(k)+\phi_c(k)+s_c(k)) \\
&\quad -0.5T^2v_c(k)\dot{\theta}(k)\sin(\theta(k)+\phi_c(k)+s_c(k)) \\
y_c(k+1) &= y_c(k)+Tv_c(k)\sin(\theta(k)+\phi_c(k)+s_c(k)) \\
&\quad +0.5T^2\dot{v}_c(k)\sin(\theta(k)+\phi_c(k)+s_c(k)) \\
&\quad +0.5T^2v_c(k)\dot{\theta}(k)\cos(\theta(k)+\phi_c(k)+s_c(k)) \\
\theta(k+1) &= \theta(k)+T\dot{\theta}(k)+0.5T^2\ddot{\theta}(k) \\
\dot{\theta}(k+1) &= \dot{\theta}(k)+T\ddot{\theta}(k) \\
v_c(k+1) &= v_c(k)+T\dot{v}_c(k) \\
\phi_c(k+1) &= \phi_c(k)+T\dot{\phi}_c(k) \\
s_c(k+1) &= s_c(k)+T\dot{s}_c(k)
\end{aligned} \quad (2)$$

noted by:

$$\mathbf{x}(k+1) = f(\mathbf{x}(k)) + G(\mathbf{x}(k))\upsilon(k) \quad (3)$$

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

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

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

$$\begin{aligned}
\mathbf{x}(k) &= [x_c(k)\ y_c(k)\ \theta(k)\ \dot{\theta}(k)\ v_c(k)\ \phi_c(k)\ \dot{\phi}_c(k)\ s_c(k)]^T \\
\upsilon(k) &= [\ddot{\theta}(k)\ \dot{v}_c(k)\ \ddot{\phi}_c(k)\ \dot{s}_c(k)]^T
\end{aligned} \quad (5)$$

and the transition equation for this model can be easily obtained analogous to the formula 2.

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

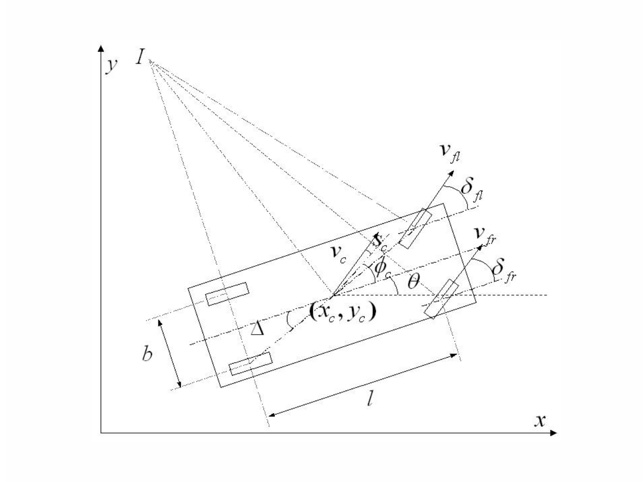

Fig. 1. The kinematical model.

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:

$$\begin{aligned}\mathbf{z}(k) \quad = \quad & [x_c^G(k)\; y_c^G(k)\; x_c^I(k)\; y_c^I(k) \\ & \theta^I(k)\; \dot{\theta}^O(k)\; v_c^O(k)\; \phi_c^O(k)\; v_c^I(k)]^T \qquad (6)\end{aligned}$$

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. 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 $v_c^I(k)$, as the rest of the observation variables can be easily obtained from the sensor measurements.

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

$$v_c^O(k) = v_{fl}(k)\frac{\cos(\Delta - \delta_{fl}(k))}{\cos(\Delta - \phi_c(k) - s_c(k))} \qquad (7)$$

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:

$$\dot{\theta}^O(k) = v_{fl}(k)\frac{\sin(\delta_{fl}(k))}{l} \qquad (8)$$

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:

$$\begin{aligned} d &= \frac{l}{\tan(\delta_{fl})} + \frac{b}{2} \\ \tan(\phi_c(k) + s_c(k)) &= \frac{l/2}{d} \qquad (9)\end{aligned}$$

Thus, the angle of the velocity is given by the equation

$$\phi_c^O(k) = \arctan\left(\frac{l \cdot \tan(\delta_{fl}(k))}{2l + b \cdot \tan(\delta_{fl}(k))}\right) - s_c(k) \qquad (10)$$

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

Firstly, whereas low cost inertial sensors are used, error models must be considered, so 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 [16], and can be described by the expression:

$$\varepsilon = C_1\left(1 - e^{\frac{-t}{\tau}}\right) + C_2 \qquad (11)$$

where ε represents the error model for the acceleration in the body frame of the sensor and C_1, C_2 (in m/s^2.) and τ (in seconds) are model parameters. The adjustment of the model parameters was performed by using a Nelder-Mead non-restricted non-linear multidimensional method where the minimizing function was the mean squared error.

During a test where no forces were applied to the sensors (but the Earth gravity) and no external updates were performed the values of the parameters obtained were $C_1 = -0.0043$, $C_2 = -0.007$ and $\tau = 500$, resulting a mean value of -3.2172×10^{-4} and a standard deviation of 0.0033. With these values, the position drifted 70 cm. after 60 seconds. In the same test, but without applying any error model, the position drifted up to 55 m.

Note that, in order to avoid the interference of gravity components, the inertial measurement unit was stabilized by using calibrated gyros and tilts [17].

Secondly, in order to obtain the acceleration vector referred to the global frame (North-East-Down) (**G**) from the local reference (**S**), we can use the rotation matrix ${}^{GS}\mathbf{R} =$

$$\left[\begin{array}{ccc} \cos\theta\cos\psi & \sin\phi\sin\theta\cos\psi - \cos\phi\sin\psi & \cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi \\ \cos\theta\sin\psi & \sin\phi\sin\theta\sin\psi + \cos\phi\cos\psi & \cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi \\ -\sin\theta & \sin\phi\cos\theta & \cos\phi\cos\theta \end{array}\right] \qquad (12)$$

where $\psi = yaw$, $\theta = pitch$ and $\phi = roll$ in the body frame.

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 be -9.81 m/s^2. in the z axis, being zero the two other components in 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

$$x_c^I(k+1) = x_c(k) + v_{c_x}(k)T + 0.5 \cdot a_x T^2 \qquad (13)$$

$$y_c^I(k+1) = y_c(k) + v_{c_y}(k)T + 0.5 \cdot a_y T^2 \qquad (14)$$

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, 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

$$v_{c_x}(k) = v_c(k)\cos\left(\theta(k)+\phi_c(k)+s_c(k)\right) \tag{15}$$

$$v_{c_y}(k) = v_c(k)\sin\left(\theta(k)+\phi_c(k)+s_c(k)\right) \tag{16}$$

The observation v_c^I can be calculated as

$$v_c^I(k+1) = v_c(k) + a_t^I T \tag{17}$$

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 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

$$\alpha = \arccos\left(\frac{a_x}{a}\right) \quad , \quad a = \sqrt{a_x^2 + a_y^2} \tag{18}$$

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

$$a_t^I = a\cos\left(\alpha - (\theta + \phi_c + s_c)\right) \tag{19}$$

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

$$a_t^I = \sqrt{a_x^2 + a_y^2}\cdot\cos\Bigg(\arccos\left(\frac{a_x}{a}\right) - \left(\theta(k)+\phi_c(k)+s_c(k)\right)\Bigg) \tag{20}$$

B. The Extended Kalman Filter Implementation

The execution of the extended Kalman filter can be divided in three phases, presented next.

1) Prediction and Observation: We have already seen the kinematical models of the vehicle. These models are now used to perform the state prediction. Taking into account the formula 3, the equation for the state prediction is:

$$\hat{\mathbf{x}}(k+1|k) = f(\hat{\mathbf{x}}(k|k)) \tag{21}$$

where f represents the transition matrix. The covariance of the state prediction $P(k+1|k)$ is calculated as:

$$P(k+1|k) = F_x(k)P(k|k)F_x^T(k) + G(k)Q(k)G(k)^T \tag{22}$$

where $G(k)$ is the gain matrix multiplying the noise vector $\upsilon(k)$. Finally, $F_x(k)$ is the Jacobean of the transition matrix regarding the state.

$$F_x(k) = \left.\frac{\partial f(\mathbf{x}(k))}{\partial \mathbf{x}(k)}\right|_{\mathbf{x}=\hat{\mathbf{x}}(k|k)} \tag{23}$$

and $Q(k)$ the covariance noise matrix of the noise vector $\upsilon(k)$. The observation model is described by the equation

$$\mathbf{z}(k) = H\cdot\mathbf{x}(k) + \omega(k) \qquad \omega(K) \sim N(0, R(k)) \tag{24}$$

The relation between the vector state and the vector observation is linear and constant (matrix H) and the equation can be expressed as:

$$\hat{\mathbf{z}}(k+1) = H\cdot\hat{\mathbf{x}}(k+1|k) \tag{25}$$

2) Validation: After obtaining the observation vector $\mathbf{z}(k+1)$, the innovation vector can be calculated as:

$$\nu(k+1) = \mathbf{z}(k+1) - \hat{\mathbf{z}}(k+1) \tag{26}$$

The validation region is calculated following a χ^2 distribution like:

$$\nu^T(k+1)S^{-1}(k+1)\nu(k+1) \leq g^2 \tag{27}$$

This expression represents an ellipsoid of probability called NIS or Normalized Innovation Squared, where the threshold g is the number of sigmas of the region. The innovation covariance is:

$$S(k+1) = HP(k+1|k)H^T + R(k+1) \tag{28}$$

3) Update: Once known the innovation covariance S, the Kalman gain can be calculated as:

$$W(k+1) = P(k+1|k)H^T S^{-1}(k+1) \tag{29}$$

The estimate position of the vehicle supplied by the filter is:

$$\hat{\mathbf{x}}(k+1|k+1) = \hat{x}(k+1|k) + W(k+1)\nu(k+1) \tag{30}$$

and the updated covariance:

$$P(k+1|k+1) = P(k+1|k) - W(k+1)S(k+1)W^T(k+1) \tag{31}$$

Details of the EKF equations for both the maneuvering and the non-maneuvering models can be found in [17].

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 Markovian model for the transition between maneuver states. To implement the Markovian model, it is assumed that at each scan time there is a probability P_{ij} that the vehicle will make a transition from model state i to state j. These probabilities are assumed to be known a priori and can be expressed in a probability transition matrix such as shown in formula 32, for our case with two models ($r = 2$)

$$P_T = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix} \tag{32}$$

Note that the sum of transition probabilities for any given state must sum to unity.

The likelihood calculation and the model probability update are performed according to the statistical distance value, given by

$$d^2 = \nu^T S^{-1} \nu \tag{33}$$

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

$$\Lambda_j(k) = \frac{exp[-d_j^2(k)/2]}{\sqrt{(2\Pi)^M |S_j(k)|}} \tag{34}$$

Using Bayes's rule, the updated model probabilities become

$$\mu_j(k) = \Lambda_j(k) C_j(k-1)/C \tag{35}$$

where $C_j(k-1)$, the probability after interaction that the vehicle is in state j, can be calculated as

$$C_j(k-1) = \sum_{i=1}^{r} P_{ij}\mu_i(k-1) \tag{36}$$

and the normalization constant C is

$$C = \sum_{j=1}^{r} \Lambda_j(k) C_j(k-1) \tag{37}$$

Due to the reduced number of models used, the process of data association, discussed extensively in the actual literature, is simplified in our case, and the state and covariance estimates are described by the equation:

$$\begin{aligned} \hat{\mathbf{x}}(k|k-1) &= \textstyle\sum_{j=1}^{r} C_j(k-1)\hat{\mathbf{x}}_j(k|k-1) \\ P(k|k-1) &= \textstyle\sum_{j=1}^{r} C_j(k-1) P_j(k|k-1) \end{aligned} \tag{38}$$

1) Combining Different State Models: As seen previously, the state vectors for the straight and curved models are respectively

$$\begin{aligned} \mathbf{x}_s(k) &= [x_c(k)\ y_c(k)\ \theta(k)\ \dot{\theta}(k)\ v_c(k)\ \phi_c(k)\ s_c(k)] \\ \mathbf{x}_c(k) &= [x_c(k)\ y_c(k)\ \theta(k)\ \dot{\theta}(k)\ v_c(k)\ \phi_c(k)\ \dot{\phi}_c(k)\ s_c(k)] \end{aligned}$$

In this case, the transformation between state vectors is evident, but it is not so obvious for the covariance matrices. Matrix P_{sc}, will be the equivalent transformed matrix from the straight model to the curved one

$$P_{sc} = A_{sc} P_s A_{sc}^T \tag{39}$$

The elements of the transformation matrix A_{sc} are given by the appropriate partial derivatives

$$A_{sc} = \left.\frac{\partial \mathbf{x}_{sc}}{\partial \mathbf{x}_s}\right|_{\mathbf{x}_{sc}}$$

where $\mathbf{x}_{sc}$ and $\mathbf{x}_s$ are the straight state vector transformed to the curved model definition and the straight state vector respectively. Similarly, the inverse transformation will be

$$P_{cs} = A_{cs} P_c A_{cs}^T \tag{40}$$

III. TRIALS WITH ABRUPT MANEUVERS

In most of the usual situations 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, the single model (SM) approach cannot represent properly the behavior of the vehicle, and the use of a curved trajectory model is advisable. Unfortunately, the assumption of every movement as a curve increases unrealistically the noise considerations,

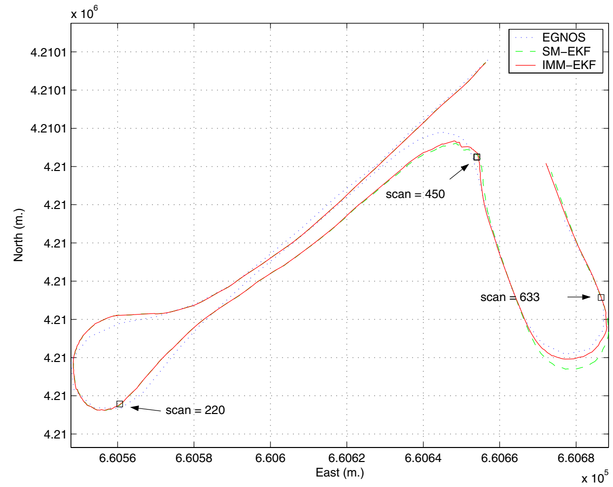

Fig. 2. Comparison of the SM-EKF (single model extended Kalman filter) and the IMM-EKF trajectories obtained in the test performed.

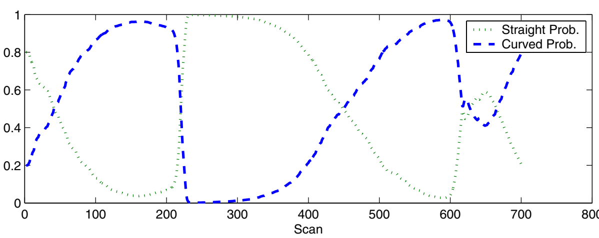

Fig. 3. Model probabilities in test performed.

having repercussions on the position quality. The IMM-EKF filter implemented runs both filters (straight and curved) in parallel, estimating the probabilities of defining the vehicle 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, it is assumed that no GNSS information is supplied to the filter during the trials performed in the closed scenario.

In Fig. 2, a comparison between the trajectory offered by the IMM-EKF filter and the single model solution in our test scenario is shown. The nature of the Markov transition process generates the switching aspect of the IMM-EKF solution, where the periods of dominance of one model correspond to high probability values for this model. Fig. 3 presents the values of the model probabilities during the trajectory. The relation between the model probability values 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 in the trajectory shown in Fig. 2. As observed, those scan values correspond to changes in the state maneuver, changing from a curved path to a straight one and vice versa.

Since real trials were performed, no certain values for the vehicle positions are available. Nevertheless, the EGNOS

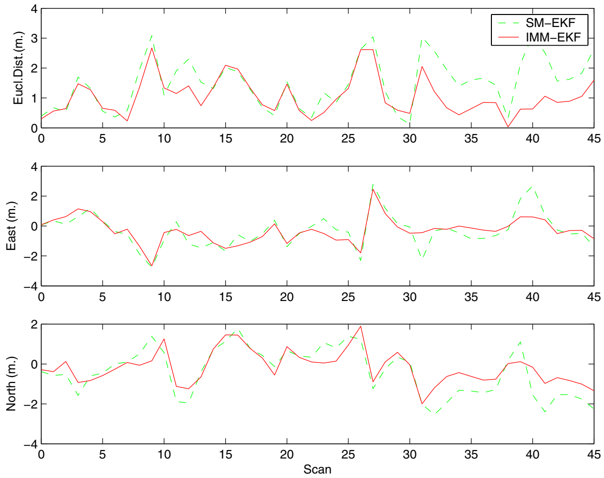

Fig. 4. Comparison of the position error estimate obtained by the SM-EKF and the IMM-EKF.

positions serve as the best reference for our tests. The results of the position estimate errors for the trajectory performed in the test scenario (Fig. 2) by using a single model filter (SM-EKF) and the IMM-EKF implemented can be seen in Fig. 4. When observing these results, a CEP value of 3 m. for the EGNOS reference must be considered. As can be seen, when using the IMM-EKF approach the value of the Euclidean Distance is smaller than in the SM-EKF case, and remains below 3 m. during the whole trajectory. Table I shows a comparison of the RMS values for both the single model and the interactive multi-model solutions. In a test of only 390 m., a reduction of 0.484 m. is achieved by using the IMM-EKF implementation.

TABLE I

RMS VALUES FOR THE POSITION ESTIMATE ERRORS.

	SM-EKF	IMM-EKF
RMS	1.703 (m.)	1.219 (m.)

IV. CONCLUSIONS

An interactive multi-model based method to improve the results obtained by the extended Kalman filter implementation in low cost navigation units for road vehicles has been presented. Two models (straight and curved) have been developed and implemented in the navigation system. These models represent different maneuvering states of the vehicle, defining most of the usual driving situations in which a vehicle is involved, including maneuvers with brusque accelerations and sharp turns. The IMM-EKF filter designed chooses anytime the model combination defined by the model probabilities, calculated attending the observation innovations for every model and the sensor covariances, solving the problem of a unique model to define all the vehicle maneuvers without increasing the noise considerations, or assuming restrictions on the maneuvers performed. The equations employed in the filter development have been presented and explained in this paper. According to our tests, the use of our IMM-EKF approach improves the results obtained by the single model solution, diminishing the position error estimate while increasing the level of confidence on the solution.

Future research will be focused on the application of the IMM techniques to determine particular vehicle maneuvers on the road.

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