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IMM based Maneuver Detection and Navigation for Road Vehicles with Low Cost GPS/IMU

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

Abstract— **The issue of collision avoidance in road vehicles has been investigated for years from very different points of view. A very interesting approach consists of the creation and interpretation of a scene of the vehicles that can be involved in a conflictive situation. In order to determine the role of the vehicle in the scene, having information of its position, orientation and velocity, as well as its current maneuver state is advisable. This paper is to present a solution based on a very low cost GPS/IMU navigation unit running an interactive multimodel filter (IMM). The description of the proposed architecture for scene creation, the multimodel filter developed and experimental trials in urban and highway scenarios are presented in this paper. The results obtained show the suitability of the proposed solution to the problem under consideration.**

I. INTRODUCTION

The current development of new services and advanced driver assistance systems (ADAS) allows supplying new interesting features in our vehicles. A few examples of these are:

- Collision avoidance,
- Detection of unfriendly situations and risky scenes,
- Emergency vehicle management,
- Automation of tasks, such as parking maneuvering,
- Adaptive cruise control.

To obtain this, new ADAS demand higher level of performance of the supporting onboard equipments (OBE). In a low level of abstraction, applications based on the denominated Location Based Services (LBS), such as fleet management, hazardous good tracking, or automated emergency calls mainly rely on communication availability and a reliable navigation system aboard. The main requirements regarding the navigation system concern continuity of an accurate positioning, fault detection and the provision of an integrity parameter. In more complex ADAS, a decision making process encourages the creation and interpretation of a scene in order to determine the vehicle role in its environment. In this frame, the need of high level abstraction cannot be fulfilled by traditional multi-sensor data fusion filters. The issue of situation awareness has been pointed by several authors from the point of view of the artificial intelligence, specially for military purposes [1] – [5]. Most of these authors agree to divide multi-sensor data fusion into four levels of increasing situation complexity. Some other approaches, like the one proposed by University of Melbourne, prefer different architecture schemas not necessarily oriented to military scenes [6].

Regarding maneuver detection, very different approaches depending of the sensors used can be found in the current literature. Several authors have been focusing their efforts in the recognition of vehicle behaviors by using a set of diverse kinematical models. Each model is developed to represent the vehicle behavior in a particular maneuvering state. In [7] a concrete model is selected according to its dynamic state. In [8], FIR filters are used to detect maneuvers and track targets.

The work presented in this paper proposes a low cost GPS/INS based solution for the problem of navigation and maneuver recognition in highways, as a part of the investigations performed in our group regarding navigation systems for road vehicles. Previous papers published by the authors presented the GPS/INS solution as suitable for unfriendly scenarios, such as built-up environments with low GPS coverage [9]. In [10], an extensive study of GPS/INS navigation systems is done. The work presented in [11] focus on the benefits of the interactive multimodel (IMM) approach for improving the positioning quality. In this paper, the IMM method will be analyzed to test its suitability to detect maneuvers in road vehicles.

The rest of the paper is organized as follows. Section II presents briefly the four layer based architecture Quadrant, including the hardware of the OBE. In Section III, dedicated multiple model filtering techniques are explained. Trials in urban (Section IV) and highway scenarios (Section V) are next presented. Finally, conclusions of the results obtained are commented and future works of the group in this topic introduced.

II. THE QUADRANT ARQUITECTURE

Quadrant is an architecture for ADAS applications based on the separation of four layers according the level of abstraction of the fusion performed, paying special attention to its communication framework [12]. The first layer (or sensor layer) is in charge of the measurement collection, sorting and synchronization. These measurements are sent to upper layers via the sensor network, consisting of RS-232 serial ports for the INS and the GPS device, and CAN bus for the odometry. Secondly, the fusion layer fuses the data coming from the sensors. This layer, oriented to the interpretation of the vehicle behavior to be performed in the following phase, is described by an IMM-EKF multisensor data fusion filtering algorithm in which the vehicle models represent different maneuver states, to determine the role of the vehicle

Rafael Toledo-Moreo, Miguel A. Zamora-Izquierdo and Antonio F. Gómez-Skarmeta are with Faculty of Computer Science, Dept. of Information and Communication Engineering, University of Murcia, 30070 Spain toledo@um.es, mzamora@um.es, skarmeta@dif.um.es

in a concrete scene. Fused data are then supplied to the third layer via ad hoc networks in the vehicle environment. Those networks are supported by WLAN connection availability, thanks to the WIFI PCMCIA card installed in the vehicle computer. Third layer or interpretation layer is in charge of the dynamic classification of the vehicle and the scene interpretation. The use of the IMM method in the lower layer eases the dynamic classification process, according to the probability values of the maneuver states of the vehicle, that will be calculated as explained in subsequent Sections. Finally, the interpreted data (and any other data coming from previous phases) can be used by the application in order to provide the final service to the user.

A. Maneuver Detection in Quadrant

This paper is focused on the second layer of Quadrant, and the maneuver recognition performed by the IMM method. Fig. 1 shows schematically the Quadrant proposal for maneuver detection and scene interpretation.

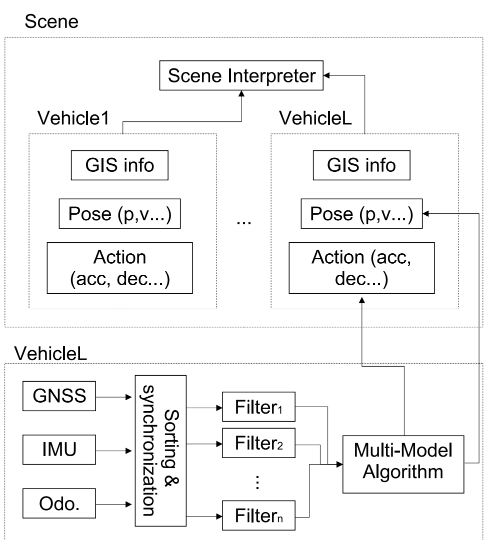

Fig. 1. Maneuver detection and scene interpretation in Quadrant.

A scene will be defined by the information of the vehicle itself, those surrounding, and geographical information of interest in the area (type of road, speed limits, geographical accidents, etc.). Each vehicle in the scene is in charge of identifying its maneuver state and reporting it, along with its pose, to the rest of vehicles in the scene (typically a few close enough to be involved and capable to communicate via ad hoc WLAN). In this frame, the IMM method presented in this paper presents several benefits:

- Improving the quality of the positioning of the vehicle,
- Providing more precise and realistic confidence values of the navigation solution,
- Enabling maneuver recognition by using individual models oriented to maneuver states.

First and last benefits will be analyzed in subsequent Sections. Future works will extend this investigation to analyze further possible improvements of the filter. In our architecture we have defined five maneuver states, intended to be recognize in highway scenarios: lane change, keep the lane, accelerations and decelerations, cruise navigation and stop. This paper is focused only on the longitudinal movements of the vehicle.

B. Onboard Equipment

The hardware architecture of the OBE 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 monitor, keyboard and mouse. Serial buses communicate the sensors with the PC via RS232 and CAN bus. Some other additional communication networks are also available. A BlueTooth wireless link can be used to connect the vehicle PC 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 supplies Internet connection to the system. The GPRS/UMTS link is used for receiving the EGNOS messages via SISNeT [13], and can be also used to communicate the vehicle with remote stations (or other vehicles), for location based services.

The IMU sensor used is a low cost MEM (Micro-electro-mechanical) MT9-B XSens. Although different 2D and 3D models were tested, in this paper only 2D models will be considered, and the assumption of a bicycle model with the acceleration and the velocity vectors defined by the same angle is done. Therefore, only one yaw gyro and one accelerometer will be used in our tests. For the GNSS receiver, a Trimble DGPS was employed to evaluate the system performance with a position accuracy of 15 cm. within the 95% of fixes. Nevertheless, single GPS positions were considered as filter inputs to emulate a low cost receiver.

III. MULTIPLE MODEL FILTERING: IMM METHOD

The basic idea of using multiple models is based on the fact that a vehicle performs very different maneuvers depending on the scenario features. For a road vehicle, typical maneuvers in highways differ from those usual in city environments. Thus, a single vehicle model can hardly represent all possible maneuvers, and the use of multiple models, representing different maneuver states and running in parallel is advisable. The output of the multiple model approach is typically the model with highest probability value, or a weighted composite of the individual filters [20].

A. Interactive Multiple Model (IMM)

In the last years, the implementation of interacting multiple models in aerial navigation systems has been proved to be very efficient [14] – [20]. In the IMM approach, the manner in which the state estimates from the individuals filters are combined depends on a Markovian model for the transition between maneuver states. The IMM method can be described according to four different parts.

1) Interaction: In this part, individual filters are mixed according to the predicted model probabilities. The predicted model probability is given by the model probability in the previous cycle, $\mu^{(j)}_{k-1|k-1}$ and the probability that a transition from state j to state i occurs, π_{ji},

$$\mu^{(i)}_{k|k-1} = \sum_j \pi_{ji}\mu^{(j)}_{k-1|k-1} \tag{1}$$

being the conditional model probability, given the object is in state i that the transition occurred from state j

$$\mu^{(j|i)}_{k-1|k-1} = \frac{\pi_{ji}\mu^{(j)}_{k-1|k-1}}{\mu^{(i)}_{k|k-1}} \tag{2}$$

and the mixing of the state estimates $\hat{\mathbf{x}}^{(j)}_{k-1|k-1}$ and covariances $\mathbf{P}^{(j)}_{k-1|k-1}$,

$$\bar{\mathbf{x}}^{(i)}_{k-1|k-1} = \sum_j \mu^{(j|i)}_{k-1|k-1}\hat{\mathbf{x}}^{(j)}_{k-1|k-1} \tag{3}$$

$$\bar{\mathbf{P}}^{(i)}_{k-1|k-1} = \sum_j \mu^{(j|i)}_{k-1|k-1}\Big[\mathbf{P}^{(j)}_{k-1|k-1} + \big(\bar{\mathbf{x}}^{(i)}_{k-1|k-1} - \hat{\mathbf{x}}^{(j)}_{k-1|k-1}\big)\big(\bar{\mathbf{x}}^{(i)}_{k-1|k-1} - \hat{\mathbf{x}}^{(j)}_{k-1|k-1}\big)'\Big]. \tag{4}$$

The probabilities π_{ji} that a transition occurred from state j to state i are calculated according to a Markovian process, as described in [21], and will depend on the statistics of real traffic situations.

2) Model individual filtering: Now, individual filters predict and update their state and covariance, by using their kinematical assumptions. Predicted state estimates $\hat{\mathbf{x}}^{(i)}_{k|k-1}$ and covariances $\mathbf{P}^{(i)}_{k|k-1}$ will be calculated by using a loosely coupled extended Kalman filter (EKF), as described in [20]. The kinematical models used will be presented in next Sections. Innovations and their covariances are calculated in this phase, also following [20].

3) Model probability update: In this part, each model probability is updated according to the innovation error. Assuming Gaussian statistics, the likelihood for the observation can be calculated from the innovation vector $\nu^{(i)}_k$ and its covariance $\mathbf{S}^{(i)}_k$ following

$$\Lambda^{(i)}_k = \frac{exp\big[-(1/2)(\nu^{(i)}_k)'\big(\mathbf{S}^{(i)}_k\big)^{-1}\nu^{(i)}_k\big]}{\sqrt{\big|2\pi\mathbf{S}^{(i)}_k\big|}}, \tag{5}$$

updating the predicted model probabilities

$$\mu^{(i)}_{k|k} = \frac{\mu^{(i)}_{k|k-1}\Lambda^{(i)}_k}{\sum_j \mu^{j}_{k|k-1}\Lambda^{(j)}_k}. \tag{6}$$

4) Combination: Combined state $\hat{\mathbf{x}}_{k|k}$ and its covariance $\mathbf{P}_{k|k}$ are now calculated from the weighted state estimates $\hat{\mathbf{x}}^{(i)}_{k|k}$ and covariances $\hat{\mathbf{P}}^{(i)}_{k|k}$.

$$\hat{\mathbf{x}}_{k|k} = \sum_i \mu^{(i)}_{k|k}\hat{\mathbf{x}}^{(i)}_{k|k} \tag{7}$$

$$\mathbf{P}_{k|k} = \sum_i \mu^{(i)}_{k|k}\Big[\mathbf{P}^{(i)}_{k|k} + \big(\hat{\mathbf{x}}_{k|k} - \hat{\mathbf{x}}^{(i)}_{k|k}\big)\big(\hat{\mathbf{x}}_{k|k} - \hat{\mathbf{x}}^{(i)}_{k|k}\big)'\Big]. \tag{8}$$

IV. CITY ENVIRONMENTS

A. Vehicle Models

In city environments abrupt maneuvers are often performed. However, a single model capable to consider high dynamics maneuvers will present a poor performance when smooth trajectories are described, due to the overestimation of the filter noise considerations. The main purpose of these tests is to analyze the suitability of the IMM method to increase the positioning accuracy of the navigation system. In this case, an IMM filter with two individual models, dedicated to maneuver and non-maneuver states, was developed. The models selected (based on [22]) represent the movements of a four wheel vehicle (assumed to be a rigid solid), 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 state and noise vectors of the non-maneuvering model are

$$\begin{aligned} \mathbf{x}_{\text{NM}} &= [\,x\ y\ \theta\ \dot{\theta}\ v\ \phi\ s\,]' \\ \eta_{\text{NM}} &= [\,\ddot{\theta}\ \dot{v}\ \dot{\phi}\ \dot{s}\,]' \end{aligned} \tag{9}$$

where x, y are the coordinates of the center of mass (COM) of the vehicle, θ the vehicle orientation, v the velocity in the COM, ϕ is the angle of the velocity v, and s the slide correction angle. The s term represents the slip bias angular component in the COM that effectively causes the vehicle to deviate from its ideal course, typically as a consequence of unbalanced weight distribution and inaccurate wheel alignment. Thus, the final velocity angle, referred to the North, is given by the addition of θ, ϕ and s. In this non-maneuvering model, constant acceleration and constant yaw angle rate are assumed.

In the maneuvering model, a second order equation for yaw rate is assumed, being its state and noise vectors

$$\begin{aligned} \mathbf{x}_{\text{M}} &= [\,x\ y\ \theta\ \dot{\theta}\ v\ \phi\ \dot{\phi}\ s\,]' \\ \eta_{\text{M}} &= [\,\ddot{\theta}\ \dot{v}\ \ddot{\phi}\ \dot{s}\,]' \end{aligned} \tag{10}$$

GPS, odometry, and inertial measurements will form the observation vector as described in [10].

B. Experimental Tests

The results of the experimental tests performed in this scenario are shown in Fig. 2. In the upper graph, the trajectories supplied by single model (SM) and IMM approaches, as compared to the ground reference can be seen. In tests performed, DGPS data were used as ground truth reference. The difference between both solutions will be much clearer next. The probability values of the models show how the suitability of the non-maneuvering model (Nmm) and the maneuvering model (Mm) change depending on the trajectory features. Finally, the reduction of the estimated position error during this test can be seen graphically. Despite the fact that both models behave acceptably during the test, the RMS value of the estimate position error (calculated as the Euclidean distance with the ground truth) decreased from 1.703 to 1.219 m. using the IMM method suggested. In order to dismiss the influence of the satellite coverage on the test, no GPS data were supplied to both filters during this trial.

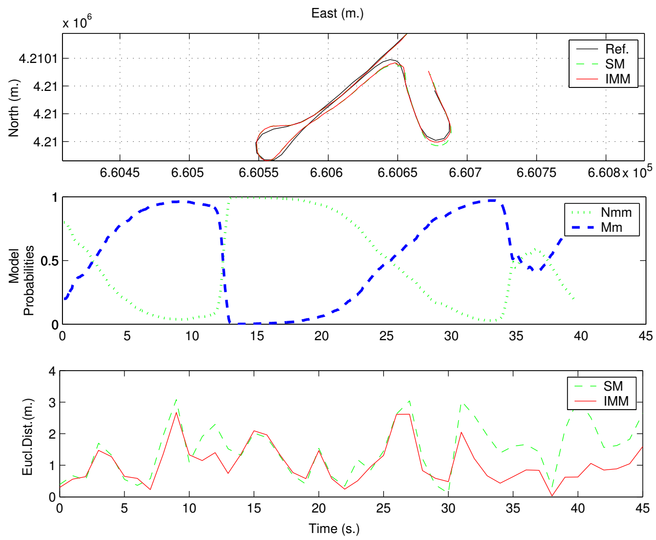

Fig. 2. Trajectory during the positioning accuracy test performed in an urban scenario. Single model (SM dashed green) and IMM (solid red) present similar results referred to the ground truth (solid black). Below, the probability values for non-maneuvering model (Nmm) and maneuvering model (Mm) during the test, and the estimated position error calculated as the Euclidean distance with the ground truth.

V. HIGHWAY SCENARIOS

In Section IV, two models were used to distinguish between maneuver (high dynamics) and non-maneuver states. The results presented showed the suitability of that approach to increase the positioning accuracy. In case of highway scenarios, our attention is focused on maneuver recognition for a collision avoidance application. Two typical conflictive situations are considered: stop&go and lane change scenes. Our investigations aim at the detection of these maneuvers, in order to serve this information to upper levels of the Quadrant architecture. In this paper, due to size constraints, we only present the study of stop&go situations.

A. Vehicle Models

Different model-sets are used separately for lateral and longitudinal movements. In stop&go situations main features of interest are concentrated on the longitudinal axis of the vehicle. In the current literature, models representing constant acceleration (CA) and constant velocity (CV) maneuver states are commonly used. However, in our tests, interesting results are achieved by using another approach, based on two different constant acceleration models with different noise parameter adjustments. Moreover, a stationary model is included to considered this non-maneuver state. The combination of CV and CA models has been analyzed lately in the literature [23], [24]. However, some of these authors found problems with the transition to the CA model, including those who used the IMM method [25]. In this interesting paper, the tuning of the CA noise parameters to avoid often unrealistic switches from one state to the other was found problematic, impoverishing the perception of the situation. In case of highways, typical accelerations and decelerations do not last long enough to accomplish the transition from the CV state, to the CA state, diminishing the IMM benefits.

In the approach presented in this paper, three possible maneuver states are defined to detect stop&go situations. As previously commented, the kinematic model proposed is a simplified bicycle model, in which the orientation of the acceleration and velocity are assumed to be equal. The results achieved will show that this assumption can be done for highway scenarios.

1) Acceleration/deceleration (AD): The state vector of the acceleration/deceleration model is $\mathbf{x}_{\mathrm{AD}} = (x, y, \phi, v, \omega, a)$, representing north, east, velocity angle, velocity, yaw rate of turn, and the acceleration, in the center of mass of the vehicle. The similar nature of accelerations and decelerations from the point of view of vehicle dynamics, allow us to propose a common model for both, described by

$$\dot{\mathbf{x}}_{\mathrm{AD}} = \begin{bmatrix} (v+at)\cos(\phi) \\ (v+at)\sin(\phi) \\ \omega \\ a \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \eta_{\omega_{\mathrm{AD}}} \\ \eta_{a_{\mathrm{AD}}} \end{bmatrix} \tag{11}$$

where $\eta_{\omega_{\mathrm{AD}}}$ and $\eta_{a_{\mathrm{AD}}}$ are white noise terms representing the errors due to model assumptions of constant acceleration and constant yaw rate.

2) Cruise (CR): The state vector of the cruise model is the same as in the AD model. However, in this case constant yaw rate is assumed, being $\omega = 0$, and the differential equation

$$\dot{\mathbf{x}}_{\mathrm{CR}} = \begin{bmatrix} (v+at)\cos(\phi) \\ (v+at)\sin(\phi) \\ 0 \\ a \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \eta_{\phi_{\mathrm{CR}}} \\ 0 \\ \eta_{\omega_{\mathrm{CR}}} \\ \eta_{a_{\mathrm{CR}}} \end{bmatrix} \tag{12}$$

In this case, a new term $\eta_{\phi_{\mathrm{CR}}}$ must be considered for errors in the constant yaw assumption. In addition, noise parameters due to ω and a must be much lower to represent the cruise vehicle dynamics.

3) Stationary (S): In this case, the vector state is simplified being $v = \omega = a = 0$, and the differential equation

$$\dot{\mathbf{x}}_{\mathrm{S}} = [\, \eta_{x_{\mathrm{S}}} \;\; \eta_{y_{\mathrm{S}}} \;\; \eta_{\phi_{\mathrm{S}}} \;\; 0 \;\; 0 \;\; 0 \,]' \tag{13}$$

where $\eta_{x_{\mathrm{S}}}$ and $\eta_{y_{\mathrm{S}}}$ are white noise terms representing the errors due to the model assumptions. All the noise parameters will be fixed in the tuning process of the filter, starting from the sensor datasheet error values. Observations for the AD, CR and S individual filters are GPS north and east values (x_{gps}, y_{gps}), odometry velocity (v_{odo}) and inertial measurements for angular rate (ω_{ins}) and longitudinal acceleration (a_{ins}).

B. Experimental Trials

Different tests have been performed in order to check the suitability of the proposed method to the problem under consideration. Due to the number of pages constraint, only a situation with abrupt deceleration, stop and go is presented in this paper. The results achieved during this highway test are shown in Fig. 3. As can be seen, the velocity of the vehicle decreased suddenly until the vehicle finally stops. After a few seconds of stop, the vehicle accelerates to achieve a normal value of velocity in a Spanish highway. Observing the two lower graphs, we can appreciate that the sigma value of the velocity is strongly related to the maneuver state anytime. During cruise maneuver state, this value remains very low, being increased when AD state appears.

The main aim of the algorithm is to detect the vehicle maneuver state and report it to upper levels of the architecture. Comparing the graph of the velocity reference and the model probability values in Fig. 3, we can appreciate that cruise, acceleration, deceleration and stationary states are clearly detected by the algorithm implemented. Figs. 4 – 6 show the behavior of the detector in several cases with GPS coverage gaps. The system performs well in typical cases with a few seconds of GPS outage in highways (Fig. 4 and Fig. 5), typically due to crossing roads, but also presents a robust performance in case of longer periods without GPS measurements (Fig. 6), such as tunnels.

Regarding latency for maneuver recognition, although it depends on IMM parameters, such as the π_{ij} matrix, in the different tests performed values surrounded 0.2 seconds, regardless of the status of the GPS coverage. In this sense, the use of inertial sensors not only allows continuous positioning but also shortens the reaction time for maneuver recognition.

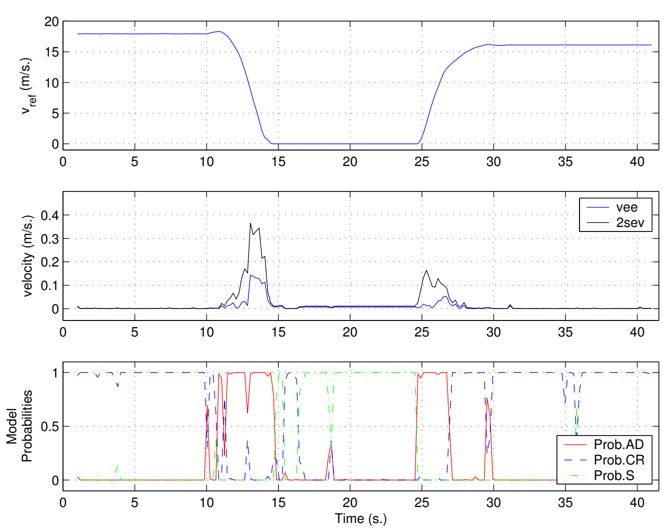

Fig. 3. Velocity reference (v_{ref}), calculated according to the ground truth. Below, velocity estimated error (vee solid blue), 2-sigma envelope of the velocity (2sev solid black) and probability values of the acceleration/deceleration (AD), cruise (CR) and stationary (S) maneuver models during the test.

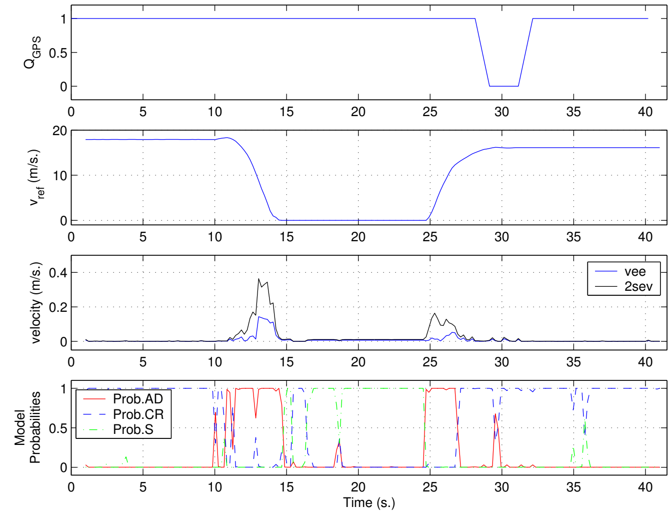

Fig. 4. GPS availability ($Q_{GPS} = 0$ means no GPS and $Q_{GPS} = 1$ means single position). In this test, 2 seconds of coverage outage (30 to 32) are simulated. Below, velocity reference (v_{ref}), calculated according to the ground truth, velocity estimated error (vee solid blue), 2-sigma envelope of the velocity (2sev solid black) and probability values of the acceleration/deceleration (AD), cruise (CR) and stationary (S) maneuver models during the test.

VI. CONCLUSIONS AND FUTURE WORKS

This paper presents the suitability of the proposed IMM method for detecting vehicle maneuvers in highways, as a part of a scene interpreter system. Besides, results show that the accuracy of the positioning can be improved, as compared with single model solutions. Real trials in city and highway environments have tested the performance of the system. In cities, the use of two models based on a four wheel vehicle definition, with different constant yaw and constant yaw rate assumptions has been found to be useful to increase the positioning accuracy, along with detect abrupt turns. In this case, both filters assumed constant acceleration. In highway scenarios, three maneuver states were used for stop&go situations: stationary, cruise and acceleration/deceleration. In order to avoid problems found in the literature, cruise state has not been defined by a constant velocity model, unlike some authors. Both acceleration/deceleration and cruise maneuver states employ constant acceleration models, with very different noise parameters. The results achieved show the suitability of this option in the cases analyzed. Finally, the proposed low cost GPS/INS unit has been proven to be a reliable navigation unit (the system performs correctly in absence of GPS coverage), as well as an efficient maneuver detector with short latency values.

Future works will extend this investigations to analyze the benefits of the IMM filter in different acceleration/deceleration situations, lateral movements and integrity provision.

VII. ACKNOWLEDGMENTS

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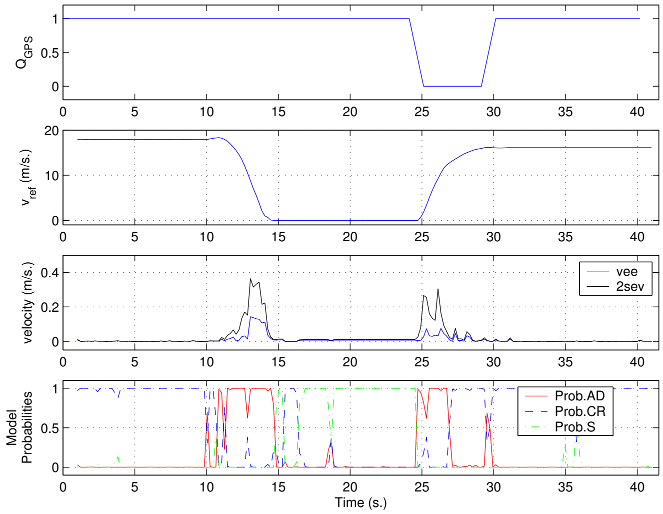

Fig. 5. GPS availability ($Q_{GPS} = 0$ means No GPS and $Q_{GPS} = 1$ means Single Position). In this test, 4 seconds of coverage outage (26 to 30) are simulated. Below, velocity reference (v_{ref}), calculated according to the ground truth, velocity estimated error (vee solid blue), 2-sigma envelope of the velocity (2sev solid black) and probability values of the acceleration/deceleration (AD), cruise (CR) and stationary (S) maneuver models during the test.

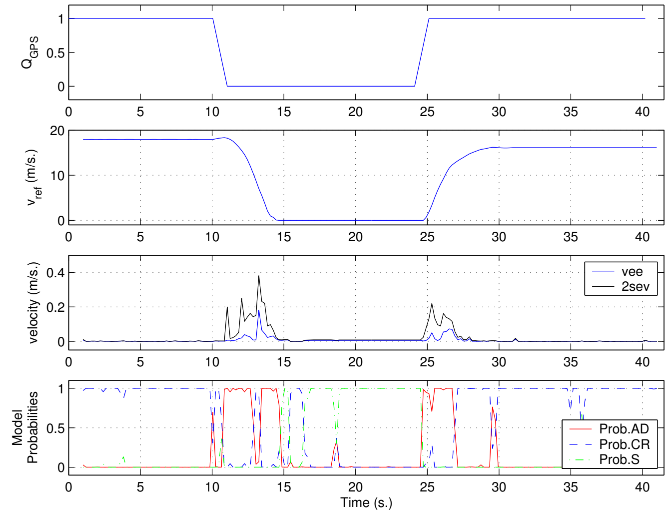

Fig. 6. GPS availability ($Q_{GPS} = 0$ means No GPS and $Q_{GPS} = 1$ means Single Position). In this test, 13 seconds of coverage outage (12 to 25) are simulated. Below, velocity reference (v_{ref}), calculated according to the ground truth, velocity estimated error (vee solid blue), 2-sigma envelope of the velocity (2sev solid black) and probability values of the acceleration/deceleration (AD), cruise (CR) and stationary (S) maneuver models during the test.

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