



Collision avoidance support in roads with lateral and longitudinal maneuver prediction by fusing GPS/IMU and digital maps

Rafael Toledo-Moreo^{a,*}, Miguel A. Zamora-Izquierdo^b

^a Technical University of Cartagena, Department of Electronics and Computer Technology, 30202 Cartagena, Spain

^b University of Murcia, Department of Information and Communications Engineering, Campus de Espinardo, 30001 Murcia, Spain

ARTICLE INFO

Article history:

Received 30 October 2008

Received in revised form 23 June 2009

Accepted 21 January 2010

Keywords:

Collision avoidance
Maneuver prediction
Extended Kalman filter
Inertial sensors

ABSTRACT

Collision avoidance in roads can be addressed in several ways, being cooperative systems one of the most promising options. In cooperative collision avoidance support systems (CCASS) the vehicles which constitute a scene share by means of communication links information that can be useful to detect a potentially risky situation. Typically, this information describes the kinematic state of each vehicle and can be complemented with a prediction of its next state. Indeed, the timely prediction of the next maneuver of a vehicle results beneficial to estimate the risk factor of a scene. This article presents a solution to the problem of maneuver prediction which employs a reduced number of sensors: a Global Navigation Satellite System (GNSS) receiver, one gyro, one accelerometer and the odometry. Predictions are made by a bi-dimensional interactive multiple model (2D-IMM) filter in which longitudinal and lateral motions of the vehicle are distinguished and maneuvering states are described by different kinematic models. A number of experiments were carried out with two vehicle prototypes in several circuits. The results achieved prove the suitability of the proposed method for the problem under consideration.

© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

The best way to decrease the number of fatal injuries caused by road accidents is to keep cars from smashing into each other (Wong and Qidwai, 2004). To do it so, collision avoidance support systems (CASS) can be developed following different perspectives. From a classical point of view, a vehicle-based autonomous system is in charge of estimating the safety distance to the surrounding vehicles and warn the driver in case of danger (Vahidi and Eskandarian, 2003). Radar and vision based systems are in this case the most common sources of information used by the subject vehicle in autonomous collision avoidance systems, and no special requirements are demanded from the navigation subsystem of the vehicle (Ferrara, 2003; Amditis et al., 2005; Shen et al., 2006; Toulminet et al., 2006; Jamson et al., 2008). These systems provide pose information about the rest of the detected vehicles in its traffic environment, and are limited to the line of sight of the sensors. Although potentially they can offer a complete vision of the obstacles for one vehicle on the road, their performance is restricted to the sensing capabilities, their accuracy is limited and generally they can be considered as high cost solutions.

A second approximation to CASS focuses on the infrastructure-based systems, where warnings and sensor elements are installed in the roadside. The information provided by the infrastructure can warn the driver through panels or messages to the drivers (Stubbs et al., 2003; Creaser et al., 2007). However, these systems do not meet the real time requirements, unlike the previously mentioned in-vehicle sensor-based CASS systems, and their information is limited.

* Corresponding author.

E-mail addresses: rafael.toledo@upct.es (R. Toledo-Moreo), mzamora@um.es (M.A. Zamora-Izquierdo).

Another approach to prevent vehicle collisions is through the cooperation of the vehicles involved in a road scenario by means of the so called cooperative collision avoidance support systems (CCASS). The concept of cooperative driving appeared in vehicular researching in the early 1990s (Varaiya, 1993) and different approximations were gradually adopted since then. Depending on the level of cooperation among vehicles, the object vehicle can track the surrounding vehicles, in order to detect risk conditions, or directly receive or send a traffic event when necessary. In the first case, a periodical transmission of state messages to close vehicles must be maintained, whereas in the second only a message sent by an affected vehicle (or the one which detects the problem) is propagated over the network when required. Even in classic Adaptive Cruise Control (ACC) systems, the cooperative point of view has already started to be introduced. Kesting et al. (2008) improve a standard ACC system by determining the traffic states (traffic jams for instance) through infrastructure-to-car and inter-vehicle communications. It can be noticed that there is a growing interest in the researcher community in cooperative systems (Misener et al., 2005; Ueki et al., 2005; ElBatt et al., 2006; Ammoun et al., 2006; Huang and Tan, 2006; Tan and Huang, 2006).

Two main subsystems can be distinguished in cooperative systems (Santa et al., 2010). On the one hand, vehicles must be connected by means of wireless communications which allow a timely propagation of messages. On the other hand, these messages must contain useful information to decide whether or not a situation is risky.

Along with the kinematic state of the vehicles, some extra information about the future state of the vehicles results useful in order to estimate the risk of the scene. The work under consideration concerns with typical maneuvers that a vehicle performs in a highway, as travelling at a steady speed, so called cruise state, and increasing or decreasing the speed (longitudinal maneuvers) or lane change and lane keeping (lateral maneuvers). This information can support the scene interpretation and help the detection of risky situations. For example, a lane change or an abrupt deceleration can be good reasons to launch an immediate notification to surrounding vehicles and to perform an analysis of the scene.

Maneuver prediction systems may be divided in two important aspects: the definition of the each maneuver and the in-vehicle sensor equipment.

On the one hand, usual maneuvering states of road vehicles in highways can be represented by the appropriate kinematics at each instant, what can be defined by different kinematic models. Approaches based on sets of multiple model filters which allow the possibility of recognizing different kinematic states of the vehicle have been found suitable in the literature (Barrios et al., xxxx; Polychronopoulos et al., 2007). As well as the maneuvering identification with models, other important aspect is the transitions among the proposed driving states. In order to solve the problem of often unrealistic switches, several authors find convenient the use of interactive multiple model (IMM) filtering in which maneuver states are formulated as Markovian processes (Kaempchen and Dietmayer, 2004; Huang and Leung, 2004; Yang et al., 2004; Toledo-Moreo et al., 2007). In Cui et al. (2005) it can be found a complete analysis and comparison of non-linear filtering tools, including IMM algorithms.

On the other hand, a second aspect of importance is the sensor system onboard the vehicle. A very well equipped vehicle with a GNSS (Global Navigation Satellite System) receiver, INS (Inertial Navigation System), radar, vision, etc., has a lot of information about itself and the surrounding vehicles, but the cost of the system determines its introduction in the mass market. For that reason, our investigations are focused on low or medium cost in-vehicle sensor systems, being this a restriction of the problem under consideration. Therefore, radar or vision devices are disregarded, and we analyze only the possibilities of sensors that are already common onboard current road vehicles, such as its odometry and a GNSS receiver, or expected to be frequently installed in a short or mid-term future, such as low cost inertial sensors or lane level digital maps.

Indeed, nowadays many vehicles have already a GPS-based navigation system for route planning applications, and in-vehicle data recorder systems to recover information start to be used in many applications, as proposed by Toledo et al. (2008) for insurance purposes. In order to cover up for the typical GNSS problems, navigation systems add additional proprioceptive sensors to the GPS-based navigation systems in hybridized multi-sensor solutions (Toledo-Moreo et al., 2007). The simplest approach is the fusion of the GPS and the odometry (ABS system or odometer of the car) readings (Boucher et al., 2004; Hay, 2005). Low-cost gyros based on Micro-Electro-Mechanical Systems (MEMS) technology can be found in the ESP systems of current vehicles, being these measurements also available for navigation purposes (Zamora-Izquierdo et al., 2008). Another important source of information is the addition of a digital map (Lahrech et al., 2004; Wang et al., 2005; Quddus et al., 2007; El Najjar and Bonnifait, 2007). Digital maps are used in conventional navigators and day by day provide more information about the roads. In navigation, maps are essential since they allow a local reference of the vehicles in the scene, but the latest researches show that they can also be employed in the data fusion process of the navigation (Peyret et al., 2008; El Najjar and Bonnifait, 2007; Quddus et al., 2007). In this line, two well-known digital map manufacturers such as Navteq and TeleAtlas are working on more complete and accurate version of their maps (<http://www.cvisproject.org>).

This article presents a solution to the problem of maneuver prediction by means of vehicle kinematics analysis and a bi-dimensional IMM filter to identify the longitudinal and lateral maneuvers. For this goal the proposed system employs only the positioning unit of a vehicle, equipped with a GPS plus standard proprioceptive sensor as the odometer of the vehicle and a gyro, one accelerometer, and the information of a digital map. The proposed system is able to estimate maneuvering state changes of interest for collision avoidance with times of response and times of prediction which result suitable for real time applications, and being independent of visibility conditions.

The rest of the article is organized as follows. Section 2 introduces the general architecture of the system. Section 3 presents a description of the multiple model filtering technique used in our approach, while Section 4 describes some selected

model-sets of interest for this study. The experimental trials performed with the vehicle prototypes are shown in Section 5. Main conclusions achieved in these investigations are discussed in Section 6.

2. Overview of the system architecture

The proposal presented in this article corresponds to the second layer of the Quadrant architecture which is shown in Fig. 1 and was introduced by the authors in (Toledo-Moreo et al., 2006).

Quadrant is an architecture oriented to Advanced Driver Assistance Systems (ADAS), where CASS are embraced. It is based on four layers dedicated to process data at different abstraction levels. Sensor layer (the first) is in charge of the collection of the measurements, ordering and synchronization. These prepared measurements are sent to the second level via serial and CAN buses. Fusion layer integrates the data coming from the previous layer by means of the proposed 2D-IMM filter. As it can be seen in the image of Fig. 1, its outputs are employed as inputs of the interpretation layer (the third). Once the scene is analyzed, this information is supplied to the application itself which is in charge of launching (or not) the corresponding action.

More details of this architecture can be found in Toledo-Moreo et al. (2006).

3. Multiple model filtering

The idea of using multiple models is based on the fact that the best way to describe the movements of a road vehicle can be very different depending on its maneuvering state. Although it is possible that a high complex model considers all kind of maneuvers, the use of more simple models presents some advantages. The implementation of a set of few simple models running in parallel is less costly from the computational point of view. But its main advantage stems from a more precise representation of the error considerations anytime. Both advantages, specially the latter, are exploited in the investigations presented in this article.

The concept of multiple models is applied to lateral and longitudinal maneuvers of the vehicle. The models are described by extended Kalman filters dedicated to *stationary/cruise/acceleration-deceleration* states for longitudinal movements (noted in the following by T) and *keep-lane/change-lane* states for lateral ones (noted by N). There are many ways to fuse a set of extended Kalman filters in just one (Bar-Shalom and Li, 1995). In this and next sections we present the development of the proposed bi-dimensional interactive multiple model (2D-IMM) method.

3.1. Bi-dimensional interactive multiple model (2D-IMM)

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 among maneuver states. The IMM method can be described according to four different phases. We argue that the nature of the vehicle movements can be separated between lateral and longitudinal motions of the vehicle, defining this approach from now on as 2D-IMM.

Fig. 2 shows a scheme of the 2D-IMM cycle that describes the different phases and the main calculations realized in each of them.

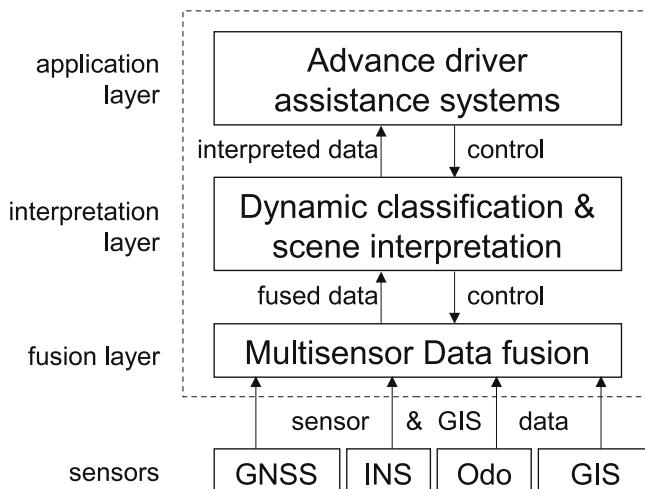


Fig. 1. Quadrant architecture scheme.

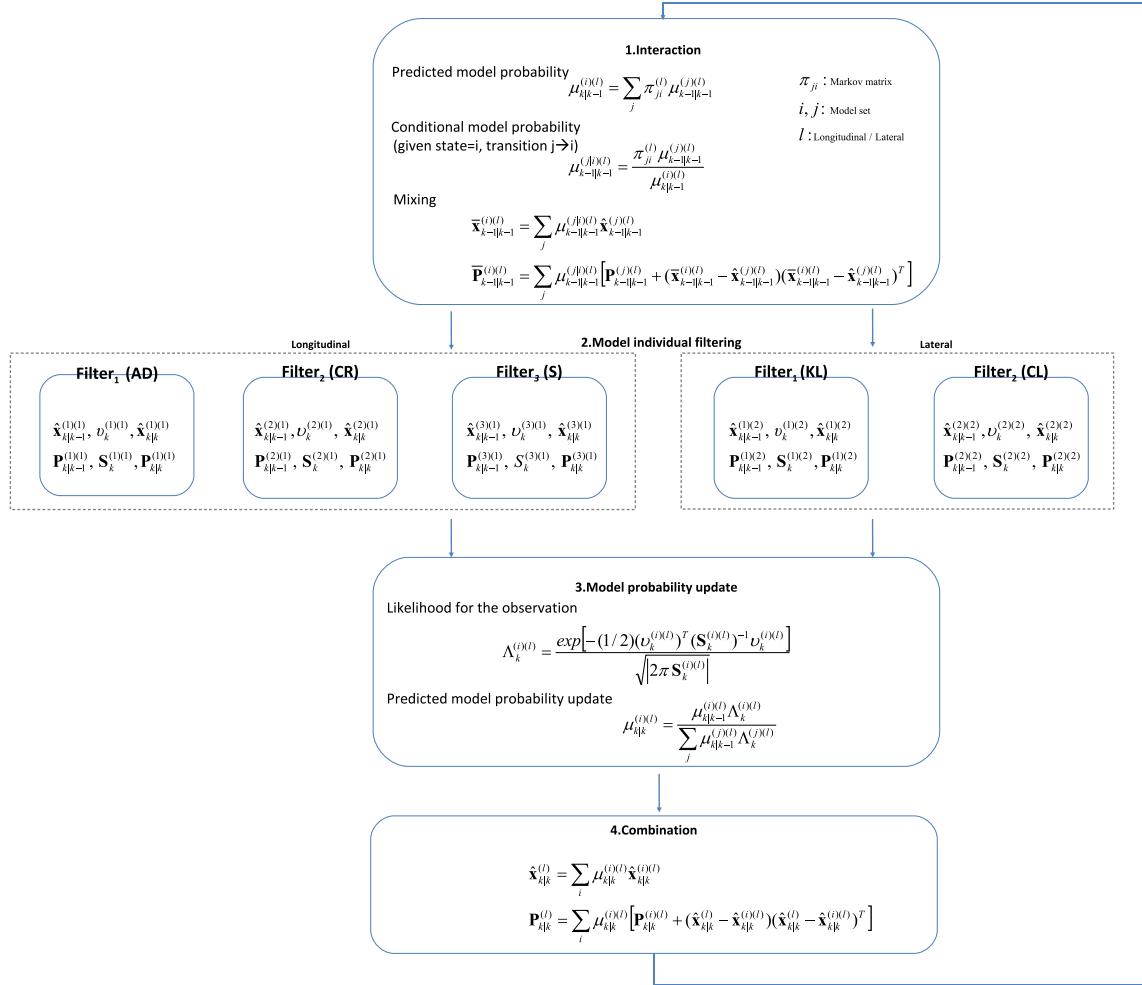


Fig. 2. 2D-IMM cycle flowchart.

- In the interaction phase, the predicted model probability is given by the model probability in the previous cycle, $\mu_{k-1|k-1}^{(j)(l)}$ and the probability that a transition from state j to state i occurs, $\pi_{ji}^{(l)}$, for both the local plane dimensions of the body frame $l = T, N$. Individual filters are mixed according to these predicted model probabilities and the conditional model probabilities. The probabilities $\pi_{ji}^{(l)}$ that a transition occurred from state j to state i for a vehicle dimension l , are calculated according to a Markovian process, and will depend on the statistics of real traffic situations related to the mean sojourn times and the sampling interval.
- The kinematical assumptions which will be presented in Section 4 are employed then to predict and update state estimates and their covariances for both longitudinal and lateral motions. Predicted state estimates $\hat{x}_{k|k-1}^{(i)(l)}$ and covariances $\mathbf{P}_{k|k-1}^{(i)(l)}$ will be calculated by using loosely coupled extended Kalman filters (EKF).
- The innovation vector $v_k^{(i)(l)}$ and its covariance $\mathbf{S}_k^{(i)(l)}$ are used to calculate the likelihood of the observations $A_k^{(i)(l)}$ at instant k and their corresponding predicted model probabilities $\mu_{k|k}^{(i)(l)}$.
- Finally, for both lateral and longitudinal dimensions, the combined states $\hat{x}_{k|k}^{(l)}$ and their covariances $\hat{P}_{k|k}^{(l)}$ are calculated from the weighted state estimates $\hat{x}_{k|k}^{(i)(l)}$ and covariances $\hat{P}_{k|k}^{(i)(l)}$.

4. Vehicle model-sets

Among the different model-sets tested, those that achieved the most interesting results are next presented. In all of them, the proposed kinematic model is based on a simplified bicycle model in which the orientations of the acceleration and velocity vectors are assumed to be equal. The results achieved show that this assumption can be done. Sensor observations supplied to all sets of extended Kalman filters are GPS east and north values (x_{gps}, y_{gps}), travelled distance (d_{odo}) and the inertial measurement of angular rate (ω_{ins}). Additionally, a measurement of the longitudinal acceleration, a_{ins} , coming from a MEMS-based IMU is employed in the model-set T2, that is dedicated to longitudinal motions. Apart from these sensor observations, models for lateral motions employ road shape information coming from a digital map as it is explained next.

Noise parameters are fixed in the design process of the algorithm, starting from the sensor specifications and adjusted according to the values collected in our experiments.

4.1. Lateral model-set

Regarding lateral motions, two different models are intended to distinguish between *keep-lane* (N/KL) and *change-lane* (N/CL) maneuvering states. In our study, different model-sets based on the nature of the vehicle kinematics in lane change maneuvers were developed and tested. Among them, only those which presented best results are next presented. To the best of our knowledge, there are no previous works – apart from our own attempts – dedicated particularly to the prediction of lane changes using only a positioning unit and the vehicle kinematic description. Therefore, it is not possible to compare in our experiments the proposed model-set with different approaches of the literature.

Toledo-Moreo et al. (2007) presents an analysis of model-sets that do not employ any kind of road shape information. According to the tests done in this publication, in order to separate lane change maneuvers from some other turning maneuvers due to the curves in the road, some information which describes the road shape must be provided to the filter. In Toledo-Moreo and Zamora-Izquierdo (2009), new experiments are carried out to demonstrate the feasibility of one solution that includes road information. These two works present some preliminary results to the task of detecting only lateral maneuvers that can lead to inter-vehicular collisions.

4.1.1. Road description and curvature estimation

The model-set suggested for lateral motion assumes that the value of the curvature of the road is available anytime and comes from a digital map. Despite the fact that the value of the curvature is well known when a road is built, this information is not currently available in road maps of the market. However, current efforts in Europe to create enhanced maps (Emaps) that support vehicles' navigation, encourage to think that this datum will be available in a short future (<http://www.cvisproject.org>). Indeed, main manufacturers are actively involved in this endeavor.

For our experiments we have employed a customized Emap of the terrain. The road is described by a set of consecutive clothoids with the assumption of linear changes in their curvature values. With the inclusion of this Emap as an input of the filter, it results easy to obtain the value of the road curvature at a given coordinate. The curvature of the road, κ , can be estimated as

$$\kappa(l) = \kappa_0 + c \cdot l$$

where κ_0 , c are the initial curvature value for a clothoid segment and its constant linear change rate respectively, and l stands for the abscissas of the clothoid in its Frenet representation that corresponds to the travelled distance through the clothoid. It can be found that there is a relation between the Frenet representation referred to a certain clothoid and the corresponding Cartesian coordinates of the navigation frame, by means of next expressions:

$$\begin{aligned} x &= x_0 + \int_0^l \cos(\tau(l))dl - d\sin(\tau(l)) \\ y &= y_0 + \int_0^l \sin(\tau(l))dl + d\cos(\tau(l)) \end{aligned}$$

where x_0 , y_0 are the east and north coordinates of the initial point of the road segment, d is the ordinate value in the Frenet representation, and $\tau(l)$ is the azimuth angle of the segment at abscissas l , given by

$$\tau(l) = \tau_0 + \kappa_0 \cdot l + \frac{c \cdot l^2}{2}$$

being τ_0 the initial heading of the clothoid. Further details of the road description by means of the proposed Emap are given by Peyret et al. (2008) and Betaille et al. (2008).

4.1.2. Change lane model (N/CL)

The state vector of the N/CL model is given by $\mathbf{x}_N^{CL} = (x_N, y_N, \phi_N, v_N, \omega_N, \kappa, c)$, representing respectively east, north, velocity angle, velocity, and yaw rate of turn in the center of mass of the vehicle for the lateral model-set (noted by subscript N), and the two parameters that stand for the road stretch shape according to the clothoid definition. The differential equations that describe its kinematics are:

$$\begin{aligned} \dot{x}_N^{CL} &= v_N \cos(\phi_N) & \dot{\phi}_N^{CL} &= \eta_{\omega_N^{CL}} \\ \dot{y}_N^{CL} &= v_N \sin(\phi_N) & \dot{\kappa}_N^{CL} &= \eta_{\kappa_N^{CL}} \\ \dot{\phi}_N^{CL} &= \omega_N & \dot{c}_N^{CL} &= \eta_{c_N^{CL}} \\ \dot{v}_N^{CL} &= \eta_{v_N^{CL}} \end{aligned} \tag{1}$$

where $\eta_{v_N^{CL}}$, $\eta_{\omega_N^{CL}}$ and $\eta_{\kappa_N^{CL}}$, $\eta_{c_N^{CL}}$ are respectively terms for the errors due to model assumptions of constant velocity and constant yaw rate, and the errors due to model assumptions for the road shape.

4.1.3. Keep lane model (N/KL)

The state vector of the N/KL model is the same as in the N/CL model. However, in this case the derivative of the angle of the velocity is assumed to follow the road shape and the set of differential equations are:

$$\begin{aligned}\dot{x}_{N^{KL}} &= v_N \cos(\phi_N) & \dot{\omega}_{N^{KL}} &= \eta_{\omega_N^{KL}} \\ \dot{y}_{N^{KL}} &= v_N \sin(\phi_N) & \dot{k}_{N^{KL}} &= \eta_{k_N^{KL}} \\ \dot{\phi}_{N^{KL}} &= K v_N & \dot{c}_{N^{KL}} &= \eta_{c_N^{KL}} \\ \dot{v}_{N^{KL}} &= \eta_{v_N^{KL}}\end{aligned}\quad (2)$$

In order to fit to the different vehicle kinematics, noise parameters of this model are different from those in N/CL, being fixed in the tuning process of this filter. The filters were tuned in such a way that the error lay on the predicted 2σ covariance envelope (assuming normal distributions).

4.2. Longitudinal model-set

In longitudinal movements, main interest is focused on the detection of the so called stop and go situations. Our approach is based on three models for acceleration-deceleration, cruise and stationary maneuvering states.

In the literature, the most common approach to describe different state kinematics in the longitudinal axis of the vehicle proposes three models that represent constant acceleration (CA), constant velocity (CV) and stationary (S) maneuvering states. However, in our experiments we found problematic the definition of CA and CV models to distinguish accelerating and cruise maneuvering states. These problems come from the transition between these two models, as it will be discussed later.

We propose two different alternatives that will be compared in Section 5. On the one hand, model-set T1 is based on two CV models for acceleration and cruise states and a state of no-motion for stationary. On the contrary, model-set T2 employs for the respective maneuvering states two CA models plus a state of no-motion. Both approaches claim to a certain originality as compared to the literature. The experiments presented along the article will show the benefits of this approach. More specifically, defining nearly constant velocity states with a constant acceleration model brings the benefit of allowing minor changes in the velocity without corrupting the interaction among models. It is the mission of the designer to find the proper tuning that distinguish acceleration/deceleration states of interest, and velocity changes of low intensity.

4.2.1. Model-set 1: acceleration/deceleration state model (T1/AD)

The state vector of the acceleration/deceleration model of model-set T1 is given by

$$\mathbf{x}_{T1}^{AD} = (x_T, y_T, \phi_T, v_T, \omega_T)$$

representing east, north, velocity angle, velocity and yaw rate of turn in the center of mass of the vehicle. The similar nature of accelerations and decelerations from the point of view of vehicle kinematics, allows us to propose a common model for both, described by

$$\begin{aligned}\dot{x}_{T1}^{AD} &= v_T \cos(\phi_T) & \dot{v}_{T1}^{AD} &= \eta_{v_{T1}^{AD}} \\ \dot{y}_{T1}^{AD} &= v_T \sin(\phi_T) & \dot{\omega}_{T1}^{AD} &= \eta_{\omega_{T1}^{AD}} \\ \dot{\phi}_{T1}^{AD} &= \omega_T\end{aligned}$$

where $\eta_{v_{T1}^{AD}}$ and $\eta_{\omega_{T1}^{AD}}$ are white noise terms representing the errors due to model assumptions of constant acceleration and constant yaw rate for model-set T1.

We would like to note here that, despite the fact that the variables of this and next models are included in the Cartesian sub-states of the models for lateral maneuvers, it is the authors argument to distinguish between both dimensions of the vehicle body frame. Therefore, both sets of state variables represent different kinematical states of the vehicle, depending on the considered dimension and indicated by the subscripts T and N for longitudinal and lateral movements respectively.

4.2.2. Model-set 1: cruise state model (T1/CR)

The state vector and the differential equations of the cruise model are the same as in the T1/AD model. However, in this case noise parameters of ω_T and v_T , $\eta_{\omega_{T1}^{CR}}$, $\eta_{v_{T1}^{CR}}$, must be lower to represent the cruise vehicle kinematics.

4.2.3. Model-set 1: stationary state model (T1/S)

In this case, the state vector is simplified being $v_T = \omega_T = 0$, and the differential equations:

$$\begin{aligned}\dot{x}_T^S &= \eta_{x_{T1}^S} & \dot{v}_T^S &= 0 \\ \dot{y}_T^S &= \eta_{y_{T1}^S} & \dot{\omega}_T^S &= 0 \\ \dot{\phi}_T^S &= \eta_{\phi_{T1}^S}\end{aligned}$$

where $\eta_{x_{T1}^S}$, $\eta_{y_{T1}^S}$ and $\eta_{\phi_{T1}^S}$ are white noise terms representing respectively the positioning and heading errors due to the static assumption for model-set T1.

4.2.4. Model-set 2: acceleration/deceleration state model (T2/AD)

The state vector of the acceleration/deceleration model is given by

$$\mathbf{x}_{T2}^{AD} = (x_T, y_T, \phi_T, v_T, \omega_T, a_T)$$

representing east, north, velocity angle, velocity, yaw rate of turn, and the acceleration, in the center of mass of the vehicle for the longitudinal axis of the body frame of the vehicle. As compared to model-set T1, the acceleration appears now in the state vector. The vehicle kinematics is described by

$$\begin{aligned}\dot{x}_{T2}^{AD} &= (v_T + a_T \Delta t) \cos(\phi_T) & \dot{v}_{T2}^{AD} &= a_T \\ \dot{y}_{T2}^{AD} &= (v_T + a_T \Delta t) \sin(\phi_T) & \dot{\omega}_{T2}^{AD} &= \eta_{\omega_{T2}^{AD}} \\ \dot{\phi}_{T2}^{AD} &= \omega_T & \dot{a}_{T2}^{AD} &= \eta_{a_{T2}^{AD}}\end{aligned}$$

where $\eta_{\omega_{T2}^{AD}}$ and $\eta_{a_{T2}^{AD}}$ are white noise terms representing the errors due to model assumptions of constant acceleration and constant yaw rate for model-set T2.

4.2.5. Model-set 2: cruise state model (T2/CR)

The state vector and the differential equations of the cruise model are the same as in the T2/AD model, being in this case the noise parameters of ω_T and a_T , $\eta_{\omega_{T2}^{CR}}$, $\eta_{a_{T2}^{CR}}$, lower to represent the cruise vehicle kinematics.

4.2.6. Model-set 2: stationary model (T2/S)

In this case, the state vector is simplified being $v_T = \omega_T = a_T = 0$, and the differential equations

$$\begin{aligned}\dot{x}_{T2}^S &= \eta_{x_{T2}^S} & \dot{v}_{T2}^S &= 0 \\ \dot{y}_{T2}^S &= \eta_{y_{T2}^S} & \dot{\omega}_{T2}^S &= 0 \\ \dot{\phi}_{T2}^S &= \eta_{\phi_{T2}^S} & \dot{a}_{T2}^S &= 0\end{aligned}$$

where $\eta_{x_{T2}^S}$, $\eta_{y_{T2}^S}$ and $\eta_{\phi_{T2}^S}$ are white noise terms that represent the errors in positioning and heading due to the static assumption of this model of model-set T2.

5. Experimental results

The main objective of the experiments is to test the suitability of the proposed model-sets to represent and distinguish different kinematic states, predicting the vehicle maneuver among a set of lateral and longitudinal alternatives, and with times of response that allow its application in frame of the aforementioned Quadrant architecture to support collision avoidance systems. For these purposes different campaigns were carried out with equipped test vehicles. Fig. 3 shows our test vehicle prototype. This vehicle is equipped with:

- Low cost MEMS based inertial measurement units MT9B by XSens and IMU400 by Xbow. Since it is assumed that acceleration and velocity vectors are defined by the same angle, only one gyro and one accelerometer are employed. To give an idea of the performance of the MEMS based inertial sensors, the specifications of the XSens IMU are shown in Table 1.
- Odometry captors in the rear wheel axis.
- A Trimble DGPS receiver. Single positions where employed as inputs of the filter (with CEP = 2 m), while DGPS values were used for evaluation (with CEP = 0.10 m).

In addition to our collection of measurements, the Division of Metrology and Instrumentation (DMI) of LCPC-Nantes Centre, allowed us to employ some extra data-sets for the experiments. These data-sets were collected with a Peugeot van equipped with a wheels axle odometer (the a priori calibrated spatial rate is 1 pulse per 24.15 cm), a fiber optic gyroscope KVH 2100 e-core FOG series, a Crossbow IMU400 (MEMS technology), and a DGPS receiver Trimble Ag132 receiving Omnistar corrections.

All the circuits employed for our tests offer good conditions for GPS observation, with no long blockages of the GNSS visibility. Therefore, GPS masks applied in the experiments were artificially simulated. Speed values during the tests vary from 0 till 20 m/s.



Fig. 3. The test vehicle is a customized prototype based on a roadster Comarth S1–50.

Table 1

MT9B XSens performance specifications.

Parameter	Rate of turn ($^{\circ}/s$)	Acceleration (m/s^2)
Full scale (units)	± 900	± 20
Linearity (% of FS)	0.1	0.2
Bias stability (units $1-\sigma$)	5	0.02
Scale factor stability (% $1-\sigma$)	–	0.05
Noise (units RMS)	0.7	0.01
Alignment error ($^{\circ}$)	0.1	0.1

5.1. Analysis of lateral maneuvers

Fig. 4 shows the test circuit in the surroundings of the city of Nantes, France, collected and prepared by the DMI-LCPC Nantes. Over the Emap (solid black), the RTK (Real Time Kinematics) positions (in dotted blue) represent the trajectory of the vehicle during the test. During the stretch under consideration the vehicle performed seven lane changes, consecutively: one to the left, two to the right, two to the left and two more to the right. Details of these lane changes can be seen in **Fig. 5**.

Fig. 6 presents the results obtained by both filters oriented to keep-lane (a) and change-lane (b) maneuvering states. To emphasize the influence of the vehicle model, a mask was applied to the GPS data during this period. As it can be seen even in the filter outputs between two consecutive GPS points, KL filter outputs trend to follow the road shape: the vehicle is committed to follow the lane in which it is. This situation does not appear in the change-lane filter. As it was presented in previous Section, the derivative of the angle of the velocity of the CL model is not dependent on the road curvature and therefore lane changes are “allowed” by this model. The consequence of this is that the KL filter behaves well when the vehicle follows the lane path, while the CL filter behaves well in both situations. Which could be the benefit then of a KL model? The answer is related to the motion considerations of the model. If we assume that the vehicle will always follow the same lane, the errors considerations due to the representation of the vehicle model can be noticeable bounded: a vehicle that follows its lane does not change abruptly its orientation and heading changes must follow the road shape. Therefore, the estimated errors for its pose variables can be constrained to the lane shape at the current vehicle position. However, if a vehicle that it is assumed to follow always the same lane performs a lane change, the change in its heading would be no longer well represented, and a model capable to represent changes different from those derived from the road path must be used.

As it has been presented previously, the IMM based method employs the innovation vectors and its covariance matrix to calculate the model probabilities. In equal conditions, models with lower noise considerations are more weighted. This decision comes from the idea that if two different models represent correctly the kinematic state of the vehicle, the one with lower noise considerations is more precise, since the level of certainty on the pose is higher. **Fig. 7** shows the probability

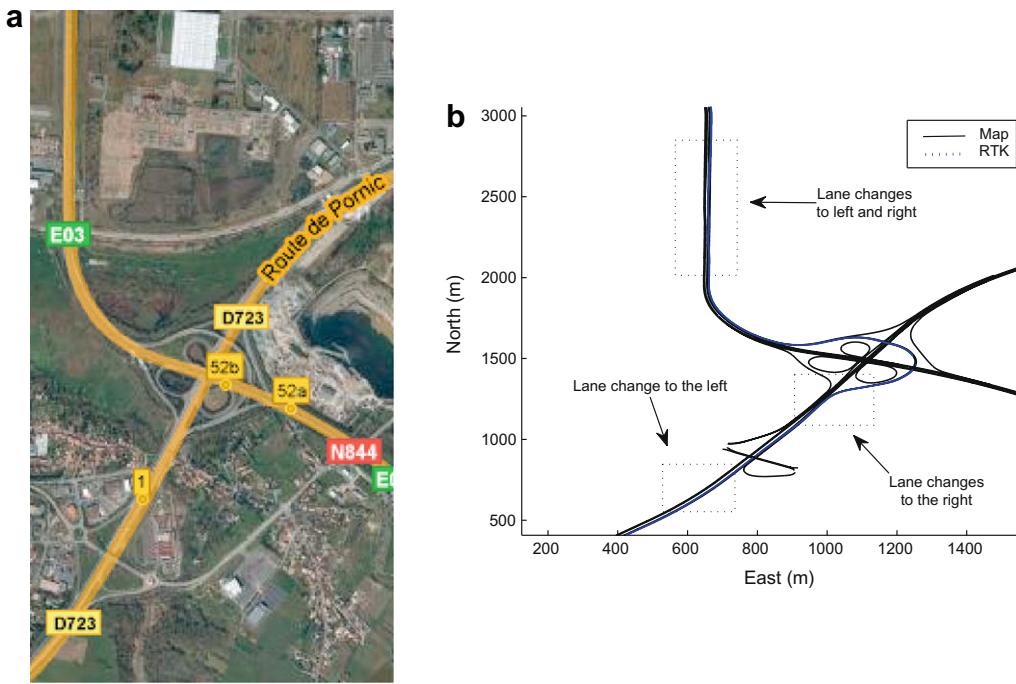


Fig. 4. Left: Google Maps image of the area of one test circuit whose data were collected by DMI, LCPC-Nantes Centre. Right: the map (solid black) is represented by a set of consecutive clothoids. RTK positions (dotted blue) represent the vehicle trajectory. Lane changes areas have been remarked. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

values of both KL and CL models given by the proposed IMM based method. When the vehicle follows the same lane, both models can represent its behavior correctly, and the lower noise assumptions of the KL model imply higher probability values of KL. However, whenever the vehicle performs a lane change, the innovation vector of the KL becomes higher and higher, and its noise considerations are not capable to represent it. The CL model is in these cases the one with higher probability values. As can be clearly seen in Fig. 7, the seven lane changes performed during the trajectory shown in Fig. 4 are properly detected by the algorithm, while no false positives are found. Nevertheless, let us mention here that a lane change at a very low lateral speed will probably pass undetected by the algorithm. Tuning the filter to detect lane changes at low lateral speed values, would increase the number of false positives, since the orientation of a vehicle is usually not exactly the same as the road even when the vehicle does not change the lane. In our experiments we assume typical intended lane change maneuvers, with maneuvering times between 3 and 4 s (Salvucci et al., 2007).

According to Olsen (2003), a lane change starts at the moment that the vehicle achieves the minimum lateral velocity and proceeds, without a lateral reversal, through the lane boundary into the destination lane. Taking into account this definition, the onset lane change times were established and the values for time of response (t_r) obtained by the algorithm were calculated. t_r values were never higher than 0.5 s, being typically between 0.3 and 0.4 s. If we consider that a lane change is performed when the four wheels of the vehicle are in the other lane, the algorithm is found to predict the lane changes with time of prediction (t_p) values of 1.2–1.7 s. According to the collision avoidance community, these values can be considered useful to prevent collisions in lane change situations.

5.2. Analysis of longitudinal maneuvers

Fig. 8 shows the velocity profile and probability values assessed by model-set T1, that employs two CV models plus one stationary, during the same circuit presented in Fig. 4 that was also employed for the study of lateral motions. During this test, the vehicle did not stop anytime, and consequently the model probability of the stationary model never arose (green dash-dotted line). It can be found that AC state probability values become higher when acceleration and deceleration appear. In Fig. 9, a representative detail of this trajectory can be seen with further detail. The vehicle velocity profile (shown in the upper image with the values of the state variable that represents the vehicle velocity), indicates that during this stretch of 80 s, the vehicle diminishes slowly its speed, until approximately instant 210 s, when brakes are applied, lasting till approximately instant 220 s. After some seconds the driver accelerates to reach velocity values of the same order as previously registered. Therefore, there are two clear instants of acceleration and deceleration, and the rest corresponds to a period of minor changes in the velocity. The IMM filter shows that these minor changes in the velocity can lay into the cruise maneuvering

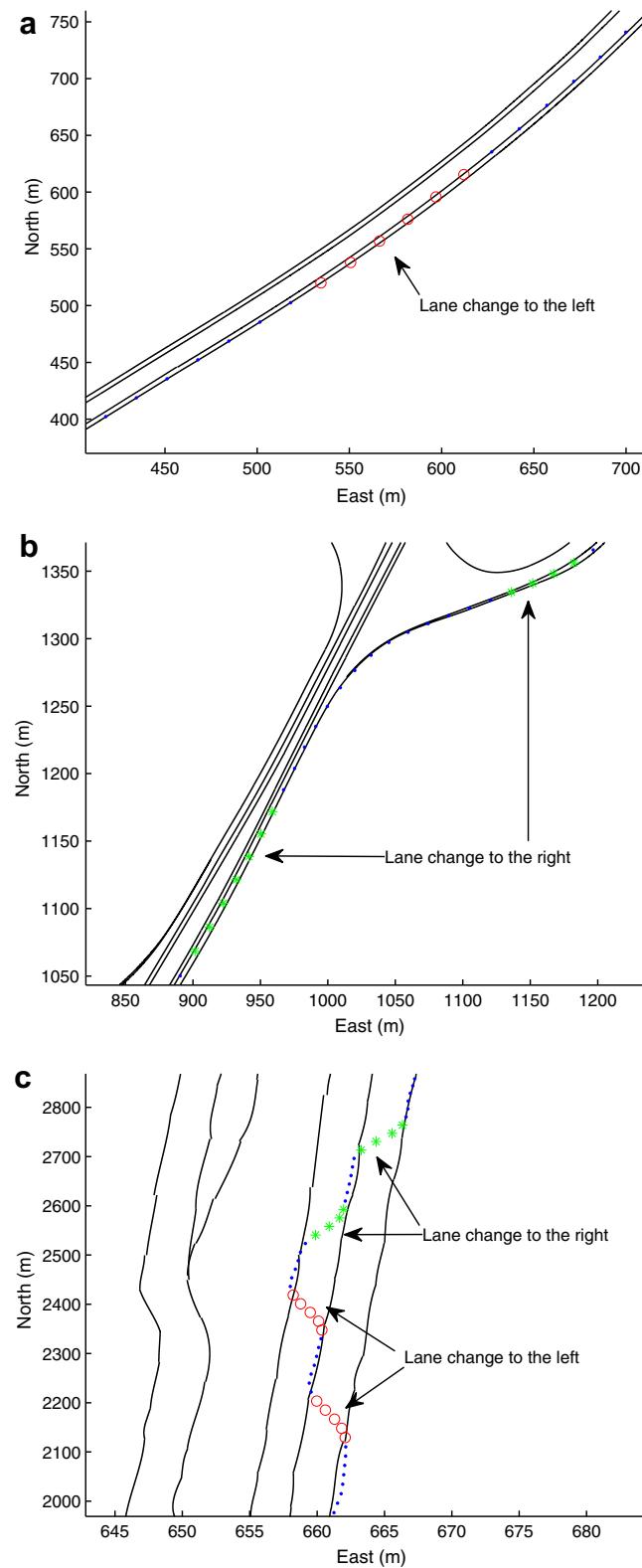


Fig. 5. Details of the vehicle trajectory (dotted blue) over the custom-made map (solid black). Lane changes to the left are represented by red circles, while lane changes to the right by means of green stars. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

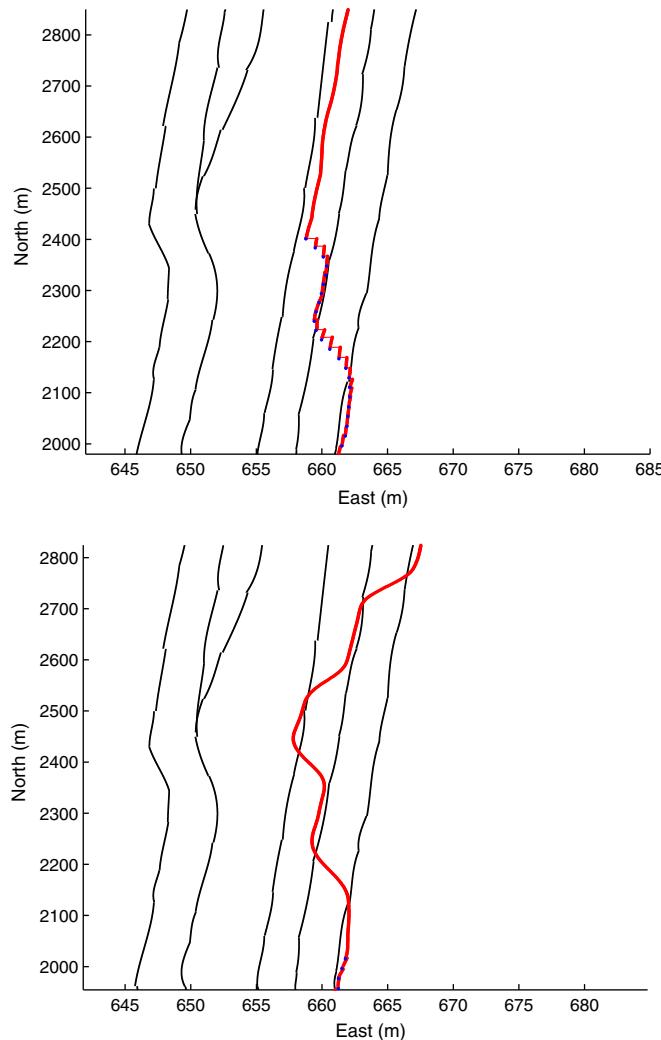


Fig. 6. In solid red: solutions provided by both the keep-lane (a) and change-lane (b) filters during a stretch of the trajectory with simulated GPS masks of different duration. Solid black: map. Blue dots: GPS positions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

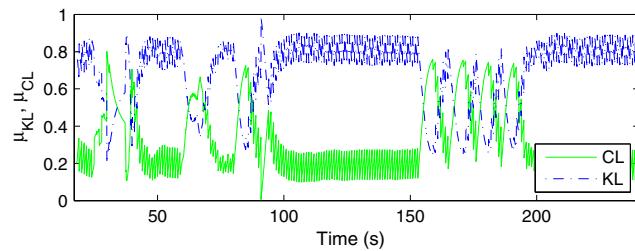


Fig. 7. Probability values of both KL (dash-dotted blue) and CL (solid green) models during the test. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

state, and only clear accelerations/decelerations require a more permissive model to be represented. Similarly to the case of lateral maneuvers, by simply applying a different tuning to the filter it is possible to classify as accelerations minor changes in the velocity. However, these situations do not correspond typically with sharp maneuvers or stop and go situations and we believe that their prediction is of no interest for collision avoidance support.

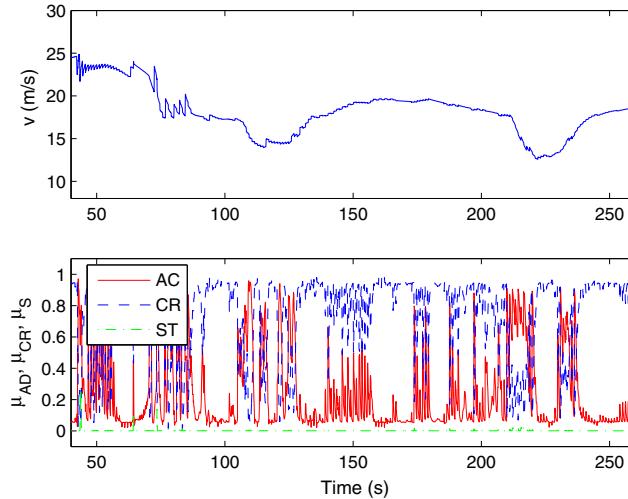


Fig. 8. In the upper image, velocity value (state variable of the IMM filter) during the trajectory shown in Fig. 4. Below, probability values of the AC (solid red) CR (dashed blue) and S (dashed-dotted green) maneuvering states during the same period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In spite of the accelerations detected by the algorithm applying model-set T1, it can be found that this model-set often suffers from peak values in the probability values of AC and CR states. According to our experiments, we find that this approach based on two CV models presents some problems in the transitions between maneuvering states. For this reason, model-set T2, based on two CA plus one stationary state was developed and evaluated.

Fig. 10 shows the performance of model-set T2 during a stretch of a test realized in the facilities of the University of Murcia. As it can be seen in the upper image, that corresponds to the velocity values during this stretch, the velocity of the vehicle remained approximately constant during some seconds, decreased after that quite abruptly until the vehicle finally stops. After a few seconds of stop, the vehicle accelerates to achieve one more time a similar value of velocity. Comparing the graph of the velocity reference and the model probability values, we can appreciate that cruise, acceleration, deceleration and stationary states are clearly detected by the algorithm implemented using model-set T2. According to our experiments, these models are capable to distinguish between AC and CR maneuvering states better than those of model-set T1. The application of a CA model with low noise assumptions to represent cruise kinematics states appears to be successful.

Regarding latency for maneuver recognition, it was found that it strongly depends on IMM parameters, and the objective situations to be predicted (how sharp an acceleration must be to be considered worth noticing). With the filter tuning performed in our tests, typical values for t_c of 0.3–0.4 s were achieved. According to the literature, these values can support the avoidance of longitudinal collisions among vehicles.

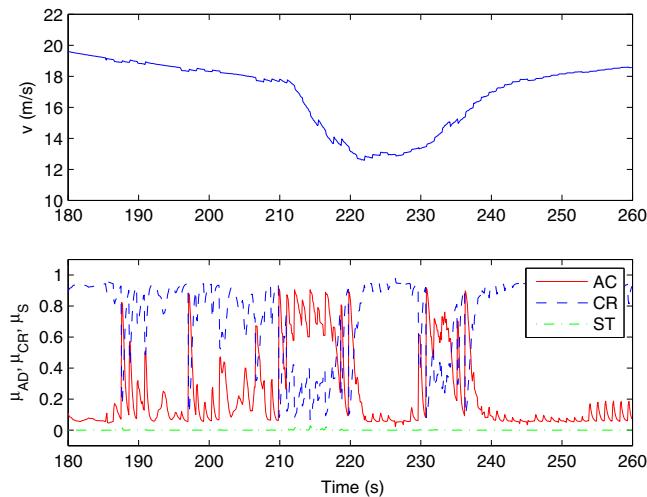


Fig. 9. Detail of the test shown in Fig. 8 with minor and major changes of speed.

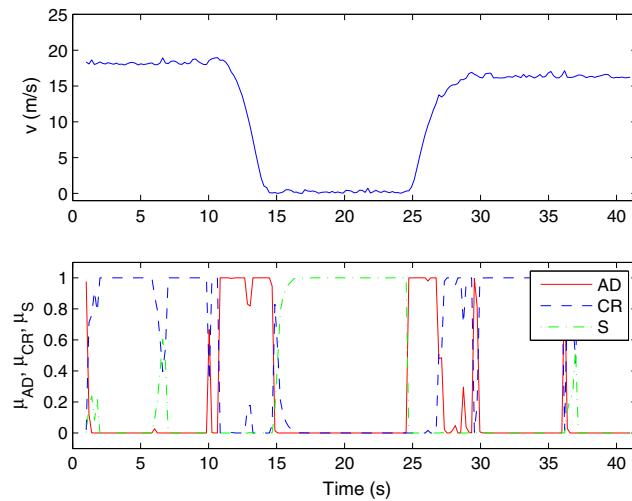


Fig. 10. A test of the model-set T2 with consecutive abrupt brake, stop period and acceleration. In the upper image, velocity profile given by the filter state variable. Below, probability values of AD (solid red) DR (dashed blue) and S (dashed-dotted green) maneuvering states. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6. Conclusions

The performance of an IMM-based algorithm for predicting longitudinal and lateral maneuvers has been presented in the article. Main contributions of these investigations can be summarized as follows:

- An algorithm for the prediction of maneuvers based on GPS/IMU units that can be integrated in the vehicles in a short or mid-term and represents no additional costs to the navigation units.
- Since predictions are based on the own vehicle kinematics, the system results independent of visibility conditions.
- Lane changes are predicted with times of response and times of prediction that can be useful for collision avoidance support.
- Abrupt accelerations and decelerations can be detected with short latency times, resulting capable to support the avoidance of longitudinal collisions.

Some other additional contributions of interest are presented in the article:

- A comparison assessment of different vehicle models to represent the vehicle behavior anytime was done. It was found that for longitudinal motions, constant acceleration models can describe both acceleration/deceleration and cruise maneuvering states, avoiding some of the problems caused by constant velocity models.
- Regarding lateral motions, the inclusion of road shape data that can be calculated from a digital map appears to be useful to eliminate false positives in lane changes due to road curves.
- It was considered an innovative description of the road based on consecutive clothoids, as a feasible way to employ road shape data as an input of a navigation data-fusion algorithm.
- A navigation algorithm that integrates road shape data with measurements coming from navigation sensors such as odometry, inertial sensors and GPS, represents a modern and interesting approach for map-aided navigation.

The analysis realized and the conclusions yielded are based on the tests performed in real environments with real data-sets obtained from two equipped vehicles.

With regard to the influence of the GNSS visibility conditions on the system performance, since GNSS measurements are employed as observations of the filter, the innovation vectors are affected by them and consequently the model probabilities. Therefore, the system performance depends on the GNSS availability to some extend. However, since odometry and inertial observations were employed as observations, the model probabilities can still be updated in absence of GPS signals. According to our tests, it can be stated that the system keep working in absence of GPS signals, as long as proprioceptive sensors represent well the vehicle pose and its kinematic state. The performance was found to be good with the most common GPS blockages of a few seconds.

Future investigations on this topic will be focused on the integration of road shape data from the digital map with measurements coming from navigation sensors by means of particle filters and multiple-model particle filters.

Acknowledgements

The authors would like to thank the Spanish Ministerio de Fomento and Ministerio de Ciencia y Tecnología for sponsoring these research activities. This work has been carried out inside the Intelligent Systems group of the University of Murcia, awarded as an excellence researching group in frames of the Spanish Plan de Ciencia y Tecnología de la Región de Murcia.

References

- Amditis, A., Polychronopoulos, A., Floudas, N., Andreone, L., 2005. Fusion of infrared vision and radar for estimating the lateral dynamics of obstacles. *Information Fusion* 6 (2), 129–141.
- Ammoun, S., Nashashibi, F., Laugueau, C., 2006. Real-time crash avoidance system on crossroads based on 802.11 devices and GPS receivers. In: IEEE Intelligent Transportation Systems Conference, Toronto, 17–20 September, pp. 1023–1028.
- Barrios, C., Himberg, H., Motai, Y., Sadek, A. Multiple model framework of adaptive extended Kalman filtering for predicting vehicle location. In: Proceedings of the IEEE Intelligent Transportation Systems Conference, Toronto, Canada, 17–20 September, pp. 1053–1059.
- Bar-Shalom, Y., Li, X.R., 1995. Multitarget–multisensor Tracking: Principles and Techniques. YBS Publishing, Storrs, CT.
- Betaille, D., Toledo-Moreo, R., Laneurit, J., 2008. Making an enhanced map for lane location based services. In: 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, China, 12–15 October 2008, ITSC 2008, pp. 711–716. ISBN: 978-1-4244-2111-4.
- Boucher, C., Lahrech, A., Noyer, J.C., 2004. Non-linear filtering for land vehicle navigation with GPS outage. In: IEEE International Conference on Systems, Man and Cybernetics, The Hague, The Netherlands.
- Creaser, J.L., Rakauskas, M.E., Ward, N.J., Laberge, J.C., Donath, M., 2007. Concept evaluation of intersection decision support (IDS) system interfaces to support drivers' gap acceptance decisions at rural stop-controlled intersections. *Transportation Research Part F: Traffic Psychology and Behaviour* 10 (3), 208–228.
- Cui, N., Hong, L., Layne, J.R., 2005. A comparison of nonlinear filtering approaches with an application to ground target tracking. *Signal Processing* 85, 1469–1492.
- ElBatt, T., Goel, S.K., Holland, G., Krishnan, H., Parikh, J., 2006. Cooperative collision warning using dedicated short range wireless communications. In: International Workshop on Vehicular Ad Hoc Networks, Los Angeles, 25–30 October, pp. 1–9.
- El Najjar, M., Bonnaffait, P., 2007. Road selection using multicriteria fusion for the road-matching problem. *IEEE Transactions on Intelligent Transportation Systems* 8 (2), 279–291.
- Ferrara, A., 2003. Automatic pre-crash collision avoidance in cars. In: 2004 IEEE Intelligent Vehicles Symposium, Parma, Italy, 14–17 June, pp. 133–138.
- Hay, C., 2005. Turn, Turn, Turn. Wheel-speed Dead Reckoning for Vehicle Navigation, GPS World, October, pp. 37–42. <<http://www.cvisproject.org/>>.
- Huang, D., Leung, H., 2004. EM-IMM based land-vehicle navigation with GPS/INS. In: Proceedings of the IEEE Intelligent Transportation Systems Conference, Washington, DC, USA, 3–6 October, pp. 624–629.
- Huang, J., Tan, H.S., 2006. Vehicle future trajectory prediction with a DGPS/INS-based positioning system. In: Proceedings of the 2006 American Control Conference, Minnesota, USA, 14–16 June, pp. 5831–5836.
- Jamson, A.H., Lai, F.C.H., Carsten, O.M.J., 2008. Potential benefits of an adaptive forward collision warning system. *Transportation Research Part C (Emerging Technologies)* 16 (4), 471–484.
- Kaempchen, N., Dietmayer, K., 2004. IMM vehicle tracking for traffic jam situations on highways. In: Proceedings 2004 International Conference on Information Fusion, Stockholm, Sweden, June 2004.
- Kesting, A., Treiber, M., Schonhof, M., Helbing, D., 2008. Adaptive cruise control design for active congestion avoidance. *Transportation Research Part C (Emerging Technologies)*. doi:10.1016/j.trc.2007.12.004.
- Lahrech, A., Boucher, C., Noyer, J.C., 2004. Fusion of GPS and odometer measurements for map-based vehicle navigation. IEEE International Conference on Industrial Technology 2, 944–948.
- Misener, J.A., Sengupta, R., Krishnan, H., 2005. Cooperative Collision Warning: Enabling Crash Avoidance with Wireless Technology. World Congress on ITS, San Francisco, 6–10 November.
- Olsen, E.C.B., 2003. Modeling Slow Lead Vehicle Lane Changing. Doctoral Dissertation, Virginia Polytechnic Institute and State University, Department of Industrial and Systems Engineering, Blacksburg, VA. <<http://scholar.lib.vt.edu/theses/available/etd-12032003-152916/>>.
- Peyret, F., Bétaille, D., Laneurit, J., Toledo-Moreo, R., 2008. Lane-level Positioning for Cooperative Systems Using EGNOS and Enhanced Digital Maps. ENC GNSS Congress, Toulouse, France.
- Polychronopoulos, A., Tsogas, M., Amditis, A.J., Andreone, L., 2007. Sensor fusion for predicting vehicles' path for collision avoidance systems. *IEEE Transactions on Intelligent Transportation Systems* 8 (3), 549–562.
- Quduss, M.A., Ochieng, W.Y., Noland, R.B., 2007. Current map-matching algorithms for transport applications: state-of-the art and future research directions. *Transportation Research Part C (Emerging Technologies)* 15, 312–328.
- Salvucci, D., Mandalia, H.M., Nobuyuki, K., Yamamura, T., 2007. Lane-change detection using a computational driver model. *Human Factors: The Journal of the Human Factors and Ergonomics Society* 29 (3), 532–542.
- Santa, J., Toledo-Moreo, R., Zamora-Izquierdo, M.A., Ubeda, B., Skarmeta, A.F., 2010. An analysis of communication and navigation issues in collision avoidance support systems. *Transportation Research Part C 18* (3), 351–366.
- Shen, S., Hong, L., Cong, S., 2006. Reliable road vehicle collision prediction with constrained filtering. *Signal Processing* 86 (11), 3339–3356.
- Stubbs, K., Arumugam, H., Masoud, O., McMillen, C., Veeraraghavan, H., Janardan, R., Papanikopoulos, N., 2003. A real-time collision warning system for intersections. In: Proceedings of Intelligent Transportation Systems America, Minneapolis, MN, USA, May 2003.
- Tan, H., Huang, J., 2006. DGPS-based vehicle-to-vehicle cooperative collision warning: engineering feasibility viewpoints. *IEEE Transactions on Intelligent Transportation Systems* 7 (4), 415–428.
- Toledo, T., Muscian, O., Lotan, T., 2008. In-vehicle data recorders for monitoring and feedback on drivers' behavior. *Transportation Research Part C (Emerging Technologies)* 16, 320–331.
- Toledo-Moreo, R., Zamora-Izquierdo, M.A., 2009. IMM-based lane change prediction in highways with low-cost GPS/INS. *IEEE Transactions on Intelligent Transportation Systems* 10 (1), 180–185.
- Toledo-Moreo, R., Sotomayor, C., Gomez-Skarmeta, A.F., 2006. Quadrant: an architecture design for intelligent vehicle services in road scenarios. In: TST-Conference, Katowice, Poland, October 2006, pp. 451–459.
- Toledo-Moreo, R., Zamora-Izquierdo, M.A., Gomez-Skarmeta, A.F., 2007. Multiple Model based Lane Change Prediction for Road Vehicles with Low Cost GPS/IMU. IEEE Intelligent Transportation Systems Conference, Seattle, 30–3 September/October, pp. 1–19.
- Toledo-Moreo, R., Zamora-Izquierdo, M.A., Ubeda-Miarro, B., Gomez-Skarmeta, A.F., 2007. High-integrity IMM-EKF-based road vehicle navigation with low-cost GPS/SBAS/INS. *IEEE Transactions on Intelligent Transportation Systems* 8 (3), 491–511.
- Toulinnet, G., Bertozzi, M., Mousset, S., Bensrhair, A., Brogi, A., 2006. Vehicle detection by means of stereo vision-based obstacles features extraction and monocular pattern analysis. *IEEE Transactions on Image Processing* 15 (8), 2364–2375.
- Ueki, J., Tasaka, S., Hatta, Y., Okada, H., 2005. Vehicular-collision avoidance support system (VCASS) by inter-vehicle communications for advanced ITS. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences A(7) (E88), 1816–1823.

- Vahidi, A., Eskandarian, A., 2003. Research advances in intelligent collision avoidance and adaptive cruise control. *IEEE Transactions on Intelligent Transportation Systems* 4 (3), 143–153.
- Varaiya, P., 1993. Smart cars on smart roads: problems of control. *IEEE Transactions on Automatic Control* 38 (2), 195–207.
- Wang, J., Schroedl, S., Mezger, K., Ortloff, R., Joos, A., Passegger, T., 2005. Lane keeping based on location technology. *IEEE Transactions on Intelligent Transportation Systems*. 6 (3), 351–356.
- Wong, C., Qidwai, U., 2004. Vehicle collision avoidance system [VCAS]. Sensors. In: Proceedings of IEEE, 24–27 October 2004, pp. 316–319.
- Yang, L.C., Yang, J.H., Feron E.M., 2004. Multiple model estimation for improving conflict detection algorithms. In: 2004 IEEE International Conference on Systems, Man and Cybernetics, 10–13 October, pp. 242–249.
- Zamora-Izquierdo, M.A., Bétaille, D.F., Peyret, F., Joly, C., 2008. Comparative study of extended Kalman filter, linearised Kalman filter and particle filter applied to low-cost GPS-based hybrid positioning system for land vehicles. *International Journal of Intelligent Information and Database Systems* 2 (2), 149–166.

Rafael Toledo-Moreo received the MS degree in automation and electronics engineering from the Technical University of Cartagena (UPCT), Spain, in 2002 and the PhD degree in computer science from the University of Murcia (UMU), Spain, in 2006. He is an associate professor with the UPCT, research member of the group of Intelligent Systems and Telematics with the UMU, member of the IFAC Technical Committee on Transportation Systems, the IEEE-RAS TC for Intelligent Transportation Systems, associate editor and IPC member of several conferences (IFAC-CTS, IEEE-ITSC, IEEE-IV, IEEE-IROS, IEEE-ICVES) and guest editor of one journal (IJIIDS). His main field of interest is road navigation systems.

Miguel A. Zamora-Izquierdo received the MS degree in automation and electronics and the PhD degree in computer science from the University of Murcia (UMU), Spain, in 1997 and 2003, respectively. In 1997, he joined the Department of Engineering and Systems, Technical University of Valencia (UPV), Spain. Since 1999 he has been an associate professor with the Department of Information and Communication Engineering, UMU. He is deputy director of the Computer Science Faculty of UMU since 2004 and he has various patents in electronic systems and numerous researching works in the ITS field.