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A Multiple Model Localization System for Outdoor Vehicles

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***Abstract*— This paper presents the problematic of localization under the IMM (Interacting Multiple Model) approach. The localization is often tackled under the accuracy problem. In order to achieve the goal of the assessment of an accurate ego localization, one often uses the merging of data coming from both exteroceptive and proprioceptive sensors. In our approach, we don't focuss much on the accuracy, but more especially on both the confidence and the robustness of this positioning. In fact, the IMM approach is based on the discretization of the vehicle evolution space into simple maneuvers, represented each by a simple dynamic model. In order to reach our objective using IMM, we assume that at every time period the true mode under which the vehicle goes is represented. After a review of different traditional filters used in vehicle localization, an IMM method is proposed and the comparison is mainly based on some robustness criteria that are presented in this paper.**

***Index Terms*— Estimation, Multiple model, Sensors Data fusion, Kalman Filtering**

I. Introduction

Most of the systems developed in the area of the driver safety have limitations resulting from the range of the perception devices. Safety system can either be automatic devices that correct vehicle trajectory, according to driver intentions, such as ESP or ABS, or systems that warn driver on incoming hazards. However, in order to include the driver in the reaction loop, safety systems must detect hazard on longer range. On highway, for instance, to warn driver on a hazard at least $5s$ before arriving on it, range of perception should be about $200m$. European project CVIS[1] and SafeSpot[2] aim at increasing road safety, cooperating with the driver. In order to achieve a long range of perception, they propose to merge data from different sources, which could be vehicles, or sensors based on the infrastructure. This fusion process will require both accurate location and good confidence in the measure. American project EDMap[3] deeply investigates this problem, creating three levels of location for each application: they are identified as a WHATROAD, WHICHLANE, or WHEREINLANE dependent applications. In increasing order of map matching accuracy, a WHATROAD application needs road-level map matching to operate; a WHICHLANE application requires map matching to a particular lane to operate, and finally a WHEREINLANE application requires map matching laterally within a lane to operate.

All these projects conclude on the critical aspect of the location task as it is used either for warning and control applications, which need not only high accuracy and confidence in the measure, but also a good robustness of the algorithm. Common localization processes use a Kalman filter in order to achieve the fusion of both proprioceptive (INS, Odometer, Steering wheels angle ...) and exteroceptive (GPS) sensors within a vehicle model [1], [2]. This approach of the problem has drawbacks, such as the confidence in the vehicle model and the quality of the modeling regarding various driving situations. This could lead to a bad confidence on the final positioning algorithm. An alternative is to use the IMM structure to solve this problem. By discretizing the vehicle evolution space into simple maneuvers - each represented by a simple model - and making these models run in parallel, we increase the robustness of the algorithm especially during strong maneuvers. So, the contribution of this work can be stated as follows: when we consider the state of art of localization methods and some robustness criteria such as the maximum position error during strong maneuvers and the uncertainty ellipse areas, the IMM method - based on an adapted model set - globally shows better performances than a single model Kalman filter.

The sequel of the document is organized in 5 sections. Next section explains traditional approaches on localization problem. Third section is devoted to the multiple model algorithm. Following section presents results on experimental data. And finally, we conclude on section five.

II. Some Traditional Methods

A. Probabilistic Localization

A number of probability based localization methods for outdoor vehicles have been studied and published since many decades. We mean by *Probabilistic Localization*, the process of getting a vehicle state vector X based on a probability determination, given some sensor inputs u_n and some executed actions $b_n (n = 1...N)$. This

[1]CVIS home page www.cvisproject.org
[2]SafeSpot home page www.safespot-eu.org
[3]Enhanced Digital Map project : www-nrd.nhtsa.dot.gov

is possible when a quasi-perfect knowledge of the data set is available. Generally, the localization algorithm is performed by combining triangulation from landmarks or map matching, with dead-reckoning that uses an *Extended Kalman filter* [1], [2]. Other famous probabilistic methods include the *Grid-based Markov localization* [3], [4] and the *Monte Carlo methods* [5].
These methods have been used and show quite good results. However, the recent particle filters, for example, remain limited by their computational cost (not yet adapted for real time problems), in spite of the good accuracy they can provide. It was proved [6] that the Kalman filtering - given good inputs - improves the effectiveness of these methods, and remains more adapted - in terms of precision - to the problem of mobile vehicles localization.

B. An Overview of Kalman Filtering Approach

In the hybrid localization systems, the vehicle state vector is estimated from exteroceptive and proprioceptive sensors data. The Kalman filter has become famous in solving this critical issue [2]. One of the characteristics of this filter is its ability to output the estimation error. Moreover, it remains optimal when the minimum of variance is considered and when the system is linear. When we assume that the sensors data have a random noise with an *a priori* known distribution, the estimation problem is reduced to solving a system of equations. This one is based on two models: a process model (1) and a measurement model (2). Let f be the process function and h the measurement function, the estimation problem is

$$X_{k+1} = f(X_k, u_k^*, w_k) \quad (1)$$
$$Y_k = h(X_k, v_k) \quad (2)$$

u_k^* is the noised input, w and v are respectively the process noise and the measurement noise. The final estimation algorithm resembles that of *a recursive predictive-corrective* algorithm for solving numerical problems as shown in *figure 1.*

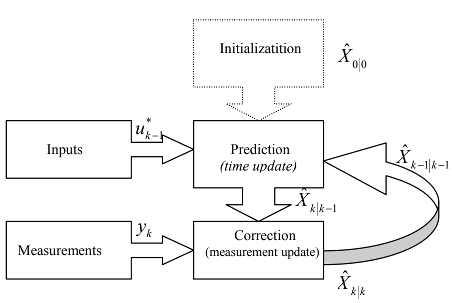


Fig. 1. Kalman Filtering Algorithm

In road vehicles localization, it is difficult to use linear functions in the process or measurement models. By linearizing the non linear functions around current estimated state, we obtain sub-optimal estimators: one of the famous, the *Extended Kalman Filter* EKF is based on the first order Taylor development of the functions around the current state. Some other methods include the *Unscented Kalman Filter* (UKF), the *Divided Differences filters of first and second order* (DD1, DD2) and the *Central Difference Kalman Filter* (CDKF). The *UKF* is founded on the (scaled) *unscented transformation*. The *DD1*, *DD2* and *CDKF* are very similar and based on the *Stirling interpolation*. For more information about these Kalman filter variants for nonlinear models, it is recommended to see [7]–[9].

III. Multiple Model for Road Vehicles Localization

A. Limitation of a mono model system

To perform a reliable maneuvering road vehicle localization, it is necessary to use a model that better fits the observed process. Therefore the vehicle model should take into account an adapted number of parameters that affect the vehicle displacement. Its complexity depends on the application for which the system is implemented for state estimation. Non linear dynamic models, for example, better suit higher speed and maneuvering road vehicle.
Problem: the complex dynamic models usually have a very specific domain of validity and their computational complexity can highly increase when a large number parameters is considered. Thus the confidence in the the final algorithm, regarding driving situation can be seriously reduced. The question is how to maintain a good robustness of our system when the observed process is not properly modeled.

B. Multiple Model applied to Maneuvering vehicles

A solution to this problem was proposed in [10]. In fact, many dynamic models are optimized to many single maneuvers (each model corresponds to a single maneuver) and the condign model is chosen following certain rules. This approach is known as a *multiple model filter*. Multiple model methods are generally applied to solve two main problems: First when the vehicle motion mode is uncertain, and second in the case of nonlinearity (maneuvering vehicle).
We define as a *mode*, a pattern of behavior of the vehicle while a *model* is the mathematical representation or description of the phenomenon pattern at a certain accuracy level. One of the main advantages of using the multiple model estimators is that not only one filter is used, but a bank of Kalman filters running in parallel and corresponding each to a particular driving situation. The model set M is obtained by discretizing the vehicle evolution space S into simple modes which are easy to

compute. Both M and S have the same cardinal at a given time. If the cardinal of S is constant during the process, the system is said to be of *fixed structure* and when it varies, it is of *variable structure* [12].

C. The Interacting Multiple Model

Many multiple model methods are available in the literature [12]. Recent study has proven that the Interacting Multiple Model *(IMM)* algorithm has the best computational complexity among the most popular algorithms that are used in tracking or localization . Its unique feature is based on the combination of the state estimates and covariance matrices according to a Markov model for the transition between vehicle maneuver states. Moreover the IMM has appeared to be the top choice for its computational cost. It is computed in four main steps:

- **Interaction:** Each filter estimate $\hat{X}^{(i)}_{k-1|k-1}$ is mixed with others using a predicted model probability $\mu^{(i)}_{k|k-1}$ and π_{ji} which are the Markov transition probability, i.e. the probability that the transition occurs from state j to state i.

$$\mu^{(i)}_{k|k-1} = \sum_j \pi_{ji}\mu^{(j)}_{k-1|k-1} \tag{3}$$

The mixing weights are given by

$$\mu^{j|i}_{k-1|k-1} = \pi_{ji}\mu^{(j)}_{k-1}/\mu^{(i)}_{k|k-1} \tag{4}$$

The mixing state estimates and their covariances can be computed as follows:

$$\bar{X}^{(i)}_{k-1|k-1} = \sum_j \hat{X}^{(j)}_{k-1|k-1}\mu^{j|i}_{k-1|k-1} \tag{5}$$

Let's take

$$\Delta\bar{X}^{(ij)}_{k-1} = (\bar{X}^{(i)}_{k-1|k-1} - \hat{X}^{(j)}_{k-1|k-1})$$

then

$$\bar{P}^{(i)}_{k-1|k-1} = \sum_j \mu^{j|i}_{k-1|k-1}[P^{(j)}_{k-1|k-1} + \Delta\bar{X}^{(ij)}_{k-1}(\Delta\bar{X}^{(ij)}_{k-1})'] \tag{6}$$

i,j = 1,2,...M (number of models).

- **Specific Filtering:** Each filter predicts its state $\hat{X}^{(i)}$ and covariance $P^{(i)}$ using a dynamic model. First, the predicted states $\hat{X}^{(i)}_{k|k-1}$ and covariances $\hat{P}^{(i)}_{k|k-1}$ are computed from the mixing states, covariances and inputs u_{k-1}. The corrective step comprises the computation of the measurement residual $\tilde{y}^{(i)}_k$, the residual covariance $S^{(i)}_k$, the updated state $\hat{X}^{(i)}_{k|k}$ estimate and its covariance $P^{(i)}_{k|k}$.
- **Mode Probability update:** Each predicted mode probability is updated with respect to the model innovation. The mode likelihoods $\Lambda^{(i)}_k$ are computed in equation (7), and then the model probabilities $\mu^{(i)}_{k|k}$ are updated (8).

$$\Lambda^{(i)}_k = \frac{\exp[-0.5(\tilde{y}^{(i)}_k)'(S^{(i)}_k)^{-1}\tilde{y}^{(i)}_k]}{|2\pi S^{(i)}_k|^{1/2}} \tag{7}$$

$$\mu^{(i)}_{k|k} = \frac{\mu^{(i)}_{k|k-1}\Lambda^{(i)}_k}{\sum_j \mu^{(j)}_{k|k-1}\Lambda^{(j)}_k} \tag{8}$$

- **Estimate fusion:** The output estimate and its covariance are computed from weighted state estimates.

$$\hat{X}_{k|k} = \sum_i \hat{X}^{(i)}_{k|k}\mu^{(i)}_{k|k} \tag{9}$$

$$P_{k|k} = \sum_i \mu^{(i)}_{k|k}[P^{(i)}_{k|k} + (\hat{X}_{k|k} - \hat{X}^{(i)}_{k|k})(\hat{X}_{k|k} - \hat{X}^{(i)}_{k|k})'] \tag{10}$$

D. Vehicle evolution models

In this subsection, we present the vehicle models that were used to perform localization. To derive the vehicle dynamic models, it is assumed that the evolution sequence is divided in almost constant dynamic behavior. The free motion models can be represented by the *quasi-Constant Velocity* (CV) and the *quasi-Constant Acceleration* (CA) models. For the lateral dynamics, we can use the quasi-constant yaw rate with constant velocity: the *Constant Turn* model (CT). In order to take into account both the longitudinal and lateral dynamics, a simple BICYCLE model (BIC) and a General Curvilinear model (GC) have been derived.

1) Linear models: The dynamic state of the vehicle for linear models is given by the state vector $X_{LM} = [x, y, \dot{x}, \dot{y}]'$. $[x, y]'$ is the position vector and $[\dot{x}, \dot{y}]'$ is the velocity vector. The acceleration vector $[\ddot{x}, \ddot{y}]'$ is the input vector for the constant acceleration model, and the yaw rate ω is used to periodically update the CT transition matrix. The transition matrix for the CV and CA are taken identical:

$$F^{CV} = F^{CA} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{11}$$

where T is the time period. The CT transition matrix is:

$$F^{CT}_{\omega|k} = \begin{bmatrix} 1 & 0 & \dfrac{sin\omega_k T}{\omega_k} & \dfrac{cos\omega_k T - 1}{\omega_k} \\ 0 & 1 & \dfrac{1 - cos\omega_k T}{\omega_k} & \dfrac{sin\omega_k T}{\omega_k} \\ 0 & 0 & cos\omega_k T & -sin\omega_k T \\ 0 & 0 & sin\omega_k T & cos\omega_k T \end{bmatrix} \tag{12}$$

The GC model takes as input the tangential acceleration γ_t and has the same transition matrix with the CT model ie $F^{GC}_{\omega_k} = F^{CT}_{\omega_k}$ [11]. The input matrix is given by

$$B^{GC}_{\gamma_T(\theta,\omega_k)} = \begin{bmatrix} -\frac{1}{\omega_k^2}cos\xi_{k+1} + \frac{1}{\omega_k^2}cos\theta_k - \frac{1}{\omega_k}Tsin\theta_k \\ -\frac{1}{\omega_k^2}sin\xi_{k+1} + \frac{1}{\omega_k^2}sin\theta_k + \frac{1}{\omega_k}Tcos\theta_k \\ \frac{1}{\omega_k}sin\xi_{k+1} - \frac{1}{\omega_k}sin\theta_k \\ -\frac{1}{\omega_k}cos\xi_{k+1} + \frac{1}{\omega_k}cos\theta_k \end{bmatrix} \quad (13)$$

with

$$\xi_{k+1} = \theta_k + \omega_k T \quad (14)$$

where θ_k is the yaw angle at time k.

The model noise covariances were calculated according to the strategy described in [13]. These matrices are obtained from a general white noise covariance matrix Q^*_T and σ^2 which is the model process noise variance, according to equation (15):

$$Q_k = \sigma^2 Q^*_T \quad (15)$$

with $Q^*_T = \begin{bmatrix} 0.25T^4 & 0 & 0.5T^3 & 0 \\ 0 & 0.25T^4 & 0 & 0.5T^3 \\ 0.5T^3 & 0 & T^2 & 0 \\ 0 & 0.5T^3 & 0 & T^2 \end{bmatrix}$

2) Nonlinear model: The *BIC* dynamic state is given by $X_{NLM} = [x, y, v, \theta]'$. v is the vehicle velocity and θ the yaw angle. Equations (16) show the discrete computation of the state vector.

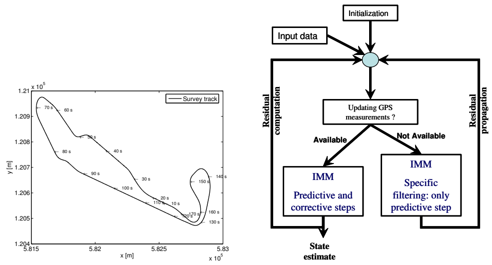
$$\begin{cases} x_{k+1} = x_k + v_k T cos(\theta_k) \\ y_{k+1} = y_k + v_k T sin(\theta_k) \\ v_{k+1} = \frac{\triangle Top}{T} D \\ \theta_{k+1} = \theta_k + \omega_k T \\ or \\ \theta_{k+1} = \theta_k + T\frac{1}{l}v_k tan(\phi_k) \end{cases} \quad (16)$$

Where l is the distance between the two axles of the vehicle, ϕ_k is the steering angle of the wheels; D is the vehicle displacement between two odometer measurements and $\triangle Top$ is the number of odometer tops during a time period T. When an odometer measurement is not available, v_{k+1} can be computed from the acceleration $\gamma_{t|k}$ as follows:$v_{k+1} = v_k + \gamma_{t|k} T$

IV. Results based on Real Measurements

A. Measurements and Test road Track

Data from various sensors was analyzed. The position, velocity and acceleration were obtained using a *GPS* at 1Hz, an Inertial Navigation System *INS* at 100Hz and an odometer at higher frequency. The yaw rate measurement was obtained by a VG400 gyrometer. The rough Data were time stamped and post-processed with the SensorHub tool chain. Therefore the GPS data were filtered before being used; this filtering module corrected relevant problems regarding multipath propagation or sensor outages occurrence. The car true trajectory was obtained using a RTK GPS. Data exploited in this work were collected from the Satory test road track in Versailles, France, See figure 2.a.



(a) (b)

Fig. 2. **(a)**: Survey track, **(b)**: Localization system based on IMM

B. System Architecture and model-set parameters

The system that was implemented can be described as a ***FSIMM*** with *model adaptation* at every time period, when a new proprioceptive sensor measurement is available; i.e. the system updates the various model transition matrices and predicts the vehicle state vector. The correction occurs only when a new GPS measurement is available, then the output is computed. See figure 2.b. The Markov transition probability matrix is set as $\Pi_1$for the first IMM system with CA, CT and CV models, with initial probabilities $\mu_1 = [0.400; 0.400; 0.200]$. For the second IMM with CA and CV models, this matrix is Π_2; The initial probabilities are $\mu_2 = [0.550; 0.450]$

$$\Pi_1 = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.9 & 0.05 \\ 0.05 & 0.05 & 0.9 \end{bmatrix} \text{ and } \Pi_2 = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$$

The standard deviation of the noise in the position estimate of various models are taken as follows: $\sigma^v_{CV} = 1m/s$, $\sigma^v_{CA} = 2m/s$, $\sigma^v_{CT} = 1.5m/s$ and $\sigma^v_{GC} = 2m/s$. For the BIC model, $\sigma^{vx}_{BIC} = 2.5m/s$ and $\sigma^{vy}_{BIC} = 0.5m/s$, while the noise in the yaw angle is $\sigma^\omega_{BIC} = 0.05rad/s$

C. Longitudinal and Lateral dynamics

1) Vehicle dynamic behavior: Strong accelerations and decelerations occur in various situations: at the starting, turnings and at the stop. Two model-sets CA-CV-IMM and CA-CT-CV-IMM were implemented and performed a good estimation on straight lines with quasi constant velocity. On figure 3.a, it is shown the estimation error of the velocity. This error increases when the vehicle strongly accelerates or decelerates. The multiple model systems and the general curvilinear model perform better than the EKF, their maximum velocity errors around 65s, are all under 5 m/s. The EKF

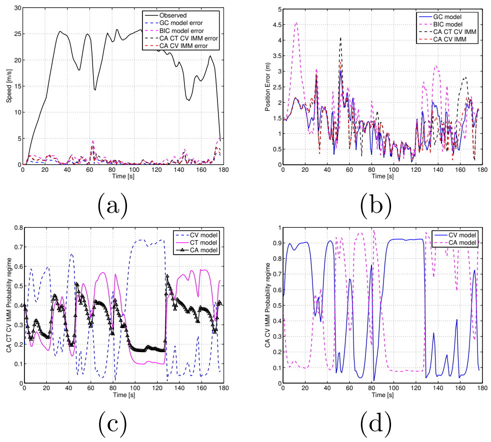


Fig. 3. **(a)**: Observed Velocity and Velocity estimation error, **(b)**: Estimation Error, **(c)**: CACTCV-IMM probability regimes, **(d)**: CACV-IMM probability regimes

velocity maximum error, which is about 5m/s is obtained at the end of course.

The IMM position error generally remains less than those for single models. At times the IMM position error can grow higher than that of single models: this is mainly observed when the vehicle passes from a straight line to a turning. Around 50s, the CACTCV-IMM position error peak is the higher. An analysis of the probability regimes (figure 3.c and figure 3.d) shows an increase of the position and velocity error on figure 3.a, but also an increase of the uncertainty ellipse areas (figure 4) when the true mode is changing.

2) Estimation uncertainty: The Kalman filter gives an a posteriori position with an uncertainty symbolized by an ellipse. We can compute the size of the axes of that ellipse by getting the eigenvalues of the covariance matrix $P_{k|k}$ weighted by the factor $k = \sqrt{-2log(1-P_a)}$, where P_a is the membership probability [7]. In our system, $P_a = 0.55$. The uncertainty ellipse areas are shown on figure 4. Strong variations are visible on the multiple model uncertainty ellipse areas, while monomodels are almost constant, but they globally remain higher.

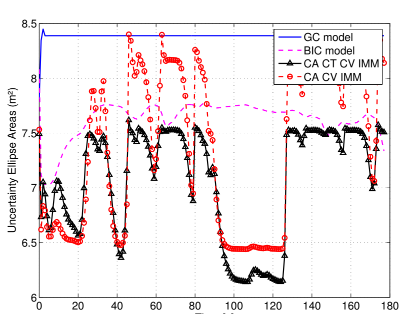


Fig. 4. Uncertainty Ellipse areas

D. Discussion

To study both the longitudinal and lateral behaviors of the vehicle, we used IMM with simple models specialized for the longitudinal and lateral control. Results from a CACTCV IMM and CACV IMM were compared to simple BICYCLE model and to General Curvilinear model. This comparison is based on the following criteria, to evaluate each system robustness regarding modeling errors. The first criterion concerns the peak of the position error during strong longitudinal and lateral dynamics, the second concerns the mean area of the uncertainty ellipses, see Table 1. First, the CACV-IMM shows as good results on straight lines as traditional EKF. The position and velocity during longitudinal maneuvers are better estimated using adapted models CA and CV. The CACVCT-IMM appeared better adapted than a simple EKF or a GC, to estimate the position in turnings and straight lines. However, this IMM architecture shows some deviations from some assumptions which are constant velocity and zero turn rates on straight lines, hence the frequent switchings between models: Figure 3.c and 3.d. On straight lines, the turn rate is assumed zero, but this assumption is not so true. The fact that non zero turn rates are detected implies that the CT model doesn't have a zero probability. Same for the CA model when a non zero acceleration is detected. But for both IMM architectures, a good noise reduction was obtained and the uncertainty ellipse areas were also reduced, compared to EKF or GC model. A low uncertainty ellipse area means that there is a better confidence in the estimation output. Finally, it is remarkable that IMM

Localization Algorithm	Peak Position Error (m)		Peak Speed Error (m/s)		Mean Uncertainty Ellipse Areas (m²)
	Longitudinal Dynamics	Strong Lateral Dynamics	Longitudinal Dynamics	Strong Lateral Dynamics	
EKF	4.5	3.3	1.0	5.0	7.75
GC Model	3.0	3.1	0.9	3.0	8.4
CACV IMM	2.9	3.6	1.0	4.0	7.5
CACTCV IMM	3.0	4.1	1.0	4.0	7.0

TABLE I

Comparison of Localization algorithm performances

is a good estimator for vehicle localization because it shows a high flexibility for dynamic systems. From Table 1 above, we conclude that in some situations, multiple model may degrade the accuracy of the localization. In fact if we consider that only one mode is true at a given time, this degradation comes from the use of other modes with non zero likelihoods - see the error peaks - However, the multiple model increases the confidence in the estimation through the reduction of areas of uncertainty ellipses.

V. Conclusion

A multiple model approach for outdoor vehicle localization is presented. IMM is proposed and compared to single Extended Kalman filters in the situation of longitudinal and lateral dynamics. The performances were evaluated with measurements from an INS, a GPS, an odometer and a gyrometer. The CACV-IMM and CACVCT-IMM show good results in estimation error reduction for maneuvering vehicles. The comparison was done on the basis of two robustness criteria which are the position and velocity error peaks, and the mean uncertainty ellipse areas. One of the main advantages of this approach is its ability to model the vehicle evolution space at any time from very simple dynamic models. In order to avoid the variations observed in the estimation error covariances, future work could use instead of probability, another sensors data modeling. The aim would be to better characterize the different dynamic models, to quantify and reduce conflict and to assess the confidence on the various integrated models. All this improvement will be done using the belief theory. Finally, to get the vehicle state estimation without exteroceptive data, it could be interesting to optimize the IMM estimator during the predictive step by using an adaptive model switching mechanism.

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