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Maneuver Classification for Road Vehicles with Constrained Filtering Techniques ⋆

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Abstract: Environment perception and situation awareness are keystones for autonomous road vehicles. The problem of maneuver classification for road vehicles in the context of multi-model state estimation under model uncertainty is addressed in this paper. The conventional approach is to define different motion models that match the desired type of movements. In this work we used a single motion model as a starting point and applied constraints to construct such filters that are fine tuned for the predefined maneuvers. The estimation is carried out in the interacting multiple model framework, where the elemental filters are constrained Kalman filters. To capture the characteristics of the considered maneuvers linear equality and non-equality state constraints were used. The performance of the proposed method is demonstrated in a simulation environment participating an observer and a maneuvering vehicle.

Keywords: Manoeuvring target, Road traffic, Constraints, Estimation algorithms, Simulation, Filtering

1. INTRODUCTION

Environment perception is an actively researched domain in the vehicle industry. Both active safety and autonomous functions need situation awareness and robust sensing of the surrounding objects and traffic participants to work safely and effectively. The amount of available sensors and the possible combinations for fusion is vast, offering a wide spectrum in terms of cost and performance (Van Brummelen et al., 2018, Zhu et al., 2017). As the autonomous vehicle industry grows the demand for physical test environments and proving grounds, although being expensive, increase (Szalay et al., 2018). On the other hand, a considerable part of development and testing of autonomous functions are done in simulated environments (Rosique et al., 2019, Amer et al., 2017), which is especially true for safety functions (Kale et al., 2019). Current sensors, software and data fusion techniques cannot ensure fully autonomous vehicles to operate. De Ponte Müller (2017) and Kuutti et al. (2018) conclude that the fusion of observations acquired in cooperative and non-cooperative ways could produce the best relative position estimation performance.

State estimation of maneuvering vehicles can be considered as a problem where the motion model is uncertain, that is we do not know in advance what motion model to use in the estimation algorithm. One way to handle this uncertainty is to design multiple filters, one for each maneuver to be considered and accept the output of the best according to some measure. Multiple-model filtering has an extended literature and applications in the field of maneuvering target tracking (Li and Jilkov, 2005). The exact solution of the multiple-model estimation problem considers every possible combinations of the predefined models at each timestep, rendering the problem computationally intractable due to the exponentially increasing complexity. Practical algorithms reduce the problem in a way that the lookback horizon is only one or two timesteps long, as conceptualized in the generalized pseudo-Bayesian estimator of first and second order by Watanabe and Tzafestas (1993). The interacting multiple model (IMM) estimator is another approximate solution to the multiple-model problem, presented by Blom and Bar-Shalom (1988). The algorithm is capable of working with Kalman filters of different kind as well as particle filters (Törő et al., 2019).

In cases where the reachable states of a system are limited by physical bounds the performance of the estimation can be increased by inserting this additional information into the filtering process as constraint equations (Gupta and Hauser, 2007). Maneuvering target tracking has extended

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literature featuring sophisticated methods. Ormsby et al. (2006) analysed the multiple model estimation problem using pre-fit, post-fit and generalized residuals. Seifzadeh et al. (2013) used a multiple-model particle filter constrained with human-generated soft data for target tracking. Jia and Evans (2017) presented a method for camera video smoothing with multiple-model filtering where linear non-equality constraints represented the image black boarders.

In this work we present a method that can be used to recognize or classify maneuvers of road vehicles. The main elements of our solution are multi-model estimation and constrained filtering. Using refined motion models and vehicle dynamics was not the intent of this study thus constant velocity model with additive noise in the form of random accelerations was applied. The constrained filters are arranged in the structure of the interacting multiple model estimator. Each filter is customized by constraints to match a specific type of maneuver. The quality of a filter is determined by examining the post-fit residual.

The paper is structured as follows. Section 2 summarizes the theoretical background of the presented method. The simulation framework for testing and the maneuver detection methods are presented in Section 3. Section 4 examines the performance of the estimator. Concluding remarks are given in Section 5.

2. TECHNIQUES FOR MANEUVER CLASSIFICATION

In this study the considered system is described by a linear discrete time dynamic model with time index k:

$$\mathbf{x}_{k+1} = F_k\mathbf{x}_k + G_k\mathbf{w}_k \tag{1}$$

$$\mathbf{z}_k = H_k\mathbf{x}_k + \mathbf{v}_k\,, \tag{2}$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$ is the state vector that evolves according to the matrix $F_k \in \mathbb{R}^{n_x \times n_x}$ and $\mathbf{w}_k \in \mathbb{R}^{n_w}$ is the process noise vector which acts through the matrix $G_k \in \mathbb{R}^{n_x \times n_w}$. The measurement vector $\mathbf{z}_k \in \mathbb{R}^{n_z}$ is generated from the state through the matrix $H_k \in \mathbb{R}^{n_z \times n_x}$ and $\mathbf{v}_k \in \mathbb{R}^{n_z}$ is an additive noise vector. Both $\mathbf{w}_k$ and $\mathbf{v}_k$ are from zero mean Gaussian distributions with covariance Q_k and R_k.

The core of the proposed classification algorithm is the Kalman filter which is the optimal estimator for linear Gaussian systems. The usual formulation reads as

$$\hat{\mathbf{x}}_{k|k-1} = F_k\hat{\mathbf{x}}_{k-1|k-1} \tag{3}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F^\top + G_k Q_k G_k^\top \tag{4}$$

$$\mathbf{r}_{k|k-1} = \mathbf{z}_k - H_k\hat{\mathbf{x}}_{k|k-1} \tag{5}$$

$$S_{k|k-1} = H_k P_{k|k-1} H_k^\top + R_k \tag{6}$$

$$K_k = P_{k|k-1} H_k^\top S_{k|k-1}^{-1} \tag{7}$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k\mathbf{r}_{k|k-1} \tag{8}$$

$$P_{k|k} = (\mathbf{I} - K_k H_k)\, P_{k|k-1} \tag{9}$$

Eq. (3) and (5), using the system model, gives predictions to the state and the error covariance. The pre-fit measurement residual is given by (5) and its covariance by (6). With the help of the optimal Kalman gain (7) the updated state and error covariance is computed in (8) and (9).

The pre-fit measurement residual or innovation (5) is a commonly used quantity from which indicators about the quality of the estimation can be derived. With the help of the pre-fit measurement residual and its covariance (6) a zero mean normal PDF is evaluated:

$$\Lambda = \mathcal{N}\left(\mathbf{r}; 0, S\right) \tag{10}$$

which yields a scalar value that quantifies the estimation quality. The post-fit measurement residual is defined as

$$\mathbf{r}_{k|k} = \mathbf{z}_k - H_k\hat{\mathbf{x}}_{k|k}. \tag{11}$$

The relation between the pre-fit and post-fit residual is a linear transformation:

$$\mathbf{r}_{k|k} = \mathbf{z}_k - H_k\left(\hat{\mathbf{x}}_{k|k-1} + K_k\mathbf{r}_{k|k-1}\right) \tag{12}$$

$$= \mathbf{r}_{k|k-1} - H_k K_k \mathbf{r}_{k|k-1} \tag{13}$$

$$= (\mathbf{I} - H_k K_k)\, \mathbf{r}_{k|k-1}\,. \tag{14}$$

The covariance of the post-fit measurement residual is therefore:

$$S_{k|k} = (\mathbf{I} - H_k K_k)\, S_{k|k-1}\, (\mathbf{I} - H_k K_k)^\top\,. \tag{15}$$

2.1 Multi-model estimation

Model uncertainties can rise for several reasons. In the context of maneuvering target tracking the uncertainty is caused by the lack of our knowledge what maneuver the object is performing and the practice that we choose to use simple motion models instead of a complex one with high state space dimensions. The reason for the latter is partly that the system to be observable we would need sensors of higher number and diversity and at the same time the vehicle model would require fine tuning of higher degree (Tin Leung et al., 2011, Schubert et al., 2008).

Multi-model (MM) estimation is an approach to handle model uncertainties. If the model describing the system is not known or uncertain but we have a prior set of plausible models, multi-model estimation is a viable method. The advantage of multi-model estimation is twofold. On one hand using a model that is correct or is close to the reality, the quality of the estimation will be better. On he other hand the knowledge of the actual model can be an important information telling us how the observed system behaves. The basic principle of multi-model estimation is to design multiple filters, run them parallel and choose one with the best performance.

The IMM estimator has linear scaling characteristics in terms of the considered models (Bar-Shalom et al., 2004). The structure of the IMM estimator is depicted in Fig. 1. The inputs to the recursive algorithm at timestep k are the mode-conditioned state estimates and the mixing weights as a matrix $\nu^{(i,j)}$. The state estimates consists of a mean value and a covariance matrix, describing a Gaussian distribution. At the mixing stage the input for filter $j \in 1 \dots J$ is computed as a weighted sum of Gaussians:

$$\tilde{\mathbf{x}}_{k-1}^{(j)} = \sum_{i=1}^{J} \nu_{k-1}^{(i,j)} \mathbf{x}_{k-1}^{(i)} \tag{16}$$

$$\tilde{P}_{k-1}^{(j)} = \sum_{i=1}^{J} \nu_{k-1}^{(i,j)} \Big[P_{k-1}^{(i)} + (\mathbf{x}_{k-1}^{(i)} - \tilde{\mathbf{x}}_{k-1}^{(j)})(\mathbf{x}_{k-1}^{(i)} - \tilde{\mathbf{x}}_{k-1}^{(j)})^\top\Big] \tag{17}$$

These values and the measurement vector $\mathbf{z}_k$ are passed to the elemental filters. Beside the state estimation the filters

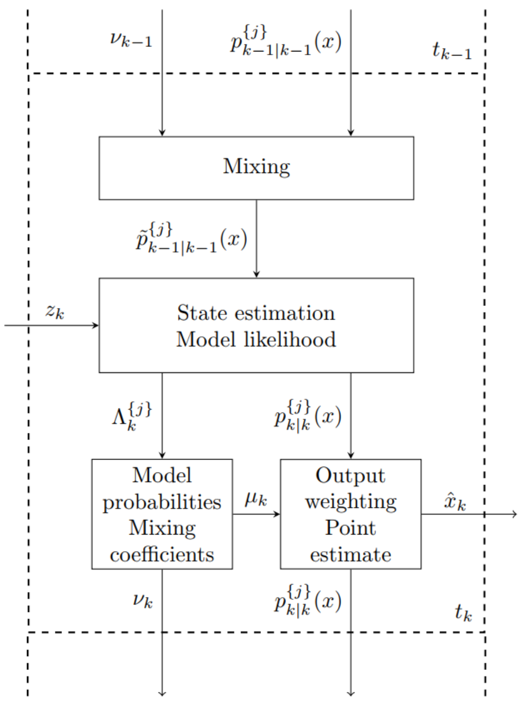

Fig. 1. One cycle of the interacting multiple model estimator

also produce the residuals and the associated covariance matrices. From these a model likelihood is computed as

$$\mathcal{L}^{(j)}_k(\mathbf{z}_k) = \mathcal{N}\left(\mathbf{r}_k; 0, S^{(j)}_k\right) . \tag{18}$$

The mode probabilities are not purely the likelihoods because mode switching dynamics are implemented with the help of the state transition matrix π through which the prior values are derived:

$$\mu^{(j)}_{k|k-1} = \sum_{i=1}^{J} \pi_{ij}\mu^{(i)}_{k-1} . \tag{19}$$

The updated mode probabilities are:

$$\mu^{(j)}_k = \frac{\mathcal{L}^{(j)}_k \mu^{(j)}_{k|k-1}}{\sum_{i=1}^{J} \mathcal{L}^{(i)}_k \mu^{(i)}_{k|k-1}} , \tag{20}$$

An overall estimate can be computed by weighting each filter output by the mode probabilities:

$$\hat{\mathbf{x}}_{k|k} = \sum_{j=1}^{J} \mu^{(j)}_k \mathbf{x}^{(j)}_{k|k} . \tag{21}$$

The associated covariance matrix is

$$P_{k|k} = \sum_{j=1}^{J} \mu^j_k \left[P^{(j)}_{k|k\cdot} + (\mathbf{x}^{(j)}_{k|k} - \hat{\mathbf{x}}_{k|k})(\mathbf{x}^{(j)}_{k|k} - \hat{\mathbf{x}}_{k|k})^\mathsf{T}\right] . \tag{22}$$

The mixing coefficients for the next step in the recursion is given by

$$\nu^{(i,j)}_{k-1} = \frac{\pi_{ij}\mu^{(i)}_{k-1}}{\sum_{m=1}^{J} \pi_{mj}\mu^{(m)}_{k-1}} \quad i, j = 1 \ldots J . \tag{23}$$

2.2 Constrained filtering

The performance of the Kalman filter, however being optimal can be increased in special cases. If the system investigated is subject to certain constraints that are not included in the system model (1)-(2) the filter may produce estimations that violate the constraints. Various methods exist that provide ways to incorporate the constraining information in either the system model or in the filtering process (Simon and Chia, 2002). The system model may be reformulated in a way that it reflects the constraints. This can be achieved by combining states or introducing generalized coordinates. The original, possibly physical meaning of the coordinates however will be lost. Leaving the system model unchanged, the filtering equations can be modified to ensure the estimation will not violate the constraints.

Constraints can be classified according to various aspects: linear or non-linear, equality or non-equality, time dependent or time independent, hard or soft constraints. In this work only linear equality and non-equality constraints will be presented which have the form

$$D_k\mathbf{x}_k = \mathbf{d}_k \tag{24}$$
$$D_k\mathbf{x}_k \leq \mathbf{d}_k , \tag{25}$$

where $\mathbf{d}_k \in \mathbb{R}^{n_c}$ is the constraint vector and $D_k \in \mathbf{R}^{n_c \times n_x}$ is the constraint matrix.

2.3 Measurement augmentation

A straightforward approach to include equality constraints in the estimation is to augment the measurement equation (2) with (24). This method is referred as the Measurement Augmentation Kalman Filter (MAKF) (Teixeira et al., 2007). If the constraints are soft, meaning that (24) should only be satisfied approximately, an additional noise term can reflect this property:

$$D_k\mathbf{x}_k = \mathbf{d}_k + \delta_k . \tag{26}$$

The augmented measurement equation reads as:

$$\begin{bmatrix} \mathbf{z}_k \\ \mathbf{d}_k \end{bmatrix} = \begin{bmatrix} H_k \\ D_k \end{bmatrix} \mathbf{x}_k + \begin{bmatrix} \mathbf{v}_k \\ \delta_k \end{bmatrix} \tag{27}$$

or in shorter form:

$$\mathbf{z}^d_k = H^d_k\mathbf{x}_k + \mathbf{v}^d_k \tag{28}$$

The covariance matrix of the augmented noise term is R^d_k which is block diagonal with entries R_k and $R^\delta_k = \mathrm{Cov}[\delta_k]$. Hard constraints are modelled with $\delta_k = 0$ and $R^\delta_k = 0$ rendering the extra measurement equation noiseless, hence the name Perfect Measurements (PM).

The MAKF uses the original KF equations for the prediction step and for the update step. The augmented equations are:

$$\mathbf{r}^d_{k|k-1} = \mathbf{z}^d_k - H^d_k\hat{\mathbf{x}}_{k|k-1} \tag{29}$$
$$S^d_k = H^d_k P_{k|k-1}\left(H^d_k\right)^\top + R^d_k \tag{30}$$
$$K^d_k = P_{k|k-1}\left(H^d_k\right)^\top + R^d_k \tag{31}$$
$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K^d_k\mathbf{r}^d_{k|k-1} \tag{32}$$
$$P_{k|k} = \left(\mathbf{I} - K^d_k H^d_k\right) P_{k|k-1} \tag{33}$$

If PM are used the $R^\delta_k = 0$ block in R^d_k will create a Kalman gain such that the updated estimate will be consistent with the constraints.

2.4 Estimate projection

Estimate projection is another way to include constraints in the filtering process. Given the updated estimate constrained optimization problem can formulated as :

$$\hat{\mathbf{x}}^d_{k|k} = \arg\min_{\mathbf{x}} \left(\mathbf{x} - \hat{\mathbf{x}}_{k|k}\right)^\top W \left(\mathbf{x} - \hat{\mathbf{x}}\right) \tag{34}$$

such that (24) or (25) is satisfied (Teixeira et al., 2009). The weighting matrix W is positive-definite and if its value is chosen as $W = P^{-1}_{k|k}$ one gets the minimum variance constrained estimator in the form:

$$\hat{\mathbf{x}}^d_{k|k} = \hat{\mathbf{x}}_{k|k} + K^p_k \left(\mathbf{d}_k - D_k \hat{\mathbf{x}}_{k|k}\right) , \tag{35}$$

where the gain K^p_k is a projector:

$$K^p_k = P_{k|k} D^\top_k \left(D_k P_{k|k} D^\top_k\right)^{-1} . \tag{36}$$

The covariance of the constrained estimation is

$$P^d_{k|k} = P_{k|k} - K^p_k D_k P_{k|k} . \tag{37}$$

The estimate projection method allows inequality constraints to be included (Simon, 2010). Given the inequality constraints in the form of (25) we choose the rows of D_k and $\mathbf{d}_k$ that correspond to active constraints, that is the ones that are violated by $\hat{\mathbf{x}}_{k|k}$. From these rows we form a new matrix D^*_k and vector $\mathbf{d}^*_k$ and solve the optimization problem of (34) subject to

$$D^*_k \hat{\mathbf{x}}_{k|k} = \mathbf{d}^*_k . \tag{38}$$

3. CASE STUDY

This section presents a case study for maneuver classification using constrained Kalman filters in the IMM structure with the following concept. The observer vehicle moves along the road and takes radar measurements on the maneuvering vehicle. The measurements are interpreted in a polar coordinate system attached to the sensor. The state vector describing the maneuvering vehicle contains position and velocity components relative to the observer. The observer vehicle is also able to detect the geometry of the lanes. This information is used to determine in which lane the observed vehicle is moving.

The observed vehicle performs a predefined sequence of maneuvers that consists of constant velocity motion in the left or right lane or lane changing. The sequence of maneuvers is listed in Table 1.

Table 1. List of front vehicle maneuvers

Maneuver	Start time	End time
CV right lane	0	2
Lane changing	2	4
CV left lane	4	8
Lane changing	8	10
CV right lane	10	14
Turning right lane	14	21
CV right lane	21	25

The radar sensor on the rear vehicle produces distance, bearing angle and speed measurements. The state space model that describes the motion of the front vehicle uses the state vector $\mathbf{x} = [x, \dot{x}, y, \dot{y}]^\top$ interpreted in the reference frame of the observer. The reason for choosing this simple state vector with Cartesian coordinates, on one hand, is that it can model practically any motion. While other motion models which include polar position or velocity components can perform better (Gustafsson and Isaksson, 1996), in the IMM algorithm pose difficulties. State vectors with different components or dimensions cannot be mixed without an additional procedure, described by Granström et al. (2015). The other reason is that the choice of the Cartesian coordinate system naturally arises because, as will be shown, in this representation the position and velocity constraints we are using are decoupled.

The radar measurements are interpreted in a polar coordinate system which requires a transformation to be compatible with the state vector. The transformation can be done at the update stage of the filtering process or prior. Since we use multiple models it is computationally less expensive to apply the transformation prior and feed the measurements in Cartesian components to the IMM estimator instead of using a non-linear measurement model in each filter.

The original measurement vector includes the bearing angle, distance and speed values: $\mathbf{z}^p = [\vartheta, r, v]$. The covariance matrix associated to the angular and distance part of the measurement vector is $R_1 = \mathrm{diag}(\sigma^2_\vartheta, \sigma^2_r)$ and for the angular and speed part is $R_2 = \mathrm{diag}(\sigma^2_\vartheta, \sigma^2_v)$. The transformed measurement vector is interpreted in the state space: $\mathbf{z} = [x, \dot{x}, y, \dot{y}]$. For brevity the calculation for the position components are presented, the velocity components can be obtained in an analogous way. The covariance matrix R^p_1 of the transformed position measurements are computed with the help of the Jacobian of the polar to Cartesian transformation:

$$R^p = J R_1 J^\top \tag{39}$$

where

$$J = \begin{bmatrix} -r\sin\vartheta & \cos\vartheta \\ r\cos\vartheta & \sin\vartheta \end{bmatrix} \tag{40}$$

The resultant matrix has the form:

$$R^p_1 = \begin{bmatrix} \sigma^2_r \cos^2\vartheta + \sigma^2_\vartheta r^2 \sin\vartheta & \left(\sigma^2_r - \sigma^2_\vartheta r^2\right)\cos\vartheta\sin\vartheta \\ \left(\sigma^2_r - \sigma^2_\vartheta r^2\right)\cos\vartheta\sin\vartheta & \sigma^2_\vartheta r^2 \cos^2\vartheta + \sigma^2_r \sin\vartheta \end{bmatrix} \tag{41}$$

3.1 Constraints

Constant velocity motion in the left or right lanes are characterized by constraints as follows. The y coordinate has hard upper and lower bounds, defining the vehicle position as in-lane or between lanes. The constraint for the velocity component $\dot{y}$ is adopted as a zero mean Gaussian. The reason for the latter is that we do not want to make a restriction on the direction and allow a high value for the lateral velocity component. For the lane changing maneuver we define upper and lower bound for y and $\dot{y}$ too. The constraints are summarized in Table 2. The methods to estimate the state vector of the front vehicle with the defined constraints are summarized in Table 3. The y coordinate in the constraint equations in Table 2 should be compensated against the curvature of the road, that is the lateral displacement at the distance of the target vehicle is subtracted from it.

The velocity constraint for the lane changing maneuver is not linear, however the implementation poses no difficulties. The sign of the estimated lateral velocity decides

Fig. 2. Observer (rear) and maneuvering (front) vehicle in the Prescan simulation

whether we should use $\dot{y} > 0.5$ or $\dot{y} < -0.5$, which is a simple linear non-equality constraint. The constraints are applied in the following way. First the soft constraints are included, if there is any, as augmented measurements. After that the estimated state vector is projected according to the velocity constraint. For the lane changing maneuver only inequality constraints are present, thus the method described in Section 2.4 is applied.

Table 2. State constraints for maneuvers. The width of a lane in denoted by l

Mode	Position constraint	Velocity constraint
Right lane CV	$1/2l - 0.5 < y < 1/2l + 0.5$	$\dot{y} \in \mathcal{N}(0,1)$
Left lane CV	$3/2l - 0.5 < y < 3/2l + 0.5$	$\dot{y} \in \mathcal{N}(0,1)$
Lane changing	$1/2l + 0.5 < y < 3/2l - 0.5$	$\lvert\dot{y}\rvert > 0.5$

3.2 Simulation environment

The testing environment was created in Prescan (Hendriks et al., 2010). The setup consists of a two-lane road with straight and curved segments Two vehicles are moving along the road, one following the other (Fig. 2). The rear vehicle is the observer which moves with constant speed of 15 m/s while the front vehicle performs maneuvers. The ground truth data and the observations generated in the Prescan simulation are transferred to Simulink with real time communications. The schematic of the data flow and estimation process is depicted in Figure 3.

4. RESULTS

The proposed filters were implemented in Simulink. The noise for the motion model is adopted as a discrete white noise acceleration with covariance $Q = \mathrm{diag}(\sigma_x^2, \sigma_y^2)$, where $\sigma_x = \sigma_y = 1\mathrm{m/s}$. The system matrices are:

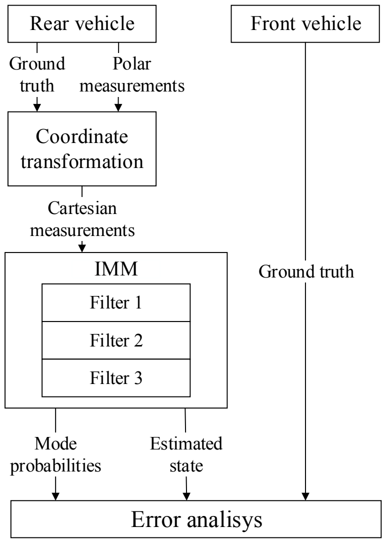

Fig. 3. Outline of data flow in the estimation process

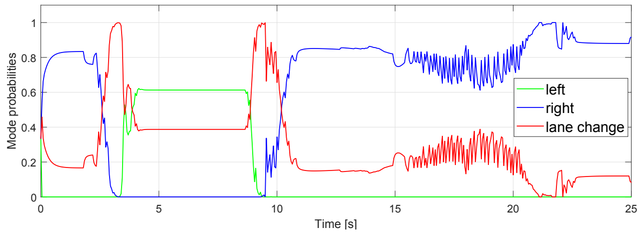

Fig. 4. Probabilities of the investigated maneuvers

$$\mathbf{F} = \mathbf{I}_2 \otimes \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \tag{42}$$

$$\mathbf{G} = \mathbf{I}_2 \otimes \begin{bmatrix} \frac{T_s^2}{2} \\ T_s \end{bmatrix}, \tag{43}$$

where $T_s = 0.1$ is the sampling time. The matrix $\mathbf{H}$, because the measurement space and the state space are identical, is a unit matrix.

The initial mode probabilities were set to equal values. The mode transition probability matrix is designed as

$$\pi = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \tag{44}$$

The probabilities of the considered maneuvers are shown in Fig. 4. The oscillation between 15. . . 20 sec is caused by the uncertainty in the lane geometry detection process while moving in curve, since the resolution of the polynomial fit in Prescan was reduced artificially for simplification purposes.

Table 3. Realization of constraints

Mode	Constraint type	Estimate method
Right lane CV	Hard inequality	Estimate projection
	Soft equality	Measurement augmentation
Left lane CV	Hard inequality	Estimate projection
	Soft equality	Measurement augmentation
Lane change	Hard inequality	Estimation projection

5. CONCLUSION

A method for maneuver classification of road vehicles is presented. The algorithm uses constrained filters in the IMM structure and at the current form is able to detect a lane changing maneuver and tell what lane the target vehicle is in. The proposed method is flexible regarding the type of constraints used and could involve other type of maneuvers too. A comprehensive study would reveal which maneuvers are best detectable by which constraint, possibly using different motion models. If curved road is detected CT motion model could be used to better estimate the state of the observed vehicle which would lead to the variable structure IMM estimator. A particle filter based solution could offer more flexibility regarding the system model and noise characteristics and, more importantly the formulation of constraints. Drawing particles from a distribution that reflects a certain constraint would allow more sophisticated classification.

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