# Road User Tracking Using a Dempster-Shafer Based Classifying Multiple-Model PHD Filter

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***Abstract*—Multi-object tracking requires appropriate motion models to predict the objects' states. In case of road user tracking, objects with different motion characteristics have to be concerned. Moreover, the motion characteristics and with that the appropriate motion model depends on the object's class. In this contribution a classifying multiple-model probability hypothesis density filter based on Dempster-Shafer theory is proposed. The object class is estimated based on features of the measurement as well as features of the estimated objects' states. Furthermore, the transition probabilities between the model modes are not static, but adapted with the estimated class probabilities of each track. It is shown, that a single multiple model filter is able to track multiple road users with different motion characteristics. Additionally, the integration of the Dempster-Shafer based classification in the filter framework improves the object class estimation significantly. Finally, an application of the filter on real world data of an intersection perception system is presented.**

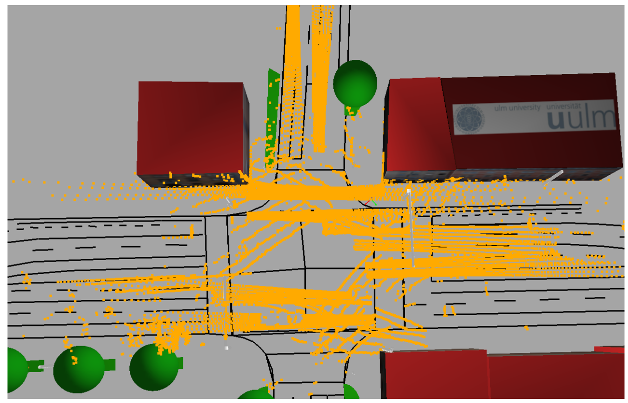



Fig. 1. Aligned range data (beam intersections with the floor) of the 14 installed laserscanners depicted in orange.

## I. Introduction

Urban intersections are a known black spot for fatal accidents [1]. Since the introduction of passive safety systems, the number of serious injured passengers inside a car deceases, but pedestrians and two-wheeler are left with limited protection. Latest German accident analysis [2] even show, that the injuries of such vulnerable road users (VRU) at urban intersections have been increased. Therefore active safety systems and especially advanced driver assistance systems (ADAS), which warn the driver early enough or even mitigate accidents are on the rise. A major part of the joint project Ko-PER which is part of of the research initiative Ko-FAS [3], is to increase traffic safety at intersections based on cooperative perception systems. Vehicles are equipped with sensors to perceive their environment and share the perceived objects and their ego position using vehicle-to-vehicle (V2V) communication. But, due to a generally high traffic density and complex topology at urban intersections, the communication and the field of perception bandwidth are restricted. Thus, a perception system which provides a occlusion free birds eye view of the intersection area has been installed at three test intersections in Germany. One of these is a public intersection in Aschaffenburg, Germany with a medium traffic volume of $22,000$ to $23,000$ vehicles per day. The perception and object recognition is base on a network of $14$ SICK LD-MRS research multilayer laserscanners mounted at infrastructure components, like lampposts and traffic lights at least four meters above street level. In Figure $1$ a 3D model of the intersection and a visualization of the aligned laser range data is shown. The system detects all road users in the intersection area, classifies the classes pedestrian, bike, car, and truck and estimates their pose, velocity, and dimension. The object information is finally broadcasted to vehicles which can fuse it in their environment perception to achieve a significant extension of their environment information.

### A. Problem addressed

The key for a system assisting the driver on its way through an intersection lies in reliable road user recognition and tracking. To cover the variety of different objects and their motion behavior a multiple-class and multiple-model filter - the Classifying Multiple-Model Probability Hypothesis Density (CMMPHD) filter - is presented. The system has to deal with two major challenges: First, the classification task can not be solved using just class specific features of the measurements and second, the used filter has to support multiple process models to model the objects motion. To solve the first challenge measurement based features as well as track specific features are used. Furthermore we allow uncertain classification decisions. For instance, consider the maximum velocity of a track, which will later be introduced as a track feature, is $1$ m/s. In this case all classes are possible, because all distinguished classes can have this velocity. But if the feature value is 20 m/s, it is very unlikely that the track is a pedestrian. In contrast to Bayes, the Dempster-Shafer theory of Evidence (DST) [4] explicitly allows an undecided state of our knowledge [5]. On the other hand Koks states in [5], that Dempster-Shafer calculations are more complex than their Bayes' analogues. Thus, in this work the classification based on measurement features is done using Bayes' theorem. In the measurement model of the tracker, the class probabilities are used as focal elements of a measurement specific basic belief assignment (BBA) according to DST. Additionally, each track holds a BBA which is updated with the BBA of the measurement in each filter cycle. The track specific BBA enables the representation of the state of being undecided and the fusion of track feature BBAs. A brief introduction to the DST is given in Section II.

The second challenge is tackled using a filter which is based on the Jump Markov Probability Hypothesis Density (JMPHD) filter introduced by Vo et al. [6] and theoretically reasoned by Mahler [7]. Instead of modelling the different motion states of an object (e.g. left turn and right turn), we use the multiple model modes to represent the motion characteristics of different object classes. Most apparent is the diversity of motion characteristics in case of pedestrians and vehicles. Due to its agility, the motion direction of pedestrians is assumed to be independent of its orientation. On the other hand, the motion of vehicles is modeled using a single track model in which the motion direction and orientation are coupled. This Gaussian Mixture Multiple Model PHD (GM-MMPHD) filter has already been introduced in [8] and [9]. In the GM-CMMPHD filter the Markovian transition matrix between the model modes is dynamic. It is demonstrated, that the elements of the transition matrix can be adapted using the current BBAs of the track. Even though the Gaussians of the GM-PHD do not mandatory represent a single track, they are used this way in this work. Due to the used merging method, it is very unlikely to have more than one object represented by one Gaussian component.

The remainder of this paper is organized as follows: In Section II a brief introduction to DST is given. Subsequently, the used methods to detect and classify moving objects is summarized in III and in IV the GM-MMPHD filter is reviewed. In Section V the extension of the GM-MMPHD filter to classify tracks using the DST is introduced. Finally, the performance of the GM-CMMPHD filter in terms of tracking and classification is demonstrated based on real world data of the public intersection.

## II. Dempster-Shafer Theory of Evidence

This section gives a brief introduction to the basics of the Dempster-Shafer theory of evidence (DST) [10]. Further informations about the DST can be found for example in [5], [11] and [12]. The DST itself is a more general formulation of the probability theory. All following equations are valid for probability functions as well. Among others, the DST is used in research on classification and sensor data fusion [13].

In DST, a set of elementary hypotheses $a_i$ called *frame of discernment* $\Omega$ is defined:

$$\Omega = \{a_i\}, \quad i = 1, \ldots, n \tag{1}$$

The elementary hypotheses have to be disjoint and are required to cover the complete event space. To get a mapping from the power set $2^\Omega$ to the interval $[0, 1]$ a basic belief assignment (BBA) $m$ is defined as:

$$m(\emptyset) = 0, \tag{2}$$

$$\sum_{A \subseteq \Omega} m(A) = 1. \tag{3}$$

Thus, the mass $m(A)$ can be interpreted as the certainty of the proposition $A$ to be correct. Consequently, it is possible to make propositions about disjoint unions of elementary events. Although it is not essential for the DST that BBAs are measurements of certainty, in this work only probability functions are used as BBAs.

A BBA is called a Bayesian BBA if all *focal elements* are elementary elements. A focal element is a subset $A$ of $\Omega$ with $m(A) > 0$. In case of only one focal element, the BBA is said to be categorical and a Bayesian BBA with exactly two focal elements is said to be binary.

Using the Dempster-Shafer rule of combination two BBAs $m_1$ and $m_2$ can be fused as follows:

$$\begin{aligned} m_{1\oplus 2}(A) &= m_1(A) \oplus m_2(A) \\ &= \frac{\sum\limits_{X \cap Y = A} m_1(X) m_2(Y)}{1 - \sum\limits_{X \cap Y = \emptyset} m_1(X) m_2(Y)} \forall A \in 2^\Omega. \end{aligned} \tag{4}$$

The denominator represents a normalization of the resulting BBA if the BBAs are partly contradictory. A contradiction means, that in BBA $m_1$ exists at least one proposition $X$ with $m_1(X) > 0$ which is not compatible to any proposition in $m_2$. It can be shown, that the combination rule above equals the Bayes rule in case of binary BBAs.

The support for the proposition $A$ of the BBA $m$ is called the degree of *belief* $Bel_m(A)$ with:

$$Bel_m(A) = \sum_{B \subseteq A, B \neq \emptyset} m(B). \tag{5}$$

The sum of all BBAs of $m$ not contradicting $A$ are referred as the plausibility $Pl_m(A)$ with:

$$Pl_m(A) = \sum_{B \cap A \neq \emptyset} m(B). \tag{6}$$

Thus, the uncertainty interval $U_m(A)$ is defined as:

$$U_m(A) = Pl_m(A) - Bel_m(A). \tag{7}$$

The uncertainty is a measure of how exact the proposition can be expressed using the BBA. Figure 2 shows a visualization of belief, plausibility and uncertainty.

In order to make a decision, a BBA can be interpreted in a pessimistic and an optimistic manner. Here, the belief $Bel_m$ can be used as the pessimistic and the plausibility $Pl_m$ as the

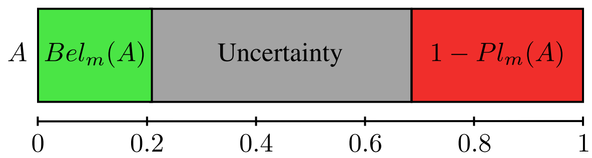



Fig. 2. Belief, plausibility and uncertainty of a BBA

optimistic guess, but there is also additional information in the uncertainty $U_m$ of every proposition. Thus, the BBA needs to be transformed into a probabilistic function in order to make decisions. One method to do this is the pignistic transformation [12]:

$$BetP_m(A) = \sum_{B \subseteq \Omega} \frac{|A \cap B|}{|B|} m(B) \tag{8}$$

where $|\cdot|$ denotes the number of elementary hypotheses of $\Omega$ in $\cdot$. Since there is no information about the distribution of the probability mass of every $A$ the mass of $A$ is equally distributed on all elements of $A$. As already mentioned, $BetP_m$ can be bounded by a pessimistic and an optimistic guess:

$$Bel_m(A) \leq BetP_m(A) \leq Pl_m(A). \tag{9}$$

If there is only a certain level of correctness of a BBA this level can be expresses as a probability $\alpha$. This probability can be used to *discount* a BBA prior to combination with another BBA. The discounted BBA $m^\alpha$ is defined as:

$$m^\alpha(A) = \begin{cases} \alpha m(A), & A \neq \emptyset \\ 1 - \alpha + \alpha m(\Omega), & A = \Omega \end{cases} . \tag{10}$$

## III. Moving Objects Detection and Classification

The input of the multi-object filter are measurements of the objects at the intersection. As described in Section I, each measurement consists of its pose, dimension, and class probabilities. To determine these values, the first step is to classify the measurement points of the sensors in background measurements, reflected from static, not moving objects and foreground measurements, reflected from dynamic, moving objects. Therefore, a statistical background model which exploits, that the mounting position of the sensors is fixed is used. Subsequently, the foreground measurements are clustered using a grid-based density-based spatial clustering for applications with noise (DBSCAN) algorithm and passed to the object classification. For further details about the object detection refer to [14] and [15]. The classification is based on point cloud features of the detected objects. A naive Bayesian classifier classifies the point clouds in pedestrians, bikes, cars, and trucks. Due to the marginal difference in the features of pedestrians and bikes, its hard to distinguish them based on static features. The popular method to extract the lags of pedestrians ([16], [17]) is not applicable here, since the laser-scanners' perspective is from above. Obviously, the dimension of the objects is a strong feature to distinguish the classes. But, due to occlusions and the perspective of the sensors the system sometimes detects just parts of an object. In case of partly detected objects the dimension feature is ambiguous. Therefore, additional features have been determined to enable a robust and reliable classification in the perception area of the system. The following features figured out to be significant:

- Absolute $x$, $y$, and $z$ value of the major axis of the point cloud
- Norm of the object dimension in $x-y$-plane which is parallel to street surface
- Height of the point cloud from street surface
- Standard deviation of the euclidean point to point distances in a point cloud

The features are calculated as in [18].

Now the class probabilities $P_{C,k}^{(z_j)}$ of the $j^{th}$ cluster can be calculated using Bayes' theorem:

$$P_{C,k}^{(z_j)} = \left[ p(c_1|F)^{(z_j)}, \ldots, p(c_{N_C}|F)^{(z_j)} \right]^T \tag{11}$$

$$p(c_j|F)^{(z_j)} = \frac{p(c_j) \prod_{l=1}^{L} p(f_l|c_j)^{(z_j)}}{\sum_{j=1}^{N_C} \left( p(c_j) \prod_{l=1}^{L} p(f_l|c_j)^{(z_j)} \right)} \tag{12}$$

Here $F$ is the union of all $L$ independent features $f_l$ ($l = 1, \ldots, K$) of the cluster $z_j$ and $C$ represents the $N_C$ object classes $c_j$ ($j = 1, \ldots, N_C$). The feature probability distributions for each class $p(f_l|c_j)$ can be arbitrary and are approximated using Gaussian mixtures. The training set consists of a large number of manually labeled real world sensor data. The a priori class probability $p(c_j)$ is region based and determined by means of the labeled data. To complete the measurement, the pose and dimensions are calculated from the point cloud of the cluster.

## IV. The GM-MMPHD filter

The aim of the filter is to estimate the number of objects and their states based on the measurements described in III. Since the number of objects as well as the object states are random variables, the multi-object state $X_k$ of $N_k$ objects to time $k$ and the multi-object measurement $Z_k$ are represented by a random finite set (RFS) [19]. This leads to the multi-object Bayes filter [19] to solve the tracking problem. The multi-object Bayes filter is in general computationally intractable, therefore the GM-PHD approximation is used [20], which propagates only the first moment of the multi-object state over time. To incorporate the motion characteristics of the road users a linear constant velocity model for pedestrians and a nonlinear single-track model for all other road users is used within the GM-MMPHD filter of [9]. The filter is summarized in the following.

The multiple-model filter additionally estimates the multiple-model mode $o$ to each track which requires an extension of the multi-object state [7].

$$\ddot{X} = \{\ddot{\mathbf{x}}_1, \ldots, \ddot{\mathbf{x}}_N\} = \{(\mathbf{x}_1, o_1), \ldots, (\mathbf{x}_N, o_N)\} \tag{13}$$

The extended multi-object state is represented by $\ddot{X}$. Assuming a Gaussian measurement and process noise, [20] introduced a Gaussian mixture approximation of the PHD-filter, which itself is a computational tractable approximation of the multi-object Bayes filter. In [6] the GM-PHD filter is extended to multiple-model systems. Here, the a posteriori PHD $v_{k-1}$ is assumed to be a Gaussian mixture of the form:

$$v'(\ddot{\mathbf{x}}) = \sum_{i=1}^{J'(o')} w'^{(i)}(o')\mathcal{N}\left(\mathbf{x}; \mu'^{(i)}(o'), P'^{(i)}(o')\right) \tag{14}$$

For readability reasons all variables to time $k-1$ are marked with the superscript $'$. With (14) the predicted PHD is a GM, too:

$$\begin{aligned} v_{k|k-1}(\ddot{\mathbf{x}}) = & \sum_{o'} \sum_{i=1}^{J_{k|k-1}(o')} w_{k|k-1}^{(i)}(o|o') \\ & \mathcal{N}\left(\mathbf{x}; \mu_{k|k-1}^{(i)}(o|o'), P_{k|k-1}^{(i)}(o|o')\right) \end{aligned} \tag{15}$$

The weights of the predicted Gaussian components

$$w_{k|k-1}^{(i)}(o|o') = p_{S,k|k-1}(o')t_{k|k-1}^{(i)}(o|o')w_{k-1}^{(i)}(o') \tag{16}$$

are calculated by the multiplication of the a posteriori weight $w_{k-1}^{(i)}(o')$ with the survival probability $p_{S,k|k-1}(o')$ and the transition probability $t_{k|k-1}^{(i)}(o|o')$ of the model mode. In contrast to common multiple-model approaches, in this work the transition matrix is not constant. It is adapted by means of track specific class BBAs, which is described in Section V-B. The mean $\mathbf{m}_{k|k-1}^{(i)}(o|o')$ and covariances $P_{k|k-1}^{(i)}(o|o')$ of the GM components are predicted using the process matrix $F_{k-1}(o)$ and process noise $Q_{k-1}(o)$ of the motion model $o$:

$$\mu_{k|k-1}^{(i)}(o|o') = F_{k-1}(o)\mu_{k-1}^{(i)}(o') \tag{17}$$

$$P_{k|k-1}^{(i)}(o|o') = Q_{k-1}(o) + F_{k-1}(o)P_{k-1}^{(i)}(o')F_{k-1}(o)^T \tag{18}$$

In (15) the sum over all permutations of the model dependent GMs is calculated and the weights are multiplied with the transition probability to predict the PHD function. This models the interaction between the models. An unscented transformation is used to transform the state and covariance between the motion models [9].

The innovation of the PHD is calculated on the lines of the standard GM-PHD filter.

$$\begin{aligned} v_k(\ddot{\mathbf{x}}) = & (1 - p_{D,k}(o))v_{k|k-1}(\ddot{\mathbf{x}}) + \\ & \sum_{\mathbf{z}\in Z_k} \sum_{i=1}^{J_{k|k-1}(o)} w_k^{(i)}(o;\mathbf{z})\mathcal{N}\left(\mathbf{x}; \mu_k^{(i)}(o,\mathbf{z}), P_k^{(i)}(o)\right) \end{aligned} \tag{19}$$

The first term of (19) represents the case that a target was not detected. Therefore, the a priori intensity $v_{k|k-1}(\ddot{\mathbf{x}})$ is weighted with the probability of a missed detection $(1 - p_{D,k}(o))$. The second term of (19) represents the creation of $|Z_k|$ new Gaussian mixtures for each of the predicted tracks according to (20) and (21), where $|Z_k|$ is the number of received measurements.

$$w_k^{(i)}(o;\mathbf{z}) = \frac{p_{D,k}(o)w_{k|k-1}^{(i)}(o)q_k^{(i)}(o;\mathbf{z})}{\kappa_k(\mathbf{z}) + \sum_o p_{D,k}(o)\sum_{i=1}^{J_{k|k-1}(o)} w_{k|k-1}^{(i)}(o)q_k^{(i)}(o;\mathbf{z})} \tag{20}$$

$$q_k^{(i)}(o;\mathbf{z}) = \mathcal{N}\left(\mathbf{z}; H_k\mu_{k|k-1}^{(i)}(o), H_kP_{k|k-1}^{(i)}(o)H_k^T + R_k\right) \tag{21}$$

$\kappa_k(\mathbf{z})$ models the intensity of the multi-object clutter process. Since the point of the GM-MMPHD filter is to more accurately estimate the object states, it is unnecessary to know the current motion model $o$. Thus, according to [7], it is marginalized over $o$ to get the PHD of the objects alone:

$$v_k(\mathbf{x}) = \sum_o v_k(\ddot{\mathbf{x}}) \tag{22}$$

To set up new tracks a measurement driven birth model is used ([13], [21]). As already mentioned, it is not mandatory that each Gaussian represents a track. But in this application the merging method of the GM is designed to avoid the representation of multiple tracks with one Gaussian. Thus, Gaussians with a weight greater $0.5$ can contribute tracks to the track set according to [22].

## V. Dempster-Shafer Based Classifying GM-MMPHD Filter

Beside the multi-object state, also the class probabilities or class BBA of the tracks are interesting. Thus, the desired a posteriori probability distribution consists of the extended state $\ddot{X}_k$ and the class BBAs $M_C$:

$$p(\ddot{X}_k, M_C|Z_k) = p(M_C|\ddot{X}_k, Z_k)p(\ddot{X}_k|Z_k) \tag{23}$$

with

$$M_C = \left\{m_k^{(1)}, \ldots, m_k^{(\hat{N}_k)}\right\}. \tag{24}$$

Due to its assumed independence, the state and class can be estimated sequentially. Starting with the estimation of the multi-object state $\ddot{X}_k$, just the class BBAs of the estimated number of objects $\hat{N}_k$ have to be concerned. In this work the classifying GM-MMPHD filter is used to track road users. Thus, the *frame of discernment* is

$$\Omega = \{B, C, P, T\}, \tag{25}$$

with bike ($B$), car ($C$), pedestrian ($P$), and truck ($T$). In order to estimate the class BBA of the tracks based on measurement and track features as well as to adapt the transition probabilities of the multiple model modes, a BBA is attached to each Gaussian component of the GM. Hence, according to [8] and [9] each distribution is represented by a triple

$$\left\{w^{(i)}, \mathcal{N}\left(x, \mu^{(i)}, P^{(i)}\right), m^{(i)}\right\}. \tag{26}$$

### A. Using BBAs for Track Classification

A major advantage of PHD filters is the missing explicit data association step. Unfortunately, object classification is often based on features which are calculated from the raw sensor measurements. So an association of the measurements and the tracks is needed. Due to that, classification results strongly depend on the feature quality in the current measurement. To reduce this dependency the classification result is filtered over time.

*1) BBA of Measurement Features:* Therefore the Bayesian class probabilities introduced in Section III are used as *focal elements* of a class BBA of the measurement as follows:

$$m_k^{z_j}(B) = p_k^{z_j}(B|M) \tag{27}$$
$$m_k^{z_j}(C) = p_k^{z_j}(C|M) \tag{28}$$
$$m_k^{z_j}(P) = p_k^{z_j}(P|M) \tag{29}$$
$$m_k^{z_j}(T) = p_k^{z_j}(T|M) \tag{30}$$

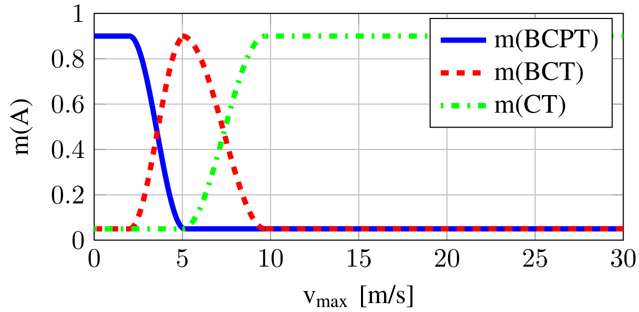
Now the a posteriori BBA can be updated with the BBA of the measurement easily by using DST fusion (4) and discounting (10):

$$m_k^{(i)} = m_{k|k-1}^{z_j} \oplus \left(m_k^{z_j}\right)^{p_{LP}} \tag{31}$$

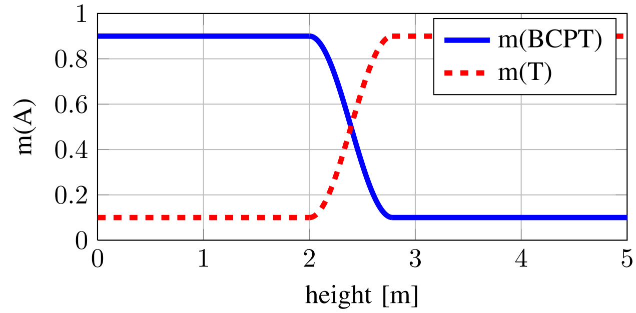
Here $\left(m_k^{z_j}\right)^{p_{LP}}$ is the BBA of measurement $z_j$ discounted with the parameter $p_{LP} \ll 1$ which acts as a low pass filter. Additionally, the BBAs have to be predicted in order to ensure that the BBA does not focus on one hypothesis. This is also done by discounting. In case of missed detections the weight of the Gaussian is decreased by the GM-MMPHD filter (19) and in the next prediction the mass is shifted towards $\Omega$ by discounting. Thus, missed detections do not require explicit handling.

*2) BBA of Track Features:* After the estimation of the multi-object state, features of the track can be used to improve the classification performance. As already motivated in Section I, there are no characteristic measurement features to distinguish a bike and a pedestrian or the front of a car, but they strongly differ in their maximum velocity. For a low maximum velocity all classes are possible, so the mass of the BBA for $\Omega$ is high and the class specific masses are low. If the maximum velocity raises, the probability for the track being a pedestrian decreases which is represented with a decrease of the mass assigned to the proposition $BCPT$ and an increase of $BCT$, and so on. The distribution of the masses is shown in Figure 3(a). The new BBA, based on the mass curves in Figure 3(a) is calculated and fused with the BBA of the track.

Additionally, track features improve the classification performance even in the case of sparse, cluttered and split measurements of an object which prevents a reliable classification using measurement features. Thus, the estimated length, width, and height of the tracks showed significance. The masses of the BBA for the height is depicted in Figure 3(b). The length and width features are just used in the central part of the intersection. Here the perception system is in general able to detect the whole object, thus the estimated object dimension




(a)




(b)

Fig. 3. Masses of the BBA for the maximum velocity (a) and height (b) of the tracks.

can be compared to common dimensions of the classes. Based on the estimated yaw angle of the objects, the length and width features of the tracks are more reliable than those of the measurements.

To make a decision about the object class, the BBA of the Gaussian has to be transformed to probabilities for the considered classes using (9). Finally, the class with the highest probability is chosen:

$$c_k^{(i)} = \underset{j}{\operatorname{argmax}}\, BetP_k^{(i)}(c_j) \tag{32}$$

### B. Using Track BBAs to Adapt Transition Matrix

The model modes represent the motion characteristic of different object classes, so the transition matrix of each track depends on its class probability. In case of road user tracking two object classes which have completely different motion principles have to be considered. On the one hand pedestrians and on the other hand bikes and vehicles. Pedestrians are very agile and their direction of motion is independent of the orientation (can move sidewards). Therefore, a constant velocity point model is used. All other road users, here bikes, cars, and trucks have constraints in their motion ability, which is commonly modeled using a nonlinear constant velocity single track model [13]. By linearizing the single track model according to the extended Kalman filter, the equations introduced in Section IV can be used for both models. Thus, the model transition matrix $T_{k|k-1}$ is $2 \times 2$ and depends on the pignistic probabilities of the track BBAs for $P$ and $BCT$:

$$T_{k|k-1}^{(i)} = \begin{bmatrix} BetP_m(P)^{(i)} & BetP_m(BCT)^{(i)} \\ BetP_m(P)^{(i)} & BetP_m(BCT)^{(i)} \end{bmatrix} \quad (33)$$

## VI. Results

For characterization of the tracking and classification performance real time capable implementations of the GM-MMPHD and the GM-CMMPHD filter are applied on a real world sequence of the public test intersection in Aschaffenburg. Since a huge number of road users crosses the intersection during the sequence, Figure 4 depicts just some exemplary tracks of the GM-CMMPHD filter. Obviously, all shown road users are tracked persistent and with smooth trajectories across the intersection. It is conspicuous, that the course of the pedestrian's trajectory is not as smooth as those of the other classes. This is due to the multiple model structure of the filter and shows the agility of the pedestrian which is tracked with a linear CV model. For the other classes a nonlinear single track CV model is used. For the perception system just the three observed approaches Figure 1 to the intersection are relevant. Since the egresses of the intersection are hardly in the field of perception, some tracks are lost. Moreover, Figure 4 shows a reliable classification of the road users.

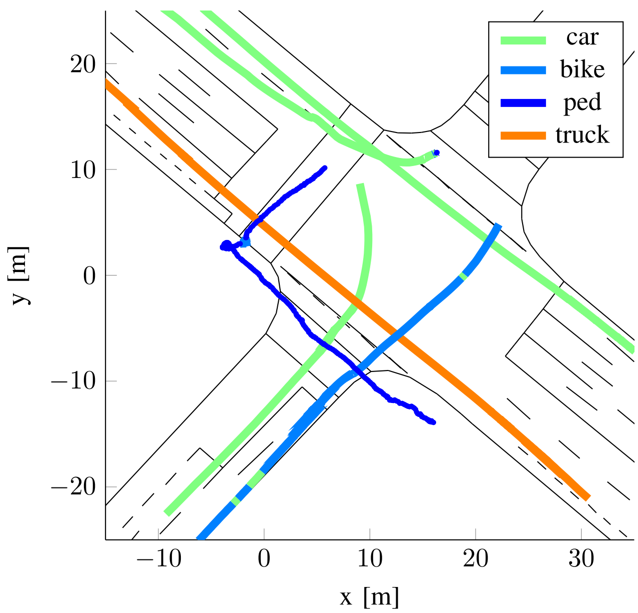
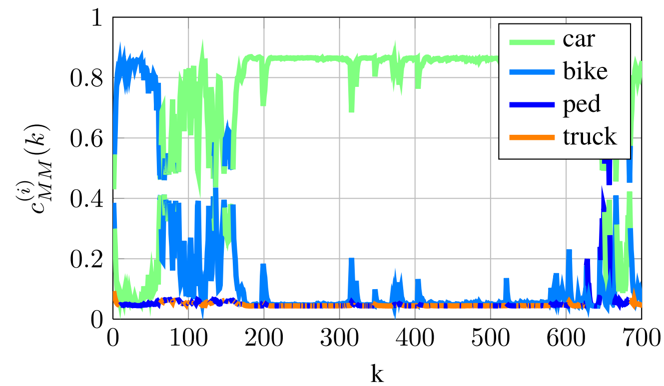
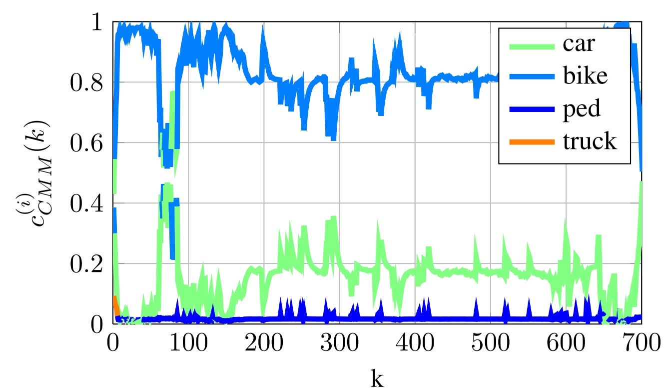



Fig. 4. Exemplary GM-CMMPHD filter tracks of one bike, pedestrian and truck respectively as well as three cars.

Especially in case of bike classification the advantage of the Dempster-Shafer based GM-CMMPHD filter becomes apparent. Thus, Figure 5 contrasts the probabilities of the three most likely bike track classes of the GM-MMPHD (Fig. 5(a)) and the GM-CMMPHD (Fig. 5(b)) filter. The GM-MMPHD filter, which does not use track features, is not able to classify the bike correctly. Due to the week feature differences of pedestrians, bike, and cars and the hard decisions of the Bayes classifier, the track is mostly recognized as car. On the contrary, the filter with track features (GM-CMMPHD) in Figure 5(b). Here the classification is mostly correct. Due to the the track features, giving mass to classes and their combinations enabled by DST, the bike can be distinguished from the other classes.




(a)




(b)

Fig. 5. Probability values of the three most probable classes of the bike track in Figure 4 crossing the intersection. (a) is the result of the filter without (MMPHD) and (b) with track features (CMMPHD).

## VII. Conclusion and Future Works

In this contribution, an approach to use Dempster-Shafer Theory to integrate measurement and track features for road user classification into a GM multiple-model probability density filter framework has been proposed. In order to estimate the class probabilities of the tracks, a BBA is attached to each Gaussian component of the GM. Class probabilities are calculated to each measurement using a Bayes classifier. With the class probabilities as *focal elements*, BBAs of the measurement are generated and fused with the BBA of the tracks in each filter cycle. Moreover, class BBAs based on track features - the estimated maximum velocity, the height, as well as the length and width - are incorporated. The results show, that the filter with track features outperforms the filter without track features in terms of classification. Thus, the approach enables to classify the road users in bike, car, pedestrian, and truck. Furthermore, additional features and classes can be added easily, due to DST representation.

Subsequently, the proposed multiple-model approach enables the tracking of road users with their appropriate motion models using a single filter. In contrast to common MM filters, in this work the transition matrix is not constant, but adapted based on the estimated class probabilities. Thus, is is shown, that the filter is able to model the agility of pedestrians as well as the smooth trajectories of bikes, cars, and trucks.

In future, a multi-sensor GM-CMMPHD filter which integrates also the measurements of a camera system at the intersection is planned. Moreover, the proposed DST based classifying multiple-model approach will be integrated in multi-target multi-Bernoulli filters.

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## REFERENCES

[1] European Road Safety Observatory, "Traffic safety basic facts 2010 junctions," European Road Safety Observatory, Tech. Rep., January 2010, safetyNet, Project co-financed by the European Commission. [Online]. Available: http://ec.europa.eu/transport/road_safety/specialist/statistics/care_reports_graphics/index_en.htm

[2] Destatis, "Press release no. 462," 2011. [Online]. Available: http://www.destatis.de/jetspeed/portal/cms/Sites/destatis/Internet/DE/Presse/pm/2011/12/PD11__462__46241.psml

[3] "Forschungsinitiative Ko-FAS," http://www.ko-fas.de, July 2012. [Online]. Available: http://www.ko-fas.de

[4] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the em algorithm," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 39, no. 1, pp. 1–38, 1977.

[5] D. Koks and S. Challa, "An introduction to bayesian and dempster-shafer data fusion," Defence Science and Tech Org, Tech. Rep., 2003.

[6] B.-N. Vo, A. Pasha, and H. D. Tuan, "A gaussian mixture phd filter for nonlinear jump markov models," in *Decision and Control, 2006 45th IEEE Conference on*, dec. 2006, pp. 3162–3167.

[7] R. Mahler, "On multitarget jump-markov filters," in *15th International Conference on Information Fusion, 2012*, 2012.

[8] D. Meissner, S. Reuter, and K. Dietmayer, "Multi-Model-PHD-Filter zur Verfolgung von Verkehrsteilnehmern an Kreuzungen mit Laserscannern," in *8. Workshop Fahrerassistenzsysteme FAS 2012*, 2012, pp. 57–66. [Online]. Available: http://www.uni-das.de/de/Veranstaltungen/fas2012.php

[9] ——, "Road user tracking at intersections using a multiple-model phd filter," in *IEEE Intelligent Vehicles Symposium (IV) to appear*, 6 2013.

[10] G. Shafer, *A Mathematical Theory of Evidence*. Princeton: Princeton University Press, 1976.

[11] R. Yager, M. Fedrizzi, and J. K. Eds, *Advances in the Dempster-Shafer Theory of Evidence*. New York: Wiley, 1994.

[12] P. Smets, "The combination of evidence in the transferable belief model," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 5, pp. 447–458, 5 1990.

[13] M. Munz, M. Mhlisch, and K. Dietmayer, "Generic centralized multi sensor data fusion based on probabilistic sensor and environment models for driver assistance systems," *IEEE Intelligent Transportation Systems Magazine*, vol. 2, no. 1, pp. 6–17, 2010.

[14] D. Meissner, S. Reuter, and K. Dietmayer, "Real-time detection and tracking of pedestrians at intersections using a network of laserscanners," in *IEEE Intelligent Vehicles Symposium (IV)*, 6 2012, pp. 630–635.

[15] S. Reuter, D. Meissner, and K. Dietmayer, "Multi-object tracking at intersections using the cardinalized probability hypothesis density filter," in *15th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 9 2012, pp. 1172–1177.

[16] H. Zhao and R. Shibasaki, "A novel system for tracking pedestrians using multiple single-row laser-range scanners," *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, vol. 35, no. 2, pp. 283–291, 2005.

[17] K. Fuerstenberg and K. Dietmayer, "Object tracking and classification for multiple active safety and comfort applications using a multilayer laser scanner," in *Intelligent Vehicles Symposium, 2004 IEEE*, June, pp. 802–807.

[18] C. Premebida, O. Ludwig, and U. Nunes, "Exploiting lidar-based features on pedestrian detection in urban scenarios," in *Intelligent Transportation Systems, 2009. ITSC '09. 12th International IEEE Conference on*, Oct., pp. 1–6.

[19] R. P. Mahler, *Statistical Multisource-Multitarget Information Fusion*. Artech House Inc., Norwood, 2007.

[20] B.-N. Vo and W.-K. Ma, "The gaussian mixture probability hypothesis density filter," *IEEE Transactions on Signal Processing*, vol. 54, no. 11, pp. 4091–4104, 11 2006.

[21] B. Ristic, D. Clark, B.-N. Vo, and B.-T. Vo, "Adaptive target birth intensity for PHD and CPHD filters," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 48, no. 2, pp. 1656–1668, 2012.

[22] K. Panta, D. E. Clark, and B.-N. Vo, "Data association and track management for the gaussian mixture probability hypothesis density filter," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 45, no. 3, pp. 1003–1016, july 2009.