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De-cluttering with Integrated Probabilistic Data Association for Multisensor Multitarget ACC Vehicle Tracking

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***Abstract*— In the field of automotive environment perception, the state estimation problem of other road users with sensors like video, radar, lidar, or combinations of them has been solved for years now. However, driver assistance systems like ACC are only available for restricted environments like highways and rural roads today. Especially in complex environments, the uncertainty of target existence induced from missing and false detections becomes the dominating error source. Traditional approaches for track verification are rule based systems and trained classifiers. In this contribution, we present an automotive application of the Integrated Probabilistic Data Association (IPDA) Filter superseding additional validation modules by modeling the probabilistic knowledge about both, state and existence, as temporal Markov chains and computing filter estimates for both issues. The temporal evolution and measurement update models for state and existence estimation are presented for the vehicle tracking problem as well as results from a sensor fusion setup with video and multibeam lidar.**

I. INTRODUCTION

Future ACC systems will be predictive and traffic situation aware in order to save ressources and to perform more adequate reactions for less driver interaction. Indispensable features of these next generation systems including emergency braking and stop-and-go are a wide field of view over several lanes, a large detection range for high speed expressway usage, the ability to robustly detect other moving and non-moving road users, and finally precise velocity and yaw rate estimates to compute meaningful time-forward predictions for situation analysis. For this purpose, but especially to overcome the detection by motion approach utilized by first generation single ranging sensor systems by substituting or reinforcing dynamic decision features with appearance features, several vehicle detection schemes based on vision [1],[2] or heterogeneous sensorfusion [3],[4] have been developed. We suggested a sensorfusion setup with lidar and vision as depicted in Figure 1. The test vehicle is equipped with an automotive CMOS video camera and a 16 channel multibeam lidar with a detection range of about 200 meters. The sensors are aligned in the spatial and temporal domains and operate at 16 Hz. Figure 2 summarizes the vehicle detection procedure as explained in detail in [5]. The focus of this contribution is the subsequent tracking stage using the IPDA filtering algorithm to increase the detection performance. The key idea of this approach is to remove hard decisions within the processing chain to reduce parameters to be optimized on the first hand and to decide about object existence based on time accumulated probabilistic evidence on the other hand.

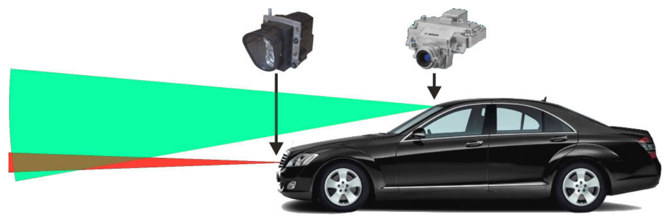

Fig. 1. Sensor mounting points and fields of view for the sensorfusion setup combining multibeam lidar and monocular vision.

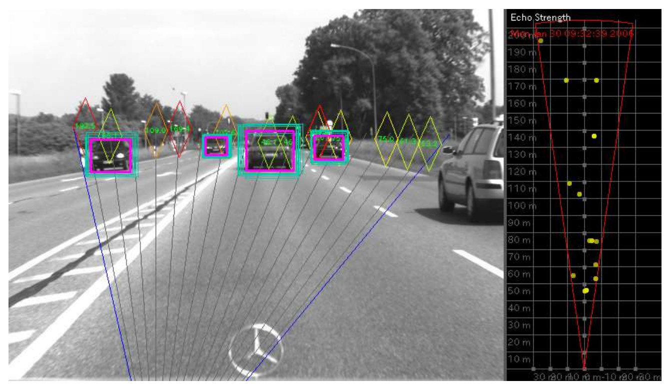

Fig. 2. Vehicle detection scheme. The lidar echoes (yellow dots in right birdview) are projected into the image domain (diamonds on gray rays in left video image). An image classifier is applied on lidar projections (cyan boxes). A detection box cluster algorithm outputs the final detections (magenta boxes).

A. Paper structure

After the introductory section I describing the application, section II reviews the classical multitarget tracking architecture and explains why FISST based tracking approaches are expected to improve the performance. Section III introduces the IPDA filter and a succeeding section IV describes the models used for the ACC application. The final section presents results and suggests further research topics.

II. FISST BASED TRACKING

A. The classical tracking approach

No matter what sensors are used in automotive multitarget environment recognition, all measurements show three independent types of uncertainty and ambiguity. They are the uncertainty of target existence, induced by false negatives and clutter, the data association uncertainty between measurements and tracks, and the uncertainty of the measured state variables due to measurement noise. The classical system architecture for resolving these uncertainties consists of several subsequent algorithms starting with a detection or segmentation stage computing the object candidate list from raw sensor data. Well studied approaches for object detection are i.e. template matching [6], learned classifiers [7], and motion based methods [1]. The next step is a data association algorithm, assigning the object candidates to already existing tracks. Among others, important members are the Kuhn-Munkres Algorithm and the Joint Probabilistic Data Association (JPDA). The succeeding recursive state estimation filters, usually Extended-Kalman, Unscented-Kalman, or Particle Filters output temprally smoothed state estimates suppressing the measurement noise. Since false positives of the detection stage sometimes also enter the track list in presence of clutter, a track validation module finally decides whether to accept the track by examining filter consistency, state constraints, or features from the detection stage again. Rule based systems and learned classifiers [8] are state of the art for this purpose.

This sequential modular concept has the advantage of early information densification leading to computational efficiency. Another benefit is the ability to optimize the modules independently. A major drawback is the early decision making in the detection and association stages. From an information theoretic view, decision making introduces information that is not present in the data at all. This is why false decisions, which grow in number as the signal to noise/clutter ratio (SN/CR) decreases, may falsify or at least negatively influence the whole future system output. Therefore the track validation module is necessary in the classical architecture to handle false detection decisions at a later point in the processing chain when dynamic features from the tracking stage are available for classification, as well. Another issue is that the detection and association decisions are made locally in time without consideration of temporal prior knowledge. Although some temporally smoothed detection algorithms are known in the image processing domain [9],[10], solving these problems in the tracking stage with an sensor independent probabilistic model is more adequate for sensorfusion applications. Tracking unresolved raw or feature level hints over time and deciding with time smoothed information is also referred to as "Track before Detect" (TBD).

The sensorfusion vehicle detection approach presented in [5] is robust in highway scenarios but Figure 3 illustrates the clutter problem in complex urban environments which would be even more severe in pure vision based approaches. Therefore TBD approaches are of intrest especially in vision supported sensing systems.

B. Finite Set Statistics Theory (FISST)

Ronald Mahler introduced the finite set statistics theory [11], which simultaneously handles joint multitarget detec-

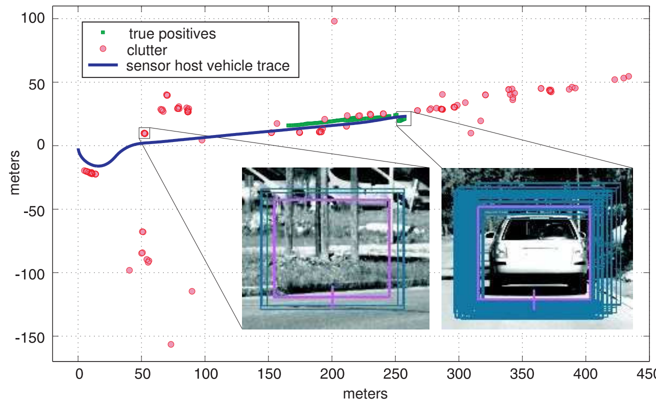

Fig. 3. Time accumulated birdview of a drive through a complex urban scene. The blue line is the trace of the sensor host vehicle, with sensed true positive measurements from three other cars (green boxes) and false positive readings in the background (red dots).

tion, association, and state estimation in one single filtering algorithm. Although computationally intractable for most non-academic applications, the theory preserves and propagates the probabilistic knowledge in all three uncertainty domains through time and extracts posterior estimates of the multitarget state in each filter cycle. The main idea is to replace the classical single target recursive Bayesian state estimation, implemented i.e. by the Kalman-Filter, that computes the posterior pdf $p(x|Z_k)$ of target state, conditioned on all measurements up to the current time step. The second Kolmogorov axiom ($\int p(x|Z_k)dx = 1$) implies that the only uncertainty in this model is about target state and therefore it is implicitly assumed that the target exists somewhere in the state space for sure. Apparently, in real applications with clutter, the elementary event that the target does not exist at all because the track was initialized by a false positive, is outside this sample set. So the key idea of FISST is to change the underlying model to incorporate existence uncertainty as well. The new approach is to assign probabilities to random finite sets (RFS) X of multitarget states:

$$p(X) = p(\{x_1, .., x_n\}) \tag{1}$$

In this model, the individual target state vectors x_i and the number of targets n are both random variables. The same model is applied for the RFS Z of measurements. Since RFS of different cardinality are allowed to coexist, including the empty set, the state evolution model $p(X_k|X_{k-1})$ has to cope with cardinality changes, like object birth, death, spawning, and fusion. In the same way the measurement likelihood function $p(Z_k|X_k)$ has to model different cardinalities of the target and measurement RFS, like missing, false, and multiple detections. Mahler developed recursive Bayesian prediction and update formulas for the RFS model as well as multitarget posterior state estimators.

III. The IPDA Filter

Almost in parallel to Mahler developing FISST, Darko Musicki et al. introduced the IPDA Filter [12] for tracking targets in clutter. In this section, Musicki's IPDA filter equations will be presented. Although the IPDA Filter uses explicit data association, it still provides a joint filtering of state and existence for each target. IPDA is of high practical interest, because the computational overhead, compared to ordinary multi instance Kalman filtering is almost negligible. Recently it has been shown [13] that IPDA can be derived from FISST theory if the following assumptions hold:

1) The objects evolve independently in state and existence, so multi instance filtering is applicable.
2) Each real object can only generate one measurement - if more are associated, all of them except one are false positives.
3) For the closed form solution, the state and measurement models must satisfy linear Gaussian assumptions.
4) False positives are Poisson distributed in number and distributed uniformly in location.

The second assumption is valid, since all boxes embracing the true object are clustered together to one single measurement [5]. Musicki et al. originally proposed two variants of IPDA. The first is to insert the single element of target non-existence into the probability sample set as mentioned before. The other is to split this event by inserting two events, one of true non-existence and the other of existence, but non-observability. In this application, we use the first variant of IPDA, summarizing the two cases of variant two. The target existence is described by the events $\exists x$ and $\nexists x$. In RFS formulation this means:

$$p(\{x\}|Z_k) = p(\exists x|Z_k) \cdot p(x|Z_k) \quad (2)$$
$$p(\varnothing|Z_k) = 1 - p(\exists x|Z_k) \quad (3)$$

We refer to $p(x|Z_k)$ as the spatial probability density function, describing state uncertainty, and $p(\exists x|Z_k)$ as the cardinal probability mass function of target x describing the existence uncertainty. IPDA uses two separate cross-coupled Markov chains for filtering state and existence uncertainty. The spatial Markov chain is an (Extended) Kalman-Filter with prediction and update steps as usual. The next subsections discuss the prediction and update steps for the cardinal Markov chain.

A. Cardinal Prediction

The Chapman-Kolmogorov equation simplifies to matrix multiplication in the discrete case:

$$\begin{bmatrix} p(\exists x) \\ p(\nexists x) \end{bmatrix}_k = \begin{bmatrix} p_p(x) & p_b(x) \\ 1 - p_p(x) & 1 - p_b(x) \end{bmatrix} \begin{bmatrix} p(\exists x) \\ p(\nexists x) \end{bmatrix}_{k-1} \quad (4)$$

with the state dependent probability of object persistence $p_p(x)$ and object birth $p_b(x)$. The cardinal time forward prediction equation therefore is:

$$p(\exists x)_{k|k-1} = p_p(x)p(\exists x)_{k-1} + p_b(x)[1 - p(\exists x)_{k-1}] \quad (5)$$

The dependence of the prediction equation on the state variables x is the first coupling point between the Markov chains. For the modeling of persistence and birth for the ACC application, see Section IV.

B. Cardinal Measurement Update

If $m_k = |Z_k|$ measurements arrived at time k, three mutually exclusive events can have occurred. The first one is that the target does not exist at all, and all m_k measurements are clutter. The second is the target exists, but none of the m_k measurements descended from the target ($x \rightarrow \varnothing$), hence all measurements are false alarms again. The final event is that one of the measurements originated from the target ($x \rightarrow z_i$), and the others are false alarms (see IPDA assumption two). The exhaustiveness of these events is given by:

$$p(Z_k) = 1 = p(\nexists x|Z_k) + p(\exists x, x \rightarrow \varnothing|Z_k) + \sum_{i=1}^{m_k} p(\exists x, x \rightarrow z_i|Z_k) \quad (6)$$

The unnormalized Bayesian posteriors (abbrev. l) of the three events are given by multiplication of their cardinal and spatial likelihoods with the prior existence probability. For example the unnormalized posterior for target non-existence is the spatial likelihood $p_s^{FP}(Z_k)$ of all measurements in Z_k being false positives (FP), multiplied by the cardinal false positive likelihood of the complete measurement set $p_c^{FP}(Z_k)$ and the prior non-existence probability from the prediction step:

$$l(\nexists x|Z_k) = p_s^{FP}(Z_k) \cdot p_c^{FP}(Z_k) \cdot (1 - p(\exists x)_{k|k-1}) \quad (7)$$

In the same way, the unnormalized posterior of the second event of (6) is:

$$l(\exists x, x \rightarrow \varnothing|Z_k) = p_s^{FP}(Z_k) \cdot p_c^{FP}(Z_k) \cdot p_c^{FN} \cdot p(\exists x)_{k|k-1} \quad (8)$$

where p_c^{FN} is the false negative probability, hence the probability of missed detections. The final event is the unnormalized Bayesian posterior for the true positive case:

$$l(\exists x, x \rightarrow z_i|Z_k) = p_s^{FP}(Z_k \setminus z_i) \cdot p_c^{FP}(Z_k \setminus z_i) \cdot p_s^{TP}(z_i|x) \cdot p_c^{TP}(z_i) \cdot p(\exists x)_{k|k-1} \quad (9)$$

Here, $p_s^{TP}(z_i|x)$ is the ordinary spatial measurement likelihood (another coupling point) and $p_c^{TP}(z_i)$ is the cardinal probability that the i'th of the m_k measurements is a true positive. With the earlier explained assumptions and given an a-priori known detection rate p_D (sensitivity, recall) and the hypervolumes V_i of the 3-σ association gates, the used probabilities are:

$$p_c^{TP}(z_i) = p_D \cdot m_k^{-1} \quad (10)$$
$$p_c^{FN} = 1 - p_D \quad (11)$$
$$p_c^{FP}(Z) = e^{-\lambda_V} \cdot \lambda_V^{|Z|} \cdot |Z|!^{-1} \quad (12)$$
$$p_s^{FP}(Z) = \prod_{i=1}^{|Z|} V_i^{-1} \quad (13)$$

The expectation value λ_V for the cardinal Poisson false alarm distribution in the gate can either be known a-priori or estimated with:

$$\lambda_V = \max(0, m_k - p_D \cdot p(\exists x)_{k|k-1}) \quad (14)$$

Fig. 4. Object persistence probability related to the sensor field of view of 16°, given the position in vehicle coordinates (green). The probability interval [0..1] is color mapped from black to white.

The posterior probability of target existence is then given by the Bayes rule:

$$p(\exists x|Z_k) = \frac{l(\exists x, x \to \varnothing|Z_k) + \sum_{i=1}^{m_k} l(\exists x, x \to z_i|Z_k)}{l(\nexists x|Z_k) + l(\exists x, x \to \varnothing|Z_k) + \sum_{i=1}^{m_k} l(\exists x, x \to z_i|Z_k)} \tag{15}$$

which simplifies to the cardinal measurement update equation:

$$p(\exists x)_{k|k} = \frac{(1-\delta)\cdot p(\exists x)_{k|k-1}}{1-\delta\cdot p(\exists x)_{k|k-1}} \tag{16}$$

$$\delta = p_D - p_D \frac{V_k}{\lambda_V} \sum_{i=1}^{m_k} p_s^{TP}(z_i|x) \tag{17}$$

The spatial Markov chain updates the target states by JPDA-like mixing of the state prediction and the innovations of the assigned measurements. The mixture weights $\beta_i, i = 0..m_k$ (β_0 is the weight of the prediction) are given by:

$$\beta_0 = \frac{l(\exists x, x \to \varnothing|Z_k)}{l(\exists x, x \to \varnothing|Z_k) + \sum_{j=1}^{m_k} l(\exists x, x \to z_j|Z_k)} \tag{18}$$

$$\beta_i = \frac{l(\exists x, x \to z_i|Z_k)}{l(\exists x, x \to \varnothing|Z_k) + \sum_{j=1}^{m_k} l(\exists x, x \to z_j|z_k)} \tag{19}$$

This is where the cardinal Markov chain couples back to the spatial one.

IV. Modeling for ACC Vehicle Tracking

A. Cardinal ACC prediction model

The cardinal process model used in the prediction step of IPDA provides the persistence $p_p(x)$ and birth probabilities $p_b(x)$, given the predicted states of the spatial Markov chain. Because the first variant of IPDA is used, the persistence probability, that is the probability of object survival from timestep $k-1$ to k, must account for observability issues like field of view (FOV) and mutual occlusion of targets as well as static and dynamic a-priori state constraints. The FOV part $p_p^{FOV}(x)$ is dominated by the smaller FOV of the lidar sensor and is shown in Figure 4. Obviously, the persistence probability must be one at any position inside the FOV, since objects cannot disappear spontaneously. The mutual occlusion part $p_p^{OCC}(x)$ of the persistence model accounts for the lack of observability if targets dive into the surveillance shadow of other targets. Only confirmed targets can throw a surveillance shadow (Fig. 5). Another possible component of the persistence model could be digital map information or the results of a lane detection system. This furthermore constraints the allowed target positions. Figure 6 exemplary shows the persistence probabilities $p_p^{DM}(x)$ resulting from a digital map of a straight forward two lane highway piece. The overall persistence probability for usage in (5) is given by the product of its components:

Fig. 5. Object persistence probability of positions relative to ego vehicle coordinates (green) induced by observation lacks in surveillance shadows of other confirmed targets (green boxes). The probability interval [0..1] is color mapped from black to white.

Fig. 6. Persistence probabilities from digital map of a two lane highway. As objects can only be on the road, all other areas have probability zero. The probability interval [0..1] is color mapped from black to white.

Fig. 7. Combined persistence probability map, composed of FOV, occlusion, and infrastructure restrictions. The probability interval [0..1] is color mapped from black to white.

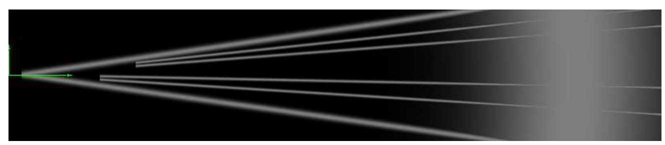

Fig. 8. Objects can only appear and vanish near the boarders of the FOV and occlusion areas. The resulting probability interval [0..1] is color mapped from black to white.

$$p_p(x) = p_p^{FOV}(x)\cdot p_p^{OCC}(x)\cdot p_p^{DM}(x) \tag{20}$$

The resulting persistence probability, depending on the target position is visualized in Figure 7. The object birth process, that is the state change between non-existence and existence, is only allowed near the boarders of the FOV and surveillance shadow areas. Therefore the object birth probability (see Fig. 8) was chosen as:

$$p_b(x) \propto \left|\nabla_{x,y}\left[p_p^{FOV}(x)\cdot p_p^{OCC}(x)\right]\right| \tag{21}$$

B. Cardinal measurement update

For the non-parametric version of the IPDA filter, hence estimating λ_V with (14), only the sensitivity measure of the detector p_D needs to be known in addition to usual Kalman-Filtering parameters. It can be directly taken from the current

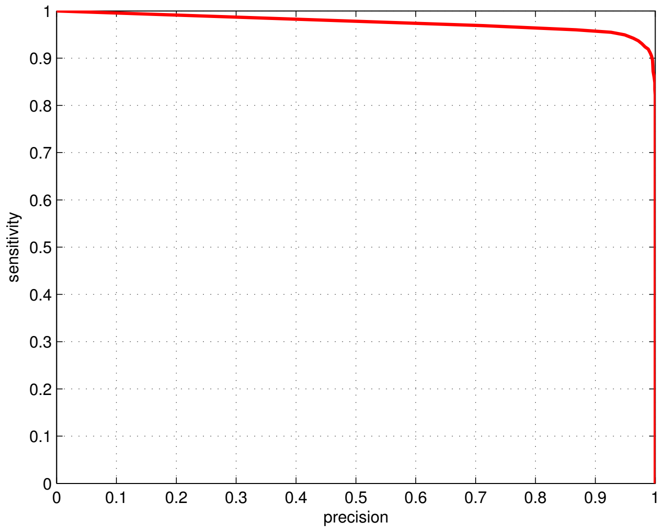

Fig. 9. Vehicle detection receiver operating characteristics (ROC) resulting from the variation of the detection decision threshold.

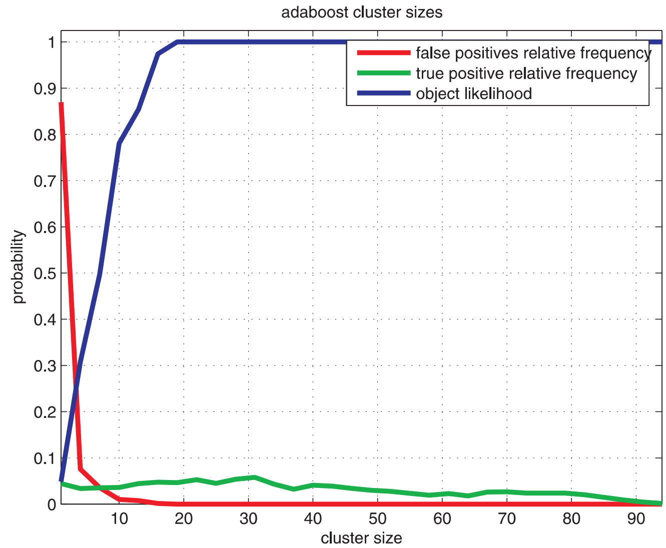

Fig. 10. Relative frequency of detection cluster sizes given the target exists (green) and given the target does not exist (red) and resulting cardial existence probability $p_c^{TP}(z_i)$ (blue).

operating point of the detection algorithms receiver operating characteristics chart. The ROC chart of our detection system is shown in figure 9. For details on its generation please refer to [5]. But in order to avoid the Poisson false alarm model (12) that may be inadequate, we extended the general detector characteristics approach of IPDA taken from the ROC chart to incorporate measurement specific existence features $f(z_i)$. This is done by redefining equations (10)-(12) with:

$$p_c^{TP}(z_i) = \frac{h_r(f(z_i)|\exists x)}{h_r(f(z_i)|\exists x) + h_r(f(z_i)|\nexists x)} \tag{22}$$

$$p_c^{FN} = h_r(f(z_i) = 0|\exists x) \tag{23}$$

$$p_c^{FP}(Z) = \prod_{i=1}^{|Z|} \frac{h_r(f(z_i)|\nexists x)}{h_r(f(z_i)|\exists x) + h_r(f(z_i)|\nexists x)} \tag{24}$$

Here, $h_r(f|\exists x)$ is the relative frequency of a feature value f given the target exists and $h_r(f|\nexists x)$ is its relative frequency given the target does not exist. These can be computed from a pre-classified ground truth data set. Figure 10 shows the graphs for the video detection cluster size feature. When using this cardinal model, the update equation does not simplify to (16) anymore, thus equation (15) is used instead.

C. Spatial modeling

The spatial process and measurement update models cannot be discussed in deep detail here. Please refer to [14] for a detailed description. The state vector of other targets was chosen as:

$$x = (x, y, z, v, \psi, \dot{\psi})' \tag{25}$$

The position components (x, y, z) and the orientation angle ψ are measured relative to the ego vehicle coordinate system, whereas the target velocity magnitude v and yaw rate $\dot{\psi}$ are estimated absolutely over ground. The motion of the sensor host vehicle is estimated from the wheel revolutions and the yaw rate sensor of the ESP system, according to an Ackermann steering geometry model, as published in [15]. The process model predicts target states by incorporating uncertainties of the applied constant turn motion model, the ego motion estimation and the unknown vehicle pitch angle. Measurement innovations are computed from the polar (r, ϕ)-coordinates of the lidar echoes and the (i, j) image coordinates of the detection box base points of the image classifier. As mentioned above, multiple measurement associations to the same track lead to innovation mixing with weights computed from (18) and (19).

V. Results and Conclusion

Compared to the classical tracking approach, FISST based techniques and especially the efficient IPDA algorithm provide a method for keeping the probabilistic nature of knowledge instead of applying decision thresholds within the processing chain. This does not only reduce decision parameters, but also produce a probabilistic track list, with posterior time smoothed existence probabilities for each track. Exemplary, the graphs of these probabilities are shown for several tracks in Figure 11 starting at each tracks initialization time. The red curves show the IPDA estimated existence probabilities for true positive tracks and the green plots are the probabilities for false positive tracks. This allows a non-heuristic way of track confirmation or track pruning by thresholding the posterior existence probability without a separate validation stage. A possible confirmation threshold is depicted by the blue line. Due to the probabilistic formulation of all system components related to track existence, only the two thresholds for confirmation and pruning need to be optimized. Instead it is also possible to pass the probabilistic track list to subsequent modules as situation analysis for even later decision making. Furthermore, the seamless integration of prior knowledge about target existence is possible in the cardinal prediction step as demonstrated i.e. for digital

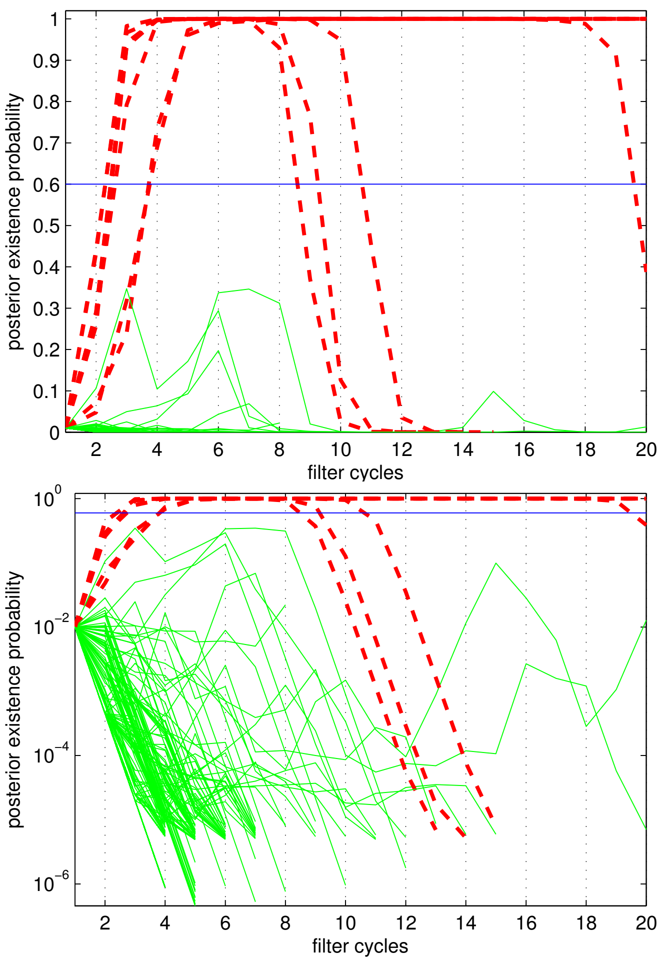

Fig. 11. Temporal evolution of the IPDA estimated posterior probabilities of existence for several true positive (red) and false positive (green) tracks in linear (top) and logarithmic scale (bottom). Tracks are confirmed and pruned by thresholding the existence probability. A possible track confirmation threshold is represented by the blue line.

map information and occlusion reasoning. In the cardinal measurement update model, the sensor specific existence hints $f(z_i)$ are transformed into sensor independent cardinal proabilities $p_c^{TP}(z_i)$ and $p_c^{FP}(Z)$ which serve as a natural interface for heterogeneous sensorfusion even in the existence domain.

The described detection and tracking system is implemented in realtime in a test vehicle equipped with sensors as described in the introduction. The current development phase allows non-synthetic in-vehicle demonstrations in real traffic scenarios where even standing vehicles are detected in distances up to 150 meters. Moreover, the system can keep track of already detected vehicles up to 200 meters.

Further research will deal with the incorporation of other - more discriminating - existence features. Especially for Boosting classifiers, a theoretically funded method for deriving existence probabilities based on the Friedmann-formula [16] is currently under investigation [17]. In the future a comparison with other tracking methods like multi hypothesis tracking (MHT, [18]) and more sophisticated FISST-based tracking algorithms like the Probability Hypothesis Density Filter [19] will be of interest. Another goal is porting the presented approaches to other applications like nightview pedestrian warning and near range applications with extended object models where several measurements contribute to the same object.

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