Self-Monitored Detection Probability Estimation for the Labeled Multi-Bernoulli Filter

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***Abstract*— Automated vehicles rely on their environment model, usually generated by a tracking module using sensor data, to make decisions. Therefore, estimating the accuracy of the tracking module is vital for the safe and reliable operation of the vehicle. This work makes a step towards this goal by providing a detection probability estimation method with a self-monitored quality assessment for the labeled multi-Bernoulli filter. We demonstrate the significance of the proposed quality index by comparing it with the actual estimation error calculated with ground truth data. This shows that the developed index is a meaningful value that can be computed online without ground truth data.**

I. Introduction

In the field of automated driving, the self-assessment of functional components is not just crucial for ensuring safe operation; it is also a gateway to unlocking advanced capabilities. This could entail, for instance, an adaptive framework where modules are chosen based on context information or a dynamic setup adjusting to performance demands [1]. The environmental model holds particular significance as both planning and decision-making depend on its accuracy. Moreover, ongoing self-monitoring might be obligatory, as mandated by legislation in Germany [2].

The monitoring of the tracking module tries to estimate its current performance optimally with respect to some ground-truth tracking metrics. Naturally, the monitoring must occur in real-time and online, i.e., without access to ground truth data. Consequently, tracking metrics such as the optimal subpattern assignment (OSPA) [3], OSPA2 [4], or generalized OSPA (GOSPA) [5] metrics are inapplicable, as they are defined with ground truth data.

Furthermore, Duník et al. [6] proposed the *reliability index*. This index is based on an ideal Bayesian filter that generates a ground truth tracking result without any assumptions, approximations, or modeling errors. Consequently, even if computable, this index is probably not accessible in real-time. The difference between the ideal filter's result and that of the evaluated filter shows the level of epistemic uncertainty. This uncertainty comes from the evaluated filter's inherent lack of knowledge, such as unknown systematic effects or approximations.

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Following some of their arguments, we suggest taking into account the following aspects to develop a practical and real-time self-monitoring system for the tracking module. Here, the first two aspects are interrelated, with the latter building upon the former, whereas the final two can be addressed separately from the rest.

- *Assessment of the tracking parameters:* This assesses whether the particular parameterization of the tracking algorithm fits the data and includes, e.g., the process and measurement noise parameters.
- *Sensitivity of the tracking parameters:* For each tracking parameter, the sensitivity to some tracking metric is evaluated. Coupled with the first point, this enables the estimation of the effect of a parameter misconfiguration.
- *Assessment of the filter design:* Each filter operates under certain assumptions. For example, the Kalman filter assumes linear models and Gaussian-distributed noise. This aspect assesses these assumptions and their impact on performance.
- *Assessment of the tracking scenario:* Scenarios vary in complexity; for instance, estimating multiple tracks in close proximity is more challenging than tracking a single one. Hence, the operational context of the filter must be considered. While this aspect cannot be altered by the filter at all, it is presumed to significantly affect the filter's overall performance and should, therefore, be considered.

This paper contributes to the first aspect of *assessment of the tracking parameters*. One important parameter is the detection probability, i.e., the probability that an object gets detected by a sensor. For this, we propose a novel detection probability estimation method for the labeled multi-Bernoulli (LMB) filter [7]. The method includes a self-monitoring that provides a quality index (QI). The QI reflects the current accuracy of the estimation, making it valuable when in future evaluating a parameter misconfiguration. The proposed method can correctly follow a jumping or drifting time-varying detection probability. Because we see this work within the broader framework of the proposed self-assessment aspects for the tracking module, we do not feed the estimated detection probability back into the filter.

Summarizing our contributions, we

- propose a novel detection probability estimation with included self-monitoring that provides a QI, and
- demonstrate the close relationship between the QI and estimation error, showing its significance as meaningful online information.

II. Related Work

The normalized innovation squared (NIS) [8] is the traditional online consistency metric for the Kalman filter, monitoring the consistency between process and measurement noise and incoming measurements. In [9], Mahler put the NIS into a broader scope and introduced the generalized NIS (GNIS) and its adaptation for multi-object tracking, the multi-target GNIS (MGNIS). These so-called divergence detectors verify the consistency of the filter noise assumptions. What unifies all three methods is their consideration of all assumptions simultaneously. In our context, this poses a significant drawback, as it prevents the differentiation of parameter-specific effects on filter performance.

Another assessment approach for single object tracking (SOT), including a component analysis of the filter assumptions, based on subjective logic (SL) is developed by Griebel et al. [10]. Note that SL is an extension of probabilistic logic that is based on subjective opinions [11]. The work was extended in [12] for SOT in clutter with the nearest neighbor association algorithm. For this, methods for the assessment of the detection and clutter rate have been developed. Similar to our method, the uncertainty value of SL expresses the statistical uncertainty and indicates the estimation quality. However, within their considered task and algorithm, i.e., tracking a single object in clutter with the nearest neighbor association, the decision of whether an object was measured or not is trivial and, therefore, the assessment of the detection probability.

In this work, we propose a method in the spirit of [12] that enables a detection probability estimation with self-monitoring for multi-object tracking. The description of our method is completely self-contained, so no knowledge of SL is required.

III. Foundations

This section briefly summarizes the main fundamentals of the LMB filter and our detection probability modeling with conjugate priors. For further insights into the LMB filter, we recommend [7], [13], and for additional information on conjugate priors, we suggest [14].

A. Labeled Multi-Bernoulli Filter

The LMB filter, introduced by Reuter et al. [7], is a multi-object tracking algorithm based on finite set statistics (FISST) [15]. Acting as a real-time feasible approximation of the Generalized Labeled Multi-Bernoulli (GLMB) filter, it replaces the updated GLMB density with an LMB density [7]. The filter comprises two main steps: Prediction and update. Since the prediction step does not affect our detection probability estimation, our focus centers on the update. During this step, the predicted LMB density gets first transformed into a GLMB density, which allows an analytical closed update with the formulas derived by [13]. Subsequently, the updated GLMB is approximated by an LMB density that matches its first statistical moment [7].

In more detail: If the predicted LMB density is given by the parameters $\{r_+^{(l)}, p_+^{(l)}\}_{l\in\mathbb{L}_+}$, the updated GLMB density is given by [13]

$$\pi(X|Z) = \Delta(X) \sum_{(I,\theta)\in\mathcal{F}(\mathbb{L}_+)\times\Theta} w^{(I,\theta)}(Z)\, \delta_I(\mathcal{L}(X)) \left[p^\theta(\cdot|Z)\right]^X. \tag{1}$$

Here, $X \in \mathcal{F}(\mathbb{X}\times\mathbb{L}_+)$ is the set of all tracks, where one track is given by its kinematic part $x \in \mathbb{X}$ and its label $l \in \mathbb{L}_+$. $\mathcal{F}(\mathbb{X})$ is the set of all finite subsets of $\mathbb{X}$, $Z \in \mathcal{F}(\mathbb{Z})$ is the multi-object measurement, Θ is the space of all valid measurement-to-track associations θ, δ is the generalized Kronecker delta with $\delta_Y(X) = 1$ if $Y = X$ and $\delta_Y(X) = 0$ otherwise, and $w^{(I,\theta)}(Z)$ is the weight of the hypothesis (I, θ).

Following [13], the weight of a hypothesis can be interpreted as its probability, i.e., if we abbreviate $H := (I, \theta)$, then $P(H \mid Z) = w^H(Z)$. Note that each hypothesis H has a clear measurement-to-track association given by the corresponding θ. For completeness, the equations for w^H and p^θ are given [13]

$$w^{(I,\theta)}(Z) \propto [r_+]^I\, [1 - r_+]^{\mathbb{L}_+\setminus I} \left[\eta_Z^\theta\right]^I \tag{2a}$$

$$p^\theta(x, l|Z) = \frac{p_+(x,l)\psi_Z(x,l,\theta)}{\eta_Z^\theta(l)} \tag{2b}$$

$$\eta_Z^\theta(l) = \langle p_+(\cdot, l), \psi_Z(\cdot, l, \theta)\rangle \tag{2c}$$

$$\psi_Z(x,l,\theta) = \begin{cases} \frac{p_D(x,l)g(Z_{\theta(l)}|x,l)}{\kappa(Z_{\theta(l)})} & \theta(l) > 0 \\ 1 - p_D(x,l) & \theta(l) = 0, \end{cases} \tag{2d}$$

where $p_+(\cdot, l)$ is the predicated state of label l, r_+ is the predicted existence probability, p_D is the detection probability, g is the measurement model, $\langle\cdot,\cdot\rangle$ denotes the scalar product in L_2 and κ is the clutter intensity, i.e., the clutter rate per volume. The detection probability influences the filter through Eq. (2d), which roughly weights the probability of receiving an object measurement against that of receiving a clutter measurement.

The LMB density that matches the first moment of Eq. (1) is given by $\{r^{(l)}, p^{(l)}\}_{l\in\mathbb{L}_+}$ with [7]

$$r^{(l)} = \sum_{\substack{(I,\theta)\in\mathcal{H}\\ l\in I}} w^{(I,\theta)}(Z), \tag{3a}$$

$$p^{(l)} = \frac{1}{r^{(l)}} \sum_{\substack{(I,\theta)\in\mathcal{H}\\ l\in I}} w^{(I,\theta)}(Z) p^\theta(x, l|Z), \tag{3b}$$

where $\mathcal{H} := \mathcal{F}(\mathbb{L}_+)\times\Theta$ is the set of all possible hypotheses.

B. Detection Model

Within the LMB filter, each object independently gets detected by a sensor with probability $p_D \in [0, 1]$. In the following, such measurements are called object measurements and are denoted by $O \subseteq Z$. The number of object measurements is denoted by $\mathcal{O} = |O|$. The detection probability p_D can theoretically depend on the state and the label of an object. However, if, like in this work, the filter gets implemented with Gaussian mixtures, the detection probability is often assumed to be constant and independent of the label. If an object gets detected, the measurement z follows the measurement model h of the sensor, i.e., $z = h(x, e)$, where e describes the measurement noise. Often, it is assumed that the noise is additive and Gaussian distributed with zero mean. So, in total, a single object measurement follows a Bernoulli RFS, and all object measurements together follow a multi-Bernoulli RFS [15].

In addition to the object measurements, so-called clutter measurements are modeled by an independent Poisson process, i.e., if we denote the clutter measurements by $C \subseteq Z$, then $\pi(C) = e^{-\langle \kappa, 1 \rangle} \kappa^C$ and $|C| \sim \text{Poi}(\langle \kappa, 1 \rangle)$ [15]. The clutter measurements are iid. with probability density function (pdf) $\kappa / \langle \kappa, 1 \rangle$. The object and clutter measurements are mutually exclusive, meaning that the number of clutter and object measurements are connected through $|C| + \mathcal{O} = |Z|$.

We model our current knowledge about the detection probability by a Beta distribution, i.e., $p_D \sim \beta(p, q)$, where $\beta(p, q)$ denotes the Beta distribution characterized by the parameters $p > 0$ and $q > 0$. Its pdf is given by [14]

$$f_{p,q}(x) = \begin{cases} \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} x^{p-1}(1-x)^{q-1}, & x \in (0,1), \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Here, $\Gamma(\cdot)$ denotes the Gamma function. The mean μ and variance σ^2 of the distribution are given by

$$\mu = \frac{p}{p+q}, \quad \sigma^2 = \frac{pq}{(1+p+q)(p+q)^2}. \tag{5}$$

In total, this yields the following model for a single object measurement Z_x belonging to an object with state x:

$$Z_x \sim \text{Bernoulli}\left(p_D, h(x, e)\right), \tag{6a}$$
$$p_D \sim \beta(p, q). \tag{6b}$$

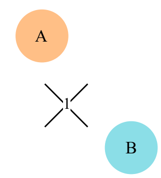
Here, Bernoulli(p, f) denotes a Bernoulli RFS with probability p and spatial distribution f. Since the Beta distribution is conjugate to the Bernoulli distribution, the posterior of Eq. (6b) after $k \in \mathbb{N}_0$ detections and $l \in \mathbb{N}_0$ misdetections is also Beta distributed with [14]

$$p_D | (k, l) \sim \beta(p + k, q + l). \tag{7}$$

IV. Detection Probability Estimation

We use the Beta distribution described in Section III-B to express our knowledge about the detection probability. The mean of the Beta distribution is the estimation of the detection probability, whereas the variance is defined as the QI for that estimation and expresses the uncertainty. This means a small QI indicates a confident estimation, and a high QI might indicate an imprecise estimation.

To update the estimation, we use the information from the filter update step: A GLMB hypothesis describes one possible association between the tracks and received measurements. The number of detections in this hypothesis is the number of all associated measurements. Using the weight of a hypothesis, we compute the distribution of the number of detections, as illustrated in Fig. 1. With the obtained distribution, we then update the current estimation. In the following, the method is formulated for the LMB filter. However, it is straightforward



$$\left.\begin{aligned} w_1 &:= w^{\{A,B\},\ (A\to 0,\ B\to 0)} \\ w_2 &:= w^{\{A,B\},\ (A\to 1,\ B\to 0)} \\ w_3 &:= w^{\{A,B\},\ (A\to 0,\ B\to 1)} \\ w_4 &:= w^{\{A\},\ (A\to 0)} \\ w_5 &:= w^{\{A\},\ (A\to 1)} \\ w_6 &:= w^{\{B\},\ (B\to 0)} \\ w_7 &:= w^{\{B\},\ (B\to 1)} \\ w_8 &:= w^{\{\}} \end{aligned}\right\} \quad \begin{aligned} o_{0,2} &= w_1 \\ o_{1,2} &= w_2 + w_3 \\ o_{0,1} &= w_4 + w_6 \\ o_{1,1} &= w_5 + w_7 \\ o_{0,0} &= w_8 \end{aligned}$$

Fig. 1: Illustration of the distribution of the number of detections. Here, two tracks, indicated by the circles, are updated with one measurement, indicated by the cross. The weights of the updated GLMB hypotheses, cf. Eq. (2), are shown on the middle, with the corresponding distribution of the number of detections on the right, cf. Eq. (8). $A \to i$ denotes that track A is associated with measurement i, where $i = 0$ expresses a misdetection.

to adapt it to other filters as long as they have an update step that allows the computation of the distribution of the number of detections, cf. Eq. (8), such as the GLMB filter.

In more detail: Let $N(H) \leq |Z|$ be the number of associated measurements of a hypothesis H with $|H|$ tracks and $O_{k,t}$ the random variable of detecting k out of t objects. Then,

$$o_{k,t} := P(O_{k,t}|Z) = \sum_{H \in \mathcal{H}} P(O_{k,t}|H) P(H|Z) \tag{8a}$$
$$= \sum_{\substack{H \in \mathcal{H} \\ N(H)=k \\ |H|=t}} w^H(Z) \tag{8b}$$

is the probability for detecting k objects out of t possible ones. Using Eq. (8) and Eq. (7), the update of the predicted estimation $p_{D,+} \sim \beta(p_+, q_+)$ is a mixture of Beta distributions given by

$$f(p_D|Z) = \sum_{k,t} f(p_{D,+}|O_{k,t}) P(O_{k,t}|Z) \tag{9a}$$
$$= \sum_{k,t} o_{k,t} f_{p_+ + k, q_+ + t - k}(p_{D,+}), \tag{9b}$$

where $f_{p,q}$ is the pdf of the Beta distribution with parameters p, q, cf. Eq. (4).

Note that the sum is actually finite since only a finite number of $o_{k,t}$ are non-zero. Note also that this computation does not introduce large overhead, as all necessary values are computed by the LMB filter anyway. The method, as shown above, is analytically closed. However, the number of mixture components grows rapidly; thus, for practical applicability, a merging strategy is introduced in the following.

We found that approximating the mixture Eq. (9) by a single Beta distribution with the same mean and variance as the mixture yields satisfying results for our use case. In detail, let the mixture be given by components $i \in \{1, 2, \dots N_C\}$ each with mean μ_i, variance σ_i^2, and weight w_i. Using the linearity of expectation and the law of total variance, we express the mean $\bar{\mu}$ and variance $\bar{\sigma}^2$ of the mixture by

$$\bar{\mu} = \sum_{i=1}^{N_C} w_i \mu_i, \tag{10a}$$

$$\bar{\sigma}^2 = \sum_{i=1}^{N_C} w_i \left[\sigma_i^2 + (\mu_i - \bar{\mu})^2\right]. \tag{10b}$$

The Beta distribution with the same mean and variance, cf. Eq. (5), is given by the parameters

$$p = \frac{\bar{\mu}(\bar{\mu} - \bar{\sigma}^2 - \bar{\mu}^2)}{\bar{\sigma}^2}, \quad q = \frac{(\bar{\mu} - 1)(\bar{\sigma}^2 + \bar{\mu}^2 - \bar{\mu})}{\bar{\sigma}^2}. \tag{11}$$

Because of the association uncertainty expressed in the distribution of $\mathcal{O}$, the variance of the mixture typically will not go to zero. However, it can still become so small that changes and jumps in the detection probability can be difficult to follow because of an over-confident predicted estimation $p_{D,+}$ in Eq. (9). Therefore, we apply two different discounting steps:

- First, we apply a static discounting step in the prediction by scaling the parameters p, q of the previous estimation by a factor $\varsigma_C \in (0, 1]$, i.e.,

  $$p_+ = \varsigma p, \quad q_+ = \varsigma q. \tag{12}$$

  This maintains the mean but increases the predicted variance σ_+^2, cf. Eq. (5). This improves the results, especially in slowly and smoothly changing situations because it prevents the estimation from becoming overly confident.
- Second, we perform a dynamic discounting after the update. Here, the discount parameter depends on the difference between the predicted and updated estimated detection probability, i.e., the mean of the estimated Beta distribution. The idea is that this will increase the variance for rapidly changing or jumping detection probabilities. In more detail, the dynamic discount parameter $\varsigma_D \in (0, 1]$ is given by

  $$\varsigma_D = \max\left\{\varsigma_{\min},\ 1 - \alpha|p_{D,+} - p_D|\right\}, \tag{13}$$

  where $\varsigma_{\min} > 0$ prevents the parameter from getting negative, $\alpha > 0$ is a scaling parameter that regulates how change results in discounting, and $p_{D,+}, p_D$ is the predicted respective updated estimation of the detection probability.

V. Handling of Grouping

The gating and grouping step [7] stands as a pivotal component for the practical implementation of the LMB filter. It subdivides the update into $n \in \mathbb{N}$ independent sub-problems, facilitating parallel processing. While this significantly enhances the filter efficiency, it complicates the computation of the distribution of the number of detections. With grouping, every group independently yields the distribution of its sub-problem, as shown in Fig. 2. Then, the overall distribution is

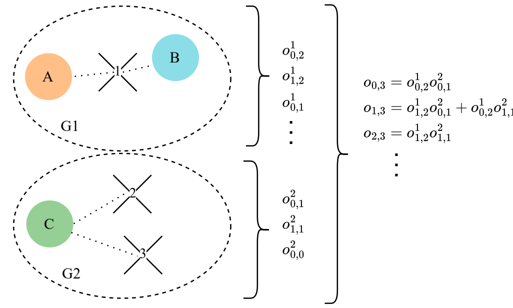


Fig. 2: When the LMB filter uses grouping, the problem is split into independent subproblems. Here, we have two groups, $G1$ and $G2$, where non-gated measurement-to-track associations are indicated by a dashed line. First, the distribution of each group is calculated as shown in Fig. 1 and Eq. (8). Then, the overall distribution is calculated by considering all possibilities of Eq. (14). Note that the figure does not show all possibilities.

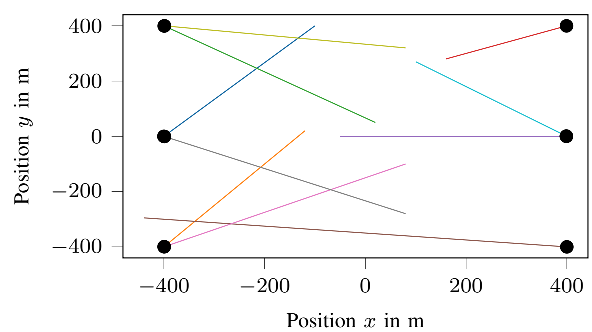


Fig. 3: The simulated tracking scenario with ten tracks. Black circles indicate the birth location of the objects.

given by

$$o_{k,t} = \sum_{\substack{k_1+k_2+\cdots+k_n=k \\ t_1+t_2+\cdots+t_n=t \\ k_i,t_i\in\mathbb{N}_0,\ \forall i=1,\ldots,n}} o^{(1)}_{k_1,t_1} o^{(2)}_{k_2,t_2} \cdots o^{(n)}_{k_n,t_n}, \tag{14}$$

where $o^{(i)}$ describes the distribution of group i according to Eq. (8). To compute this efficiently, first, the individual $o^{(i)}$ with non-zero weights are determined. Then, based on the problem size, the sum can either be calculated exactly or approximately by, e.g., a k-shortest path or a sampling-based approach that determines the $o_{k,t}$ with relevant weight, such as in [16]. Note that this step does introduce a small computational overhead.

VI. Experiments and Results

In this section, we perform simulations to test our proposed method. The LMB filter is implemented with Gaussian mixtures based on [7]. We use a simple point measurement model, which measures the (x, y)-position together with a nearly constant velocity state model and a dynamic, two-step birth model. The tracking scenario, shown in Fig. 3, is simulated with the software in the loop framework [17] and every experiment is evaluated with 50 Monte-Carlo runs.

A. Detection Probability Profiles

We simulate the tracking scenario with different detection probability profiles specified in Fig. 4. In scenario A, the

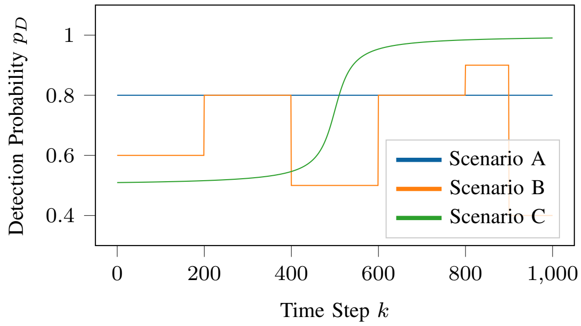


Fig. 4: Three different scenarios with varying detection probability.

detection probability is constant but is initialized incorrectly. Scenario B models a detection probability that jumps between constant values, and scenario C shows a smoothly changing detection probability.

In all scenarios, we use the Beta distribution with parameters $p = 1.8$ and $q = 1.2$ as prior. This means the prior distribution has a mean of 0.6 and a variance of 0.06, cf. Eq. (5). Note, that this value does not fit the values used to generate the scenario, cf. Fig. 4. The static discount is set to $\varsigma_S = 0.99$, and the parameters for the dynamic discounting are $\varsigma_{\min} = 0.3$ and $\alpha = 4$. The LMB filter assumes a time-invariant detection probability of 0.6. All other filter parameters match the parameters of the simulation.

B. Results

Figure 5a and Fig. 5b summarize the results for scenario A. The left figure shows the current estimation of the detection probability together with the low and high 10% quantile of the estimated Beta distribution, indicating the uncertainty of the estimation. As expected, the uncertainty drops in the beginning with an increasing number of time steps. However, note that the uncertainty does not decrease significantly because of the association uncertainty inherent to the problem and because of the proposed discount factors. It reaches its minimum in the middle of the simulation when the greatest number of tracks and, therefore, information to infer the detection probability, is present. The spikes at time points 600, 700, and 800, also visible in the other scenarios, can be explained with the GOSPA metric shown in Fig. 6. At these time points, the GOSPA metric shows a high spike in the false tracks, meaning the tracking algorithm estimated false positive tracks. Naturally, no measurement can be assigned for these false tracks, so the estimated detection probability drops at these times.

In Fig. 5b, we assess our proposed QI. For this, we compare the QI with the absolute error of the estimation. There is a correlation between the two values, indicating the QI is, in fact, a meaningful value. Note that the QI can be computed online and does not require ground truth information, whereas the estimation error is an offline value that does need ground truth. However, a quantitative evaluation of the correlation between the two values is outside this paper's scope and will be left to future work.

Figure 5c and Fig. 5d show the result for the scenario B. It can be seen that at the jumping points, the QI increases, indicating correctly an imprecise estimation.

Figure 5e shows the result for the scenario with the continuously drifting detection probability. Again, according to Fig. 5f, there is a connection between the estimation error and the QI, especially visible at the already mentioned time points with the false tracks.

To summarize, the proposed detection probability estimation with included self-monitoring correctly estimates the detection probability in all scenarios. It follows jumps and drifts of the ground truth, and the proposed QI value is an online value that indicates when the estimation is not reliable.

VII. Conclusion and Future Work

This work contributed to the *assessment of tracking parameters*. We presented a self-monitored detection probability estimation for the LMB filter. The developed method provides an estimation of the detection probability together with the QI, a value indicating the quality of the estimation.

The significance of the proposed QI was illustrated through a comparison with the estimation error derived from ground truth data. The analysis showed a correlation between the two values, suggesting that the online calculable QI can identify periods where the estimation might be less reliable.

The findings from this paper will inform future research aimed at the sensitivity of tracking parameters. Ultimately, we hope that the combined insight will enable an assessment of the consequences of parameter misconfiguration.

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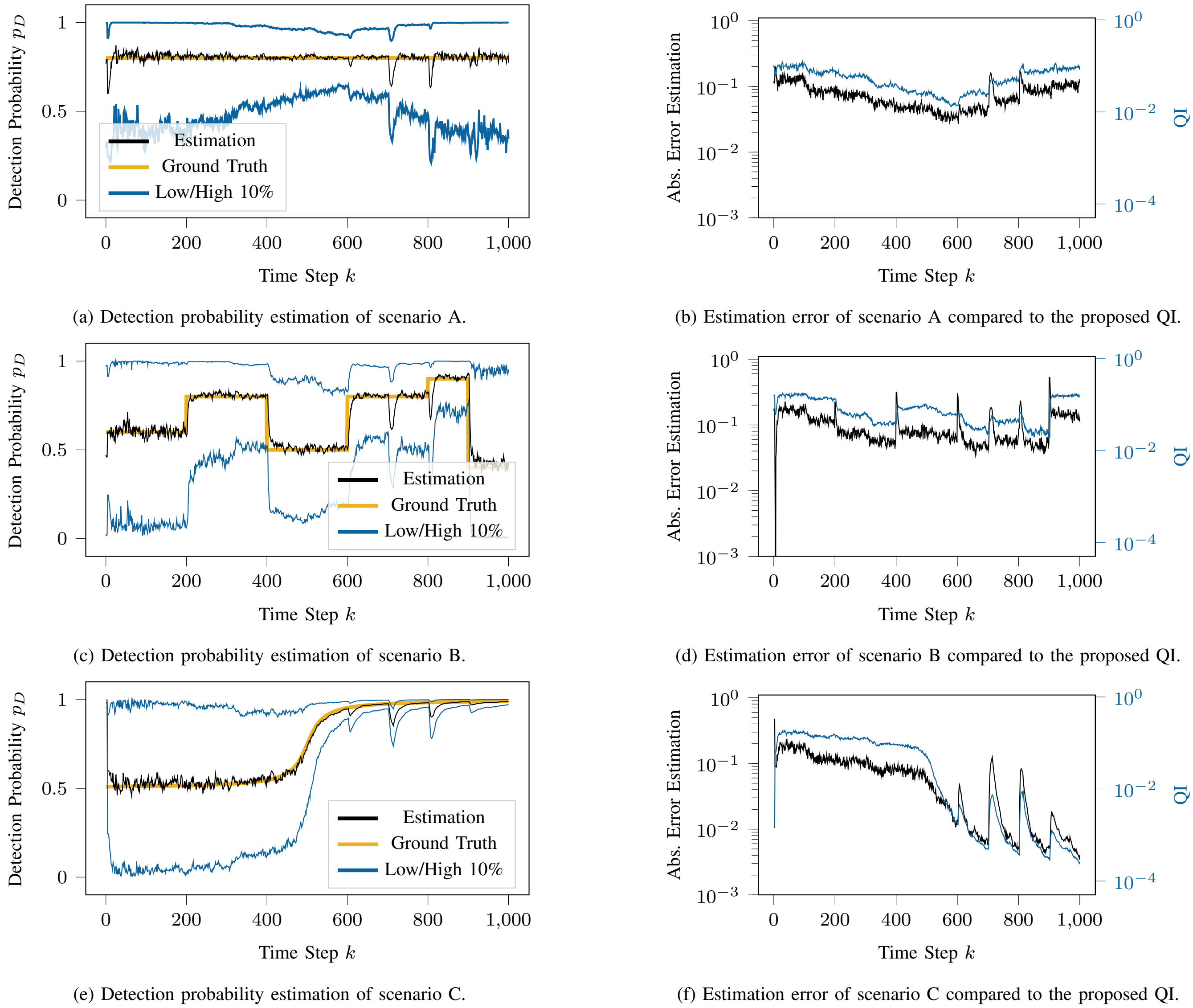

(a) Detection probability estimation of scenario A.

(b) Estimation error of scenario A compared to the proposed QI.

(c) Detection probability estimation of scenario B.

(d) Estimation error of scenario B compared to the proposed QI.

(e) Detection probability estimation of scenario C.

(f) Estimation error of scenario C compared to the proposed QI.

Fig. 5: Results for the three scenarios A, B, and C from Fig. 1. The left column shows the current estimation in black together with the high and low 10% quantile of the estimated Beta distribution. The thick yellow line shows the real value of the detection probability. On the right, we show the estimation error together with the proposed QI. Note that the estimation error requires ground truth knowledge, whereas the QI does not.

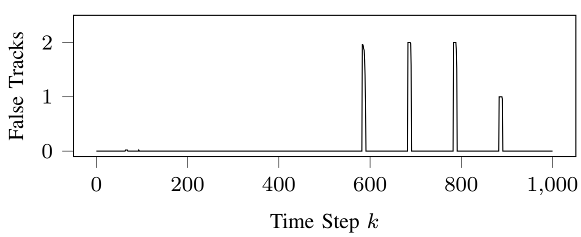

Fig. 6: Number of false tracks. The figure shows the number of false positive tracks computed with the assignment of the GOSPA tracking metric of scenario A. However, the other scenarios are similar.

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