

PHD filter with diffuse spatial prior on the birth process with applications to GM-PHD filter

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Abstract – *This paper presents a simple and efficient way to set the birth process of the Probability Hypothesis Density filter that enhances the performance of this approach when tracking multiple targets in clutter with no a priori spatial information on where targets can appear. The novelty introduced concerns the intensity of the birth Random Finite Set that models new appearing targets. In many papers, this intensity is modelled by a Gaussian mixture whose components are “deterministically distributed” across the surveillance region where targets are more likely to appear than elsewhere. Though this assumption is valid for some specific applications, it can be too restrictive in a more general case. The simple idea underlying and motivating our approach is that targets are more likely to appear around measurements and this amounts to take a single diffuse hypothesis for the birth process.*

Keywords: GM-PHD filter, birth process, Multi Target Tracking, clutter.

1 Introduction

There has been in the last decade a great interest in the finite set statistics (FISST) applied to Bayesian multitarget tracking [1, 7], which naturally enables the tracking of an unknown and time varying number of targets with false alarm, miss-detection and even more complex phenomena such as unresolved or extended targets [8, 9]. The probability hypothesis density (PHD) approximation for Bayesian filtering seems up to date the most popular approach compared to the Multi Hypothesis Tracking (MHT) alternative. One of the key points of this approach is the birth RFS that models new appearing targets and makes the filter alert to initiate new tracks on these targets. However, in many papers, the components of this birth RFS are “deterministically distributed” across the surveillance region. This is equivalent to precisely know, more or less depending on the peak covariance of the individual Gaussian of the birth RFS, where the tracks will

appear. Though this assumption is valid for some specific applications, it can be too restrictive in a more general case. The purpose of this paper is to find how PHD filter can be used when no information about the location of appearing targets is available.

The paper is organized as follows. The PHD filter (from [1]) is summarized in section 2. In section 3, after a description of a “standard” GM-PHD filter (from [2]), the new GM-PHD filter is explained along with a sketch proof for both PHD and GM-PHD filters. Some simulation results are shown in order to compare the new approach with the classical one.

2 The PHD filter

2.1 Motion model

Assume that measurement collections are made during time-steps k and $k+1$. Then target behavior is modeled as follows.

- The motion of individual targets is governed by a Markov transition density $f_{k+1|k}(x|x')$, the probability that a target will have state-vector x at time-step $k+1$ if it had state-vector x' at time-step k .
- $p_s(x') = p_{s,k+1}(x')$ is the probability that a target will persist into time-step $k+1$ if it had state-vector x' at time-step k .
- $b_{k+1|k}(X)$ is the multitarget probability density that a set X of new targets will appear at time-step $k+1$, and $b_{k+1|k}(x)$ is its PHD.
- Motions of individual targets are assumed to be statistically independent.

We do not consider the target spawning in this paper.

2.2 Measurement model

Suppose that a single sensor collects measurement-vectors from possibly multiple targets. The space of all measurement-vectors for the sensor is \mathfrak{Z}_0 . Given this, a single sensor is modeled as follows.

- $p_D(x) = p_{D,k+1}(x)$ is the probability that a target will generate a measurement-vector at time-step $k+1$ if it had state-vector x at time step $k+1$.
- If a target with state-vector x does generate a measurement-vector, the likelihood function $L_z(x) = f_{k+1}(z|x)$ is the probability (density) that this measurement-vector will be z .
- At time step $k+1$, the probability that m false alarms will be generated is $p_{FA,k+1}(m) = e^{-\lambda}\lambda^m/m!$ (Poisson distribution), where $\lambda = \lambda_{k+1}$ is the expected number of measurements. $c(z) = c_{k+1}(z)$ is the probability (density) that any given measurement-vector will be z .

2.3 The PHD filter

The probability hypothesis density (PHD) is a density function $D_{k|k}(x) = D_{k|k}(x|Z^{(k)})$, also known as an ‘‘intensity’’ or ‘‘first-moment density’’, that is defined on single-target state-vector $x \in \mathfrak{X}_0$. It is conditioned on the time-sequence $Z^{(k)} : Z_1, \dots, Z_k$ of collected measurement-sets Z_i for $i = 1, \dots, k$. The PHD filter is an approximation of the full multitarget Bayes filter and temporally propagates a PHD using the following alternating time-update and measurement-update steps:

$$\begin{array}{c} \dots \rightarrow D_{k|k}(x|Z^{(k)}) \\ \downarrow \\ D_{k+1|k}(x|Z^{(k)}) \\ \downarrow \\ D_{k+1|k+1}(x|Z^{(k+1)}) \rightarrow \dots \end{array}$$

PHD filter predictor :

Let $D_{k|k}(x) = D_{k|k}(x|Z^k)$ be the PHD at time-step k . Then the predicted PHD $D_{k+1|k}(x) = D_{k+1|k}(x|Z^{(k)})$ at time-step $k+1$ is given by the equation

$$D_{k+1|k}(x) = b_{k+1|k}(x) + D_{k+1|k}^s(x) \quad (1)$$

where

$$D_{k+1|k}^s(x) = \int F_{k+1|k}(x|x')D_{k|k}(x')dx' \quad (2)$$

where the PHD filter ‘‘pseudo-Markov density’’ is

$$F_{k+1|k}(x|x') = p_s(x')f_{k+1|k}(x|x') \quad (3)$$

PHD filter corrector :

The PHD $D_{k+1|k+1}(x) = D_{k+1|k+1}(x|Z^{(k+1)})$ at time-step k , updated to account for the latest measurement-set $Z' = Z^{(k+1)}$ is given by the approximate equation

$$D_{k+1|k+1}(x) \cong L_{Z'}(x)D_{k+1|k}(x) \quad (4)$$

where the PHD filter ‘‘pseudo-likelihood function’’ $L_{Z'}(x)$ is $L_{Z'}(x) = 1 - p_D(x)$ if $Z' = \emptyset$ and, otherwise,

$$L_{Z'}(x) = 1 - p_D(x) + \sum_{z \in Z'} \frac{p_D(x)\phi_Z(z)}{\lambda c(z) + D_{k+1|k}[p_D\phi_Z]} \quad (5)$$

where $\phi_Z(x)$ is the sensor likelihood function and

$$D_{k+1|k}[h] = \int h(x)D_{k+1|k}(x|Z^{(k)})dx \quad (6)$$

3 Description of the GM-PHD filter

Following applications are developed in the GM-PHD framework, because it is this implementation which seems to have the better compromise between simplicity, permissiveness and performance. In this section, two different approaches are described. The first one is a recall of classical GM-PHD equations with the common assumptions on the birth RFS. The second one will explain the equations of the new approach along with the theoretical origin of this modification.

3.1 Classical GM-PHD filter

Closed-form solutions to the PHD recursion require a linear Gaussian multi-target model. Along with the standard linear Gaussian model for individual target, the linear Gaussian multi-target model includes certain assumptions on the birth, death and detection of targets. These are summarized below:

A.1. Each target follows a linear Gaussian dynamical and observation model:

$$f_{k+1|k}(x|x') = \mathcal{N}(x; F_{k+1}x', Q_{k+1|k}) \quad (7)$$

$$\phi_Z(x) = \mathcal{N}(z; H_{k+1}x, R_{k+1}) \quad (8)$$

where $\mathcal{N}(\cdot; m, P)$ denotes a Gaussian density with mean m and covariance P , $F_{k+1|k}$ is the state transition matrix, $Q_{k+1|k}$ is the process noise covariance, H_{k+1} is the observation matrix and R_{k+1} is the observation noise covariance.

A.2. The survival and detection probabilities are state independent, i.e.

$$p_{s,k+1}(x') = p_{s,k+1} \quad (9)$$

$$p_{D,k+1}(x) = p_{D,k+1} \quad (10)$$

A.3. The intensities of the birth RFS is a Gaussian mixture of the form

$$b_{k+1|k}(x) = \sum_{i=1}^{N_{k+1|k}^\gamma} w_{\gamma,k+1|k}^{(i)} \mathcal{N}(x; m_{\gamma,k+1|k}^{(i)}, P_{\gamma,k+1|k}^{(i)}) \quad (11)$$

Where $N_{k+1|k}^\gamma$ is the number of new hypothesis and $w_{\gamma,k+1|k}^{(i)}$, $m_{\gamma,k+1|k}^{(i)}$, $P_{\gamma,k+1|k}^{(i)}$, $i = 1, \dots, N_{k+1|k}^\gamma$ are given model parameters that determine the shape of the birth intensity.

Initialization :

At time $k = 0$, the initial intensity $D_{0|0}$, is the sum of $N_{0|0}$ Gaussians.

$$D_{0|0}(x) = \sum_{i=1}^{N_{0|0}} w_{0|0}^{(i)} \mathcal{N}(x; m_{0|0}^{(i)}, P_{0|0}^{(i)}) \quad (12)$$

These are distributed across the state space.

GM-PHD filter predictor :

Suppose that the posterior intensity at time k is a Gaussian mixture of the form

$$D_{k|k}(x) = \sum_{i=1}^{N_{k|k}} w_{k|k}^{(i)} \mathcal{N}(x; m_{k|k}^{(i)}, P_{k|k}^{(i)}) \quad (13)$$

Then

$$\begin{aligned} D_{k+1|k}(x) &= p_{s,k+1} \sum_{i=1}^{N_{k|k}} w_{k|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) \\ &+ \sum_{i=1}^{N_{k+1|k}^\gamma} w_{\gamma,k+1|k}^{(i)} \mathcal{N}(x; m_{\gamma,k+1|k}^{(i)}, P_{\gamma,k+1|k}^{(i)}) \end{aligned} \quad (14)$$

With

$$m_{k+1|k}^{(i)} = F_{k+1|k} m_{k|k}^{(i)} \quad (15)$$

$$P_{k+1|k}^{(i)} = F_{k+1|k} P_{k|k}^{(i)} F_{k+1|k}^T + Q_{k+1|k} \quad (16)$$

GM-PHD filter corrector :

Rewrite the predicted PHD at time step k as

$$D_{k+1|k}(x) = \sum_{i=1}^{N_{k+1|k}} w_{k+1|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) \quad (17)$$

Then the PHD at time step $k + 1$ is

$$\begin{aligned} D_{k+1|k+1}(x) &= (1 - p_{D,k+1}) D_{k+1|k}(x) \\ &+ \sum_{z \in Z'} \sum_{i=1}^{N_{k+1|k}} w_{k+1|k+1}^{(i)}(z) \mathcal{N}(x; m_{k+1|k+1}^{(i)}(z), P_{k+1|k+1}^{(i)}) \end{aligned} \quad (18)$$

with

$$\begin{aligned} w_{k+1|k+1}^{(i)}(z) &= \\ &\frac{p_{D,k+1} w_{k+1|k}^{(i)} \mathcal{N}(z; \hat{z}_{k+1|k}^{(i)}, S_{k+1|k}^{(i)})}{\lambda c(z) + p_{D,k+1} \sum_{l=1}^{N_{k+1|k}} w_{k+1|k}^{(l)} \mathcal{N}(z; \hat{z}_{k+1|k}^{(l)}, S_{k+1|k}^{(l)})} \end{aligned} \quad (19)$$

$$m_{k+1|k+1}^{(i)}(z) = m_{k+1|k}^{(i)} + K_{k+1}^{(i)} (z - \hat{z}_{k+1|k}^{(i)}) \quad (20)$$

$$P_{k+1|k+1}^{(i)} = \left[I - K_{k+1}^{(i)} H_{k+1} \right] P_{k+1|k}^{(i)} \quad (21)$$

$$\hat{z}_{k+1|k}^{(i)} = H_{k+1} m_{k+1|k}^{(i)} \quad (22)$$

$$K_{k+1}^{(i)} = P_{k+1|k}^{(i)} H_{k+1}^T \left(S_{k+1|k}^{(i)} \right)^{-1} \quad (23)$$

$$S_{k+1|k}^{(i)} = H_{k+1} P_{k+1|k}^{(i)} H_{k+1}^T + R_{k+1} \quad (24)$$

4 New approach

In classical GM-PHD, the assumption of Gaussian mixture for the birth RFS is done (A.3). But, in most papers, this birth RFS just consists in few well located Gaussians. This is equivalent to know more or less exactly, depending on the prior covariance, the place where tracks appear. This approximation is actually too strong in most cases of multitarget tracking.

The purpose of this new approach is to find a weaker approximation on the birth RFS. The main idea is then to use the information contained in the measurements to set the birth RFS. In practical implementations, this approach leads to the following equations.

New initialization :

The prior intensity at time-step 0 is set to

$$D_{0|0} = 0 \quad (25)$$

The consequences on the initial random state-vector can be written as $P(X_0 = \emptyset) = 1$ (see [3]).

New GM-PHD filter predictor :

$$D_{k+1|k}(x) = p_{s,k+1} \sum_{i=1}^{N_{k|k}} w_{k|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) \quad (26)$$

Note that this equation does not include any expression related to new targets.

New GM-PHD filter corrector :

The PHD $D_{k+1|k+1}(x) = D_{k+1|k+1}(x|Z^{(k+1)})$ at time-step $k + 1$, updated to account for the latest measurement-set $Z' = Z^{(k+1)}$ is given by the equation

$$\begin{aligned} D_{k+1|k+1}(x) &= (1 - p_{D,k+1}) D_{k+1|k}(x) \\ &+ \sum_{z \in Z'} \sum_{i=1}^{N_{k+1|k}} w_{k+1|k+1}^{(i)}(z) \mathcal{N}(x; m_{k+1|k+1}^{(i)}(z), P_{k+1|k+1}^{(i)}) \\ &+ w_{k+1|k+1}^\gamma(z) \mathcal{N}(x; z^*, R_{k+1}^*) \end{aligned} \quad (27)$$

z^* has the same dimension as x and is obtained from the measurement vector z by estimating the measured components of the state space and eventually completing with zeros or a priori values. For instance,

in the case of position and velocity estimation with a sensor measuring position :

$$z^* = [H^{-1}z, 0, 0]^T \quad (28)$$

in this case H is the identity.

R_{k+1}^* is given by

$$R_{k+1}^* = \begin{bmatrix} H^{-1}R_{k+1}H^{-T} & 0_{mn} \\ 0_{nm} & V_{k+1} \end{bmatrix} \quad (29)$$

where the terms 0_{nm} and 0_{mn} are matrices of zeros and V_{k+1} is the covariance matrix describing the non measured components and in this case, velocity. A more detailed example can be found in [10].

$$w_{k+1|k+1}^{(i)}(z) = \frac{p_{D,k+1}w_{k+1|k}^{(i)}\mathcal{N}(z; \hat{z}_{k+1|k}^{(i)}, S_{k+1|k}^{(i)})}{\lambda c(z) + p_{D,k+1} \sum_{l=1}^{N_{k+1|k}} w_{k+1|k}^{(l)}\mathcal{N}(z; \hat{z}_{k+1|k}^{(l)}, S_{k+1|k}^{(l)}) + w_0^\gamma} \quad (30)$$

$$w_{k+1|k+1}^\gamma(z) = \frac{w_0^\gamma}{\lambda c(z) + p_{D,k+1} \sum_{l=1}^{N_{k+1|k}} w_{k+1|k}^{(l)}\mathcal{N}(z; \hat{z}_{k+1|k}^{(l)}, S_{k+1|k}^{(l)}) + w_0^\gamma} \quad (31)$$

With the same definition for $m_{k+1|k+1}^{(i)}(z)$, $P_{k+1|k+1}^{(i)}$, $\hat{z}_{k+1|k}$ and $S_{k+1|k}$, and w_0^γ a parameter.

In other words, it is assumed that each element of the observation-set can be a new target originated measurement with a given weight. This weight w_0^γ is practically set at a low enough level to prevent from creating false targets.

Even if this new approach seems to change deeply one of the main assumptions of the PHD on the state-set by moving the entering targets set from the prediction stage to the measurement update stage, it can be shown that this modification resulting in equations (26) and (27) can be naturally obtain by introducing several assumptions in the classical equations.

4.1 Sketch proof

The new approach is described in terms of GM-PHD filter, but the theoretical origin of this modification can be explain in a more general way. To simplify notations and without loss of generality, the following proof only concern position part of the state vector.

PHD filter predictor :

Assume that the PHD of the multitarget posterior density of entering targets takes the following general form

$$b_{k+1|k}(x) = w_0^\gamma \mathbf{1}_{\mathfrak{X}_0}(x) \quad (32)$$

With \mathfrak{X}_0 the state-space and $\mathbf{1}_S$ the indicator function of set S . Intuitively, it is equivalent to suppose that

targets can appear anywhere with a given probability w_0^γ . Then the predicted PHD $D_{k+1|k}(x)$ at time-step k is given by the equation

$$D_{k+1|k}(x) = \int p_s(x') f_{k+1|k}(x|x') D_{k|k}(x') dx' + w_0^\gamma \mathbf{1}_{\mathfrak{X}_0}(x) \quad (33)$$

This equation can be rewritten with the assumptions (A.1) and (A.2) of the GM-PHD but the third assumption (A.3) on the birth RFS cannot be maintained. With the same assumption on the posterior intensity at time k as in (13), the GM-PHD filter predictor can be written

$$D_{k+1|k}(x) = D_{k+1|k}^s(x) + b_{k+1|k} \\ = p_{s,k+1} \sum_{i=1}^{N_{k|k}} w_{k|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) + w_0^\gamma \mathbf{1}_{\mathfrak{X}_0}(x) \quad (34)$$

The parameter w_0^γ is generally taken low enough to avoid false track creation. Intuitively, targets are predicted around known targets of the previous time step with high probability and eventually elsewhere with low probability. This prediction does not take the form of a Gaussian mixture but will lead to a correct update under an additional assumption. To represent practically the GM-PHD predictor in a real Gaussian mixture frame, only the first term $D_{k+1|k}^s(x)$ is used. The second term will naturally appear in the GM-PHD corrector step.

PHD filter corrector :

By using the expression of $D_{k+1|k}^s(x)$ and the PHD filter corrector (4), it can be shown that

$$D_{k+1|k+1}(x) = (1-p_D)D_{k+1|k}^s(x) + (1-p_D)b_{k+1|k}(x) \\ + \sum_{z \in Z'} \frac{p_D D_{k+1|k}^s(x) + w_0^\gamma p_D \phi_Z(x)}{\lambda c(z) + \int p_D \phi_Z(\xi) D_{k+1|k}(\xi) d\xi} \quad (35)$$

where $p_D = p_{D,k+1}(x)$.

The additional assumption needed here is that entering targets are always detected. Indeed, a non detected new target will be easily considered when it will be detected for the first time because no assumptions about appearance location are made. With these additional considerations, predictor is given by

$$D_{k+1|k+1}(x) = (1-p_D)D_{k+1|k}^s(x) \\ + \sum_{z \in Z'} \frac{p_D D_{k+1|k}^s(x) + w_0^\gamma p_D \phi_Z(x)}{\lambda c(z) + \int p_D \phi_Z(\xi) D_{k+1|k}^s(\xi) d\xi + w_0^\gamma \int \phi_Z(\xi) d\xi} \quad (36)$$

This, written in a Gaussian mixture way, with the assumptions (A.1) and (A.2), complete a part of the proof of the new GM-PHD filter corrector.

This proof is still not complete because the last assumption on the appearance of targets implies slight modifications of the observation-set. The consequences of these modifications on the derivation of PHD filter corrector have to be studied. For the GM-PHD, an equivalent way to obtain the same results is to take as birth model a single weighted Gaussian with a large or even infinite covariance. This approach actually only works in linear measurement cases and is often prone to numerical problems. Such an initialization is used by Vihola [3] in a linear case.

5 Simulation results

In the following examples, the non-linear tracking performance of the new GM-PHD filter is demonstrated. Observations are generated by an active sensor delivering noisy bearing and range measurements. Another more complicated example with several passive sensors can be found in [10].

5.1 Filter Models

Following models are used in the three scenarios defined in parts 4.2 and 4.3. Let X_k and z_k be respectively the state and measurement vector at time k . State vector is defined at each time-step by :

$$X_{k+1} = FX_k + v_k \quad (37)$$

where

$$X_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]^T \quad (38)$$

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (39)$$

$$v_k \sim \mathcal{N}(\cdot; 0, Q) \quad (40)$$

$$Q = \sigma_v^2 \begin{bmatrix} T^3/3 & 0 & T^2/2 & 0 \\ 0 & T^3/3 & 0 & T^2/2 \\ T^2/2 & 0 & T & 0 \\ 0 & T^2/2 & 0 & T \end{bmatrix} \quad (41)$$

with T is the sensor scanning period. Measurement vector is defined by

$$z_k = h(X_k) + w_k \quad (42)$$

where

$$h(X_k) = \begin{bmatrix} \arctan\left(\frac{x_k}{y_k}\right) \\ \sqrt{x_k^2 + y_k^2} \end{bmatrix} \quad (43)$$

$$w_k \sim \mathcal{N}(\cdot; 0, R) \quad (44)$$

$$R = \begin{bmatrix} \sigma_\theta^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix} \quad (45)$$

We use the UKF update equation (see [5]) instead of (21) to (24) to take into account non linear measurement.

5.2 Scenario 1

The first scenario under consideration is depicted on figure 1. The sensor is located at the origin and observations consisting of bearing and range measurement are taken every 1s. The observation region is a disc of radius $20km$ in which a total of 6 targets enter and leave the scene at various time. Figure 1 focus on the center of the observed area where clutter is more concentrated. All the targets are originated from two specific areas defined by

$$m_{\gamma, k+1|k}^{(1)} = [-5000, 6000, 0, 0]^T \quad (46)$$

$$m_{\gamma, k+1|k}^{(2)} = [7000, 3000, 0, 0]^T \quad (47)$$

$$P_{\gamma, k+1|k}^{(i)} = [100, 100, 100, 100]^T, \quad i = 1, 2. \quad (48)$$

The probability of target detection is $p_{D, k+1} = 0.9$. There is an average number of 50 clutter points per scan over the region $[0, 2\pi[rad \times [0, 20] km$.

This case match perfectly with the assumption on birth RFS in the standard GM-PHD filter.

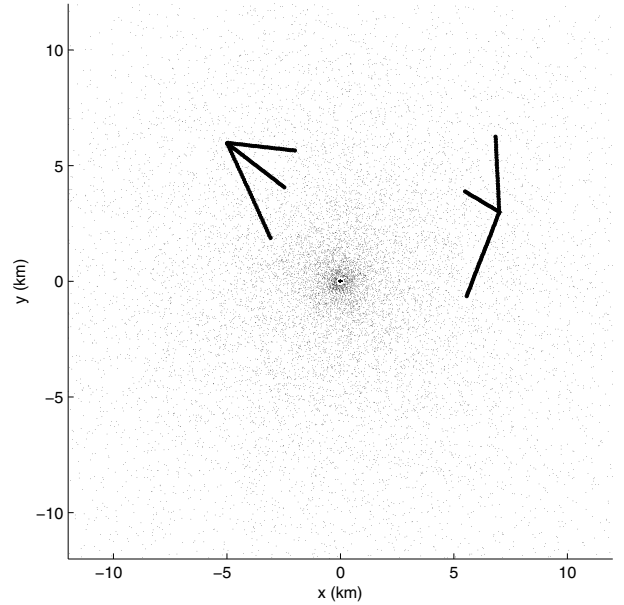


Figure 1: Target trajectories (*line*), clutter (*dot*) and sensor position (*cross*) during 300s

5.3 Scenario 2

The second scenario under consideration is roughly the same that the first, but the covariance of Gaussians describing the location of entering targets is taken larger, that is to say, $P_{\gamma, k+1|k}^{(i)} = [10^6, 10^6, 100, 100]^T$. This scenario is depicted on figure 2.

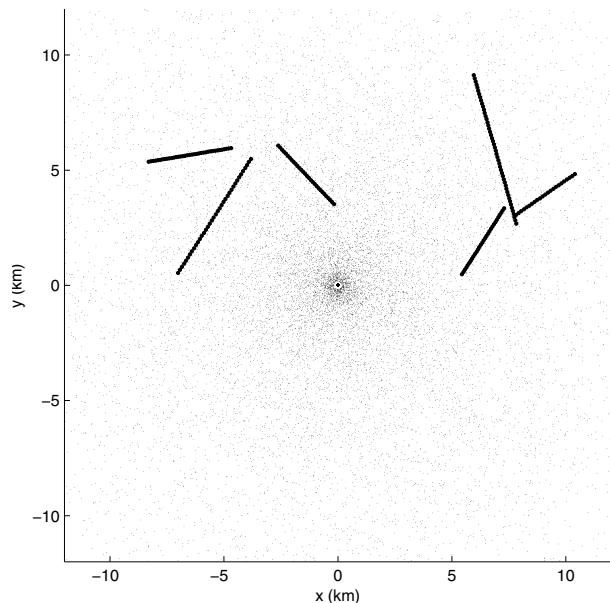


Figure 2: Target trajectories (*line*), clutter (*dot*) and sensor position (*cross*) during 300s

5.4 Scenario 3

The third scenario under consideration is depicted on figure 3. There is still the same number of targets and the time of appearance for each is the same. But in this case, there is no information about the location of entering targets.

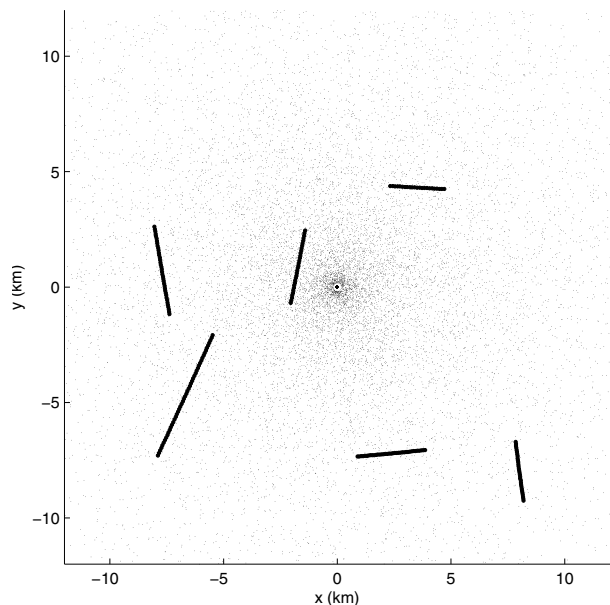


Figure 3: Target trajectories (*line*), clutter (*dot*) and sensor position (*cross*) during 300s

5.5 Parameter settings

To completely set the GM-PHD filter, some parameters have still to be defined. First, to cut combinatorial complexity, the number of Gaussians in the mixture is controlled by pruning components with low weights and merging components which are closed together (more details in [4]). These two steps are defined by two respective thresholds. The pruning threshold is set to $\tau_{prun} = 10^{-5}$ and the merging one is set to $\tau_{merg} = 25$. The value of the merging threshold is deliberately taken high enough to avoid false track initiation by duplication.

Another parameter to set is the weight of Gaussians modeling entering targets. This weight is not the same for both approaches. Since the new method don't make assumptions on the birth RFS, the value of this parameter is the same: $w_0^\gamma = 10^{-8}$. This value is calculated to be, after being updated, just over the pruning threshold at the current time. In this case, the value will fall under the threshold if no measurement matches at the following time-step. For the standard method, the choice of an initial weight will be detailed in the part 4.6, since it will be different for each scenario.

The last parameter to set is the value of the confirmation threshold τ_{conf} . This value is used to select Gaussians which are most likely to represent a real target. The value used for the following computations is $\tau_{conf} = 0.9$.

5.6 Results

The metric used to compare both methods is the OSPA metric (see [6]) with a cut-off value set to $c = 200$. The cardinality is directly plotted on another graphic to underline specific remarks.

Scenario 1

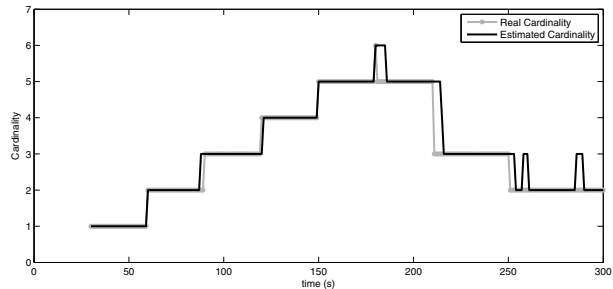


Figure 4: Real and estimated cardinality for standard GM-PHD filter

For this scenario, location of entering targets is well known and initial weight is set to $w_{\gamma, k+1|k} = 0.1$. In this case targets are detected and considered as tracks instantaneously. This is not, in real applications, a true advantage. Indeed, if a single clutter point fall into the place defined for new targets, a false track will be

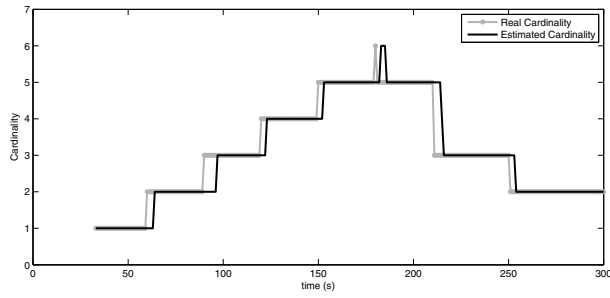


Figure 5: Real and estimated cardinality for new GM-PHD filter

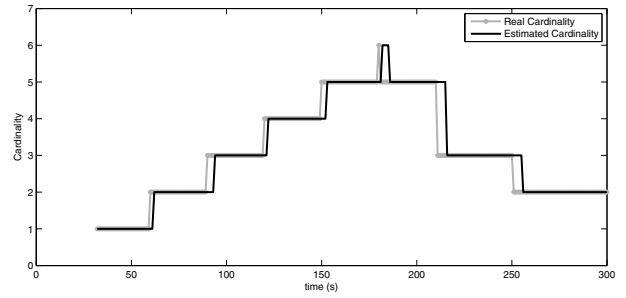


Figure 7: Real and estimated cardinality for standard GM-PHD filter

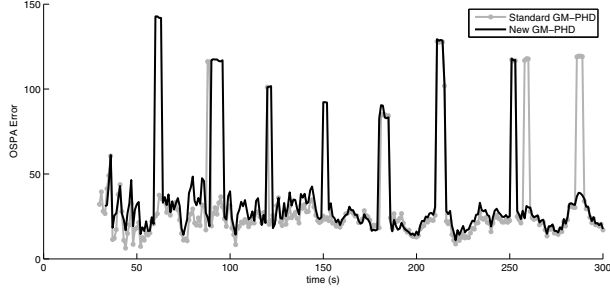


Figure 6: OSPA metric for standard and new approaches

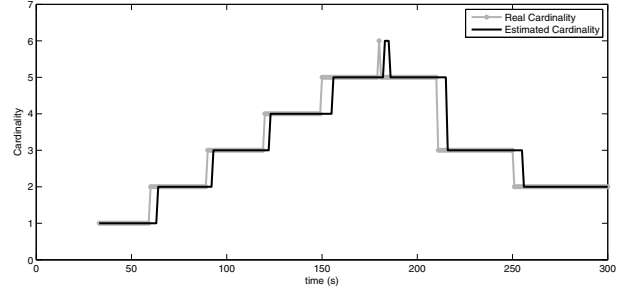


Figure 8: Real and estimated cardinality for new GM-PHD filter

immediately initialized. This phenomenon is depicted on figure 4 at time-steps $t_k = 260s$ and $t_k = 285s$. False track initialization happens more or less depending on the density of clutter around predicted location of appearance for new targets.

A lower value for the parameter $w_{\gamma, k+1|k}$ can lead to a scenario with less false tracks, but in this case, the detection of new targets will take several time-steps, and the results are then equivalent to these of the new method (figure 5).

In terms of localization, there is no real difference between both methods although the new approach has no information about location of entering targets.

Moreover, for the standard method, even in cases where location of entering targets is well known, if a track is deleted for some reason although the target still exists, then no other track will be created on this target because its position does not match with the assumption on birth RFS at a given time-step t_k with $k \neq 0$.

Scenario 2

In this scenario, the information on location of new targets is not as accurate as in the first scenario. To avoid false track creation, the initial weight in classical approach is set to $w_{\gamma, k+1|k} = 0.01$. In terms of cardinality, both methods are equivalent as it can be seen by comparing figure 7 and figure 8.

Figure 9 shows the real difference between standard and new methods. Since the information of the Gaussians

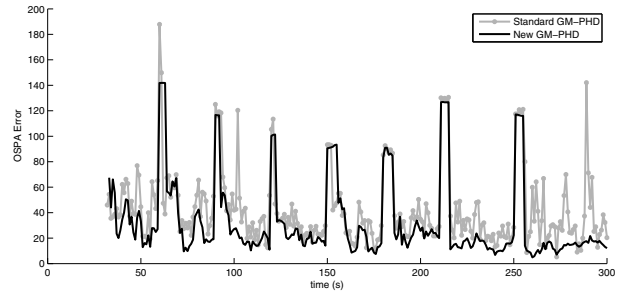


Figure 9: OSPA metric for standard and new approaches

modeling the birth intensity is less accurate about the initial position, convergence rate of the velocity is very low and then localization error is high during first time step. The results of the new approach are of the same order than in the scenario 1 because the parameter which is changed is not used by the method.

Scenario 3

In this kind of scenario, where no information about the location of entering targets is given, since measurement is non-linear the method consisting in setting a single diffuse Gaussian cannot be applied. So, the comparison depicted on figure 10 concern only the new method. Even if it is not possible to directly compare a method on two different scenarios, figure 10 shows that the new method has the same behavior with or without information on new targets location. That is not the

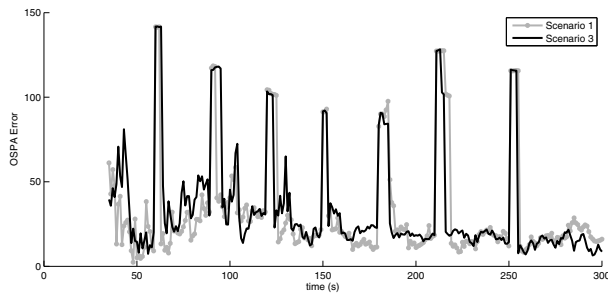


Figure 10: OSPA metric for the new approach in the cases of scenarios 1 and 3

case for the classical approach where we have not been able to obtain any results.

6 Conclusion

We have presented a simple and efficient way to use birth process in the PHD filter where no assumption is made on some particular areas where targets are more likely to appear in the surveillance region. The results shows a significant improvement compare to the classical approach in that it has an equivalent performance on a scenario where targets are originated from some known particular areas and has best performance in other cases. The new approach outperforms the classical one especially on a scenario where targets can appear everywhere. This result is simply obtained by taking a birth RFS with diffuse intensity rather than a Gaussian mixture whose peaks are located on some particular areas of the surveillance region. The interpretation of this is very intuitive and it amounts to take into account that each measurement can, in addition of updating an existing track, come from a new target.

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