

Passive Multi Target Tracking with GM-PHD Filter

Dann Laneuville

DCNS

SNS Division

Toulon, France

dann.laneuville@dcnsgroup.com

J r mie Houssineau

DCNS

SNS Division

Toulon, France

jeremie.houssineau@dcnsgroup.com

Abstract – This paper considers the challenging problem of multitarget tracking with passive data, obtained here by geographically distributed cameras. We use a Gaussian Mixture Probability Hypothesis Density filter approach to solve this difficult problem. As we make no spatial assumptions for the birth process, we use a slightly modified filter to obtain our results. We first describe the modified filter and detail our application before we present some results obtained on a realistic test scenario. Our simulations demonstrate that the proposed Probability Hypothesis Density filter is a promising candidate for three dimensional passive multi target tracking in clutter.

Keywords: Multi target tracking, 3D passive tracking, GM-PHD filter, birth process, cameras.

1 Introduction

Passive Multi Target Tracking (MTT) in clutter with unknown and time-varying number of possibly maneuvering targets has been so far and is still a great challenge. Historically, a lot of work has been done in a two dimensional (2D) context, known as Bearings Only Tracking (BOT) or Target Motion Analysis (TMA) especially in sonar applications. Most researches in the field of BOT have first concentrated on tracking a single *non maneuvering* target in a *clean* environment. In the nineties, [1] has studied a BOT maximum likelihood estimator in the presence of false alarms for a single and non maneuvering target. On the other hand, concerning maneuvering targets, [2], [3] and more recently [4], have presented different BOT estimators for a single maneuvering target in a clutter less environment. These involved EKF-IMM, UKF-IMM, particle and Gaussian sum filters. All these examples concern a single platform, the own ship, that processes the azimuth angle and has to maneuver to gain observability, and hence convergence in the filtering process, which makes the problem of BOT particularly difficult.

With several passive sensors, the problem seems easier because it is observable, but the difficulty is reported in the data association process, especially in a multitarget cluttered environment scenario. In this context, a single maneuvering target encounter in light clutter was first

studied in [5]: an IMM-PDAF approach in a three dimensional (3D) context with two infra-red sensors is presented. More recently, in a very different context, [6] has presented a multisensor (camera) debris tracking application with an UKF filter combined with a global nearest neighbor (GNN) approach to assign measurements to tracks. The number of debris (targets) is unknown and high enough to make this problem especially challenging.

In parallel, following the pioneering work of Mahler, there has been in the last decade a great interest in the finite set statistics applied to Bayesian MTT, 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. The PHD approximation for Bayesian MTT, introduced by [7], seems up to date one of the most popular approach compared to the Multi Hypothesis Tracking alternative.

There are mainly two ways to compute the PHD, the Gaussian Mixture approach denoted GM-PHD in the sequel (see for instance [8]), and the Sequential Monte-Carlo approach denoted SMC-PHD (see for instance [9]). The first implementation is easier to use in a MTT context because there is no need of some ad hoc post processing to extract the different target's states such as position and velocity, which are represented by a Gaussian density. Moreover, track labeling is naturally and easily done. The second implementation seems more difficult to use because it needs the extraction of the different target's state from a global density and requires much more computational power, though [9] presents a new attractive scheme for this SMC-PHD implementation with a Rao-Blackwellised Particle Filter (RBPF). The RBPF approach presented in this paper is shown to be applicable in a 2D bearings-only multitarget tracking scenario with three passive sensors.

The work presented here uses the GM-PHD approach and we study a 3D passive surveillance application with geographically distributed cameras. Fig.1 illustrates the general context of this application: some ships are travelling in the Field Of View (FOV) of different cameras, each of them extracting the angular coordinates consisting of the circular (c) and elevation (e) angles by means of a video extractor. This information is then sent

to the central fusion node where a 3D algorithm processes the tracks in Cartesian coordinates: this is the plot fusion issue. Another way is to establish local angular tracks which are then sent to the fusion node where a track fusion algorithm has to process the 2D angular tracks into 3D tracks: this is the track fusion issue. The choice between the two solutions has many system implications. The track fusion approach requires lower bandwidth for the communication from the sensor level nodes to the fusion node. Indeed, the filtering of elementary detections eliminates most false alarms before transmission while the complete set of raw data containing false detection is transmitted in the plot fusion solution. It is well known that the pre-filtering of track fusion solution slightly degrades the tracking accuracy, though it greatly simplifies the multitarget data association process which is made cumbersome in the plot fusion approach by the numerous combinations involved in this process leading to false tracks known as “ghosts”. We want to study here a plot fusion scheme and to test a GM-PHD filtering approach on this difficult problem. We use here a modified GM-PHD approach, detailed in [10], to solve this challenging problem.

The rest of the paper is organized as follow: in section 2, we recall the main motivations and features of this modified version of the original GM-PHD filter. In section 3, we detail the models and the parameter settings chosen for our application, show some results obtained on simulated data before we give some concluding remarks.

2 Description of the GM-PHD filter

In classical PHD filter, the assumption of Gaussian mixture for the birth RFS is done. But, in most papers, the components of this birth RFS are “deterministically distributed” across the surveillance region where targets are more likely to appear than elsewhere. 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. This approximation is actually too strong in our surveillance application where targets can appear (first detected time) everywhere in the FOV of the sensors. The main idea is then to use the measurements to set the birth RFS. In practical implementations, this approach leads to the following modified equations of the GM-PHD filter. The birth RFS process contribution in the PHD vanishes from the prediction step and is reported in the update step. More details can be found in [10].

No spawning is assumed in this paper.

2.1 GM-PHD tracker

For simplicity and without loss of generality, we describe the filter in the linear case. We will see in next paragraph which equation should be changed to take into account a non linear measurement equation, as it is the case with Cartesian state and angular measurements.

Step 0: Initialization

The prior intensity is simply set to zero, which is equivalent to start with an empty finite set of target state vector, i.e.

$$D_0 = 0 \quad (1)$$

Step 1: Prediction

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

$$D_{k|k}(x) = \sum_{i=1}^{N_k} w_{k|k}^{(i)} \mathcal{N}(x; m_{k|k}^{(i)}, P_{k|k}^{(i)}) \quad (2)$$

Then, the predicted intensity at time step $k+1$ is the Gaussian mixture,

$$D_{k+1|k}(x) = p_s \sum_{i=1}^{N_k} w_{k|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) \quad (3)$$

with

$$m_{k+1|k}^{(i)} = F_{k+1|k} m_{k|k}^{(i)} \quad (4)$$

$$P_{k+1|k}^{(i)} = F_{k+1|k} P_{k|k}^{(i)} F_{k+1|k}^T + Q_{k+1|k} \quad (5)$$

and p_s the survival probability.

Step 2: Update

Rewrite the predicted PHD at time step $k+1$ as

$$D_{k+1|k}(x) = \sum_{i=1}^{N_k} w_{k+1|k}^{(i)} \mathcal{N}(x; m_{k+1|k}^{(i)}, P_{k+1|k}^{(i)}) \quad (6)$$

Then, the posterior intensity at time step $k+1$ is the Gaussian mixture

$$\begin{aligned} D_{k+1|k+1}(x) &= (1 - p_D) D_{k+1|k}(x) \\ &+ \sum_{z \in Z'} \sum_{i=1}^{N_k} w_{k+1|k+1}^{(i)}(z) \mathcal{N}(x; m_{k+1|k+1}^{(i)}(z), P_{k+1|k+1}^{(i)}) \\ &+ w_{k+1|k+1}^y(z) \mathcal{N}(x; z^*, R_{k+1}^*) \end{aligned} \quad (7)$$

with

$$\begin{aligned} w_{k+1|k+1}^{(i)}(z) &= \frac{p_D w_{k+1|k}^{(i)} \mathcal{N}(z; \hat{z}_{k+1|k}^{(i)}, S_{k+1|k}^{(i)})}{\lambda c(z) + p_D \sum_{l=1}^{N_k} w_{k+1|k}^{(l)} \mathcal{N}(z; \hat{z}_{k+1|k}^{(l)}, S_{k+1|k}^{(l)}) + w_0^y} \end{aligned} \quad (8)$$

$$\begin{aligned} w_{k+1|k+1}^y(z) &= \frac{w_0^y}{\lambda c(z) + p_D \sum_{l=1}^{N_k} w_{k+1|k}^{(l)} \mathcal{N}(z; \hat{z}_{k+1|k}^{(l)}, S_{k+1|k}^{(l)}) + w_0^y} \end{aligned} \quad (9)$$

$$m_{k+1|k+1}^{(i)}(z) = m_{k+1|k}^{(i)} + K_{k+1}(z - \hat{z}_{k+1|k}^{(i)}) \quad (10)$$

$$P_{k+1|k+1}^{(i)} = [I - K_{k+1}H_{k+1}]P_{k+1|k}^{(i)} \quad (11)$$

$$\hat{z}_{k+1|k} = H_{k+1}m_{k+1|k} \quad (12)$$

$$S_{k+1|k} = H_{k+1}P_{k+1|k}H_{k+1}^T + R_{k+1} \quad (13)$$

$$K_{k+1} = P_{k+1|k}H_{k+1}^T S_{k+1|k}^{-1} \quad (14)$$

Note: the last term in eq. (7) is an abusive notation meaning that a Gaussian density in the state space is set up from a measurement and its covariance matrix. We will detail this procedure in the next 2.3 section.

Step 3: Pruning

The components whose weight is below the truncation threshold τ_p are eliminated. Weights of the remaining Gaussians are renormalized.

Step 4: Merging

The components whose distance between their means fall under a merging threshold U are fused. We use here exactly what is described in [11].

Step 5: Track confirmation

The components whose weight is above the confirmation threshold τ_c are declared as a track.

2.2 State and measurement models

In our surveillance application, the target state consists of position and velocity in 3D

$$X = [x \ y \ z \ v_x \ v_y \ v_z]' \quad (15)$$

and we simply use the classical near constant velocity (CV) model to describe its evolution

$$F_{(k+1|k)} = \begin{pmatrix} 1 & 0 & 0 & dt & 0 & 0 \\ 0 & 1 & 0 & 0 & dt & 0 \\ 0 & 0 & 1 & 0 & 0 & dt \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad (16)$$

with $dt = t_{k+1} - t_k$ the time interval between two reports at the fusion node coming from the different sensors S_i . The covariance matrix of the process noise is

$$Q_{(k+1|k)} = \sigma_v^2 \begin{pmatrix} \frac{dt^3}{3} & 0 & 0 & \frac{dt^2}{2} & 0 & 0 \\ 0 & \frac{dt^3}{3} & 0 & 0 & \frac{dt^2}{2} & 0 \\ 0 & 0 & \frac{dt^3}{3} & 0 & 0 & \frac{dt^2}{2} \\ \frac{dt^2}{2} & 0 & 0 & dt & 0 & 0 \\ 0 & \frac{dt^2}{2} & 0 & 0 & dt & 0 \\ 0 & 0 & \frac{dt^2}{2} & 0 & 0 & dt \end{pmatrix} \quad (17)$$

The measurement consists of two angles

$$z = \begin{pmatrix} c \\ e \end{pmatrix} = \begin{pmatrix} \tan^{-1} \frac{y-y^{S_i}}{x-x^{S_i}} \\ \tan^{-1} \frac{z-z^{S_i}}{\sqrt{(x-x^{S_i})^2 + (y-y^{S_i})^2}} \end{pmatrix} \quad (18)$$

With $(x^{S_i}, y^{S_i}, z^{S_i})$ the i^{th} sensor position, assumed to be perfectly known.

The measurement noise covariance matrix, assumed to be the same for each sensor, is given by

$$R_{k+1} = R = \begin{pmatrix} \sigma_{cir}^2 & 0 \\ 0 & \sigma_{ele}^2 \end{pmatrix} \quad (19)$$

Due to the non linear nature of the measurement model (18) consisting of two angles related to a 3D Cartesian state, we use the UKF update step to compute the predicted measurement, its covariance matrix and the filter gain. Thus, the above (12), (13) and (14) equations have to be suitably modified and the reader can refer to [12] for detailed update UKF equations.

2.3 Track initialization

As commonly done in passive applications (like in BOT), where no range measurement is available, we choose an a priori distance d_0 with a large uncertainty σ_{d0} to be able to initialize a Cartesian state on a single detection $z = (c, e)$ from a camera. This is achieved by means of a UT transform where (c, e, d_0) and the associated covariance matrix

$$R = \begin{pmatrix} \sigma_{cir}^2 & 0 & 0 \\ 0 & \sigma_{ele}^2 & 0 \\ 0 & 0 & \sigma_{d0}^2 \end{pmatrix} \quad (20)$$

are converted to Cartesian coordinates, state and covariance,

$$X_{pos} = [x_0 \ y_0 \ z_0]' \quad (21)$$

$$P_{pos} = \begin{pmatrix} P_{xx} & P_{xy} & P_{xz} \\ P_{xy} & P_{yy} & P_{yz} \\ P_{xz} & P_{yz} & P_{zz} \end{pmatrix} \quad (22)$$

This distance is set to $d_0 = 2 \text{ km}$ with $\sigma_{d0} = 500 \text{ m}$. This concerned the position part of the state vector and its covariance matrix. The velocity is initialized to zero with a large covariance, set here to $\sigma_{vx0} = \sigma_{vy0} = \sigma_{vz0} = 10 \text{ mS}^{-1}$.

Finally, this amounts to start the state vector (15) with

$$X_0 = [x_0 \ y_0 \ z_0 \ 0 \ 0 \ 0]'$$
 (23)

and with covariance matrix

$$P_0 = \begin{bmatrix} P_{pos} & 0_{3 \times 3} \\ 0_{3 \times 3} & \text{diag}(\sigma_{vx0}^2 \ \sigma_{vy0}^2 \ \sigma_{vz0}^2) \end{bmatrix}$$
 (24)

So, on each measurement coming from a camera, and in the update step of the previous section, a Gaussian density is set up with X_0 and P_0 and this what was meant with an abusive notation by

$$\mathcal{N}(x; z^*, R_{k+1}^*)$$

in the last term of eq. (7).

3 Simulation results

We present here some results obtained on a three dimensional scenario with an unknown and time varying number of targets and simulated data coming from geographically distributed cameras.

3.1 Scenario description

The scenario under consideration is depicted on figure 1. The target trajectories, corresponding to different surface targets, are plotted with a number at their starting point whereas the positions of the three sensors are indicated with a star. Targets are moving with a speed between 10 and 15 knots and some are slowly maneuvering with a turn rate of $2^\circ/s$.

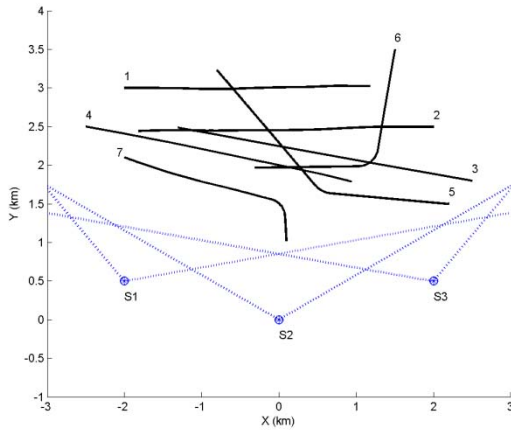


Fig.1 Scenario (vertical view)

3.2 Measurements simulation

Three cameras are used, one located at the origin and at an altitude of 50 m and the two others symmetrically disposed at (+/- 2000, 500, 50).

The look at angles of the cameras are respectively $(0^\circ, -5^\circ)$, $(20^\circ, -5^\circ)$ and $(-20^\circ, -5^\circ)$ with a field of view (FOV) of $120^\circ \times 30^\circ$. The measurements consist of circular and elevation angles with $\sigma_c = \sigma_e = 10^{-3} \text{rad}$ and are taken with a frame rate of $T = 3$ sec for each sensor and sent without delay at the fusion node. There is one second of time lag between each camera report so that the fusion node receives a report every second ($dt = 1$ s). Each camera report consists of target detections, if detected, and false alarms.

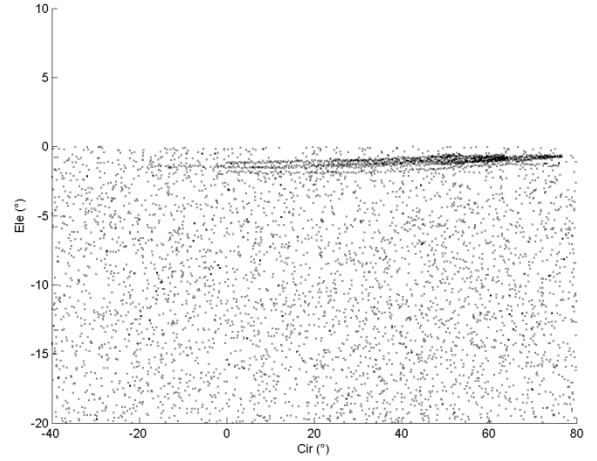


Fig.2 Measurements of camera 1

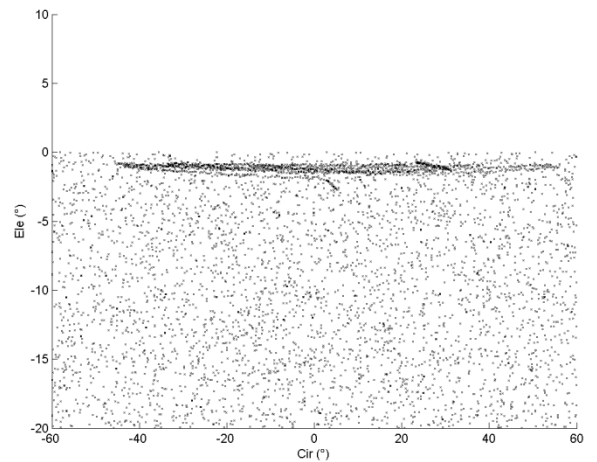


Fig.3 Measurements of camera 2

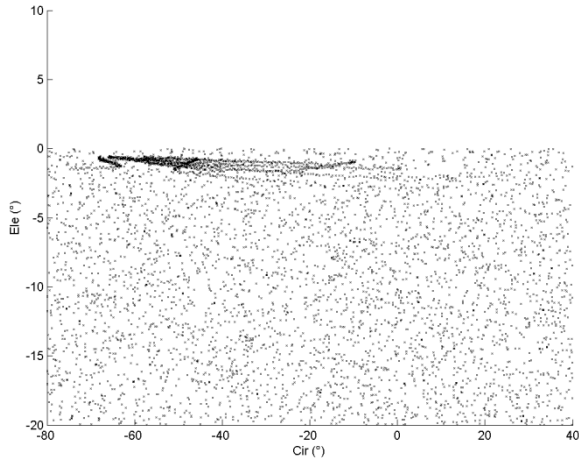


Fig.4 Measurements of camera 3

The false alarms, corresponding to “waves” detection in the video extraction process of our application, are supposed to be uniformly distributed in the image frame $c(z) = U_{[c_{min} c_{max}]} \times U_{[e_{min} e_{max}]}$ and are set to a number of $\lambda = 20$ per image, which is quite a high value. The above figures Fig.(2), Fig. (3) and Fig. (4) show the accumulated measurements obtained on the scenario in the (cir, ele) plan of the three cameras.

3.3 Results

The process noise intensity is set to $\sigma_v^2 = (0.1)^2$. The parameters of the PHD filter are set to:

- Initial weight $w_0^y = 2.10^{-6}$
- Probability of detection $P_d = 0.95$
- Probability of survival $P_s = 1$
- Pruning threshold $\tau_p = 1.10^{-6}$
- Merging threshold $U = 25$
- Confirmation threshold $\tau_c = 0.9$

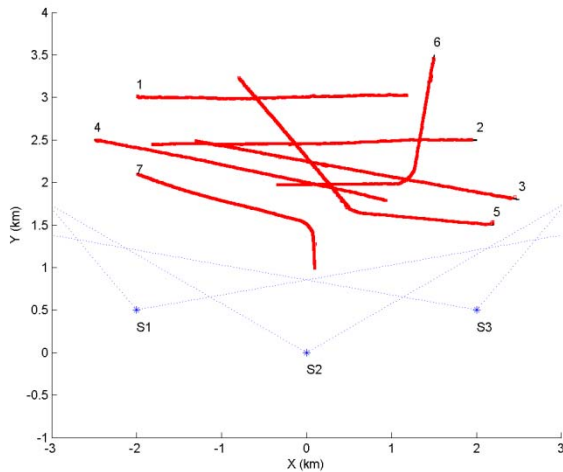


Fig.5 Estimated tracks
(True : thin black, estimated : thick red)

Fig. (5) shows the estimated tracks plotted with the ground truth. It can be seen that the filter globally performs very well, though a zoom on certain parts (crossings, maneuvers) will show some discrepancies. To be able to look closer at a glance global performance in terms of track initialization/deletion time, number of false tracks and tracking accuracy, we plot the true and estimated cardinality on the following figure Fig.(6) and the OSPA metric defined in [13] with a cut off value for the c parameter of 20 on Fig. (7).

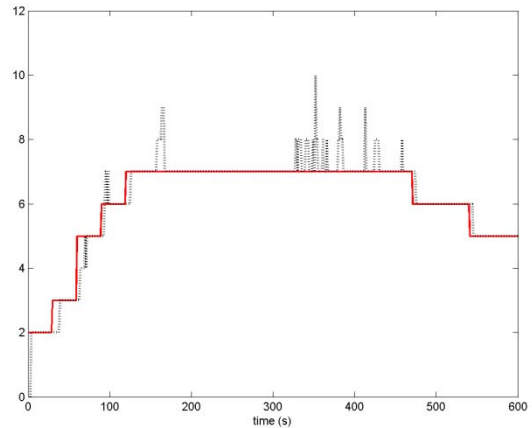


Fig.6 Cardinality
(solid line : true, dashed : estimated)

The results showed here are typically those of a medium case (there is a small process noise on the target accelerations), and they can vary (better or worse) whether the crossings are closer in space and time. The cardinality shows some disturbances around time 350 s that corresponds to different crossings between tracks 2, 5 and 3 with some few track duplications phenomena also visible on the OSPA metric above.

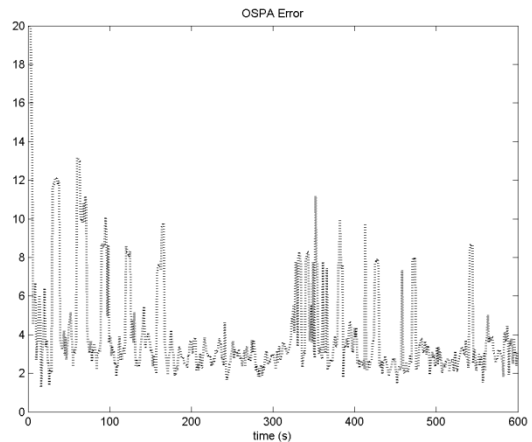


Fig.7 OSPA metric

As expected, the OSPA metric presents well localized peaks at each new appearing or disappearing target. The mean value of the RMS part is about 3 m, if we consider that the position part is dominating the total RMS error, which is a good performance.

The two following figures show a zoom on particular points. The first one (Fig.8) is at a crossing in space and time where we can see some track duplication phenomena.

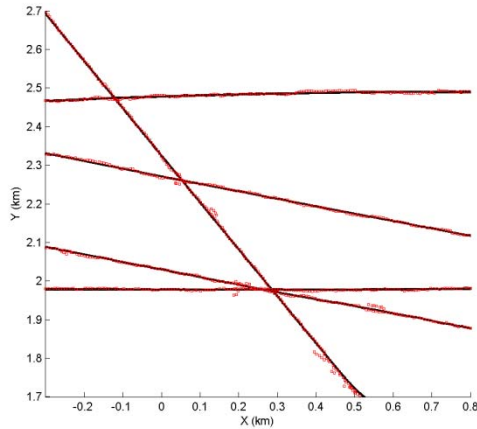


Fig.8 Zoom at a crossing point in space and time

The second one, Fig. (9), focuses on maneuvers where we can see that there is a bias, due to a crude maneuvering model (CV model with constant process noise).

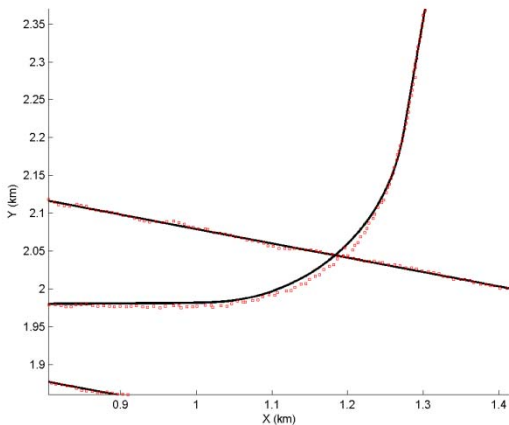


Fig.9 Zoom on a maneuver

4 Conclusion

We have presented a three dimensional passive tracking application with a modified version of the GM-PHD filter where no assumption is made on some particular areas where targets are more likely to appear in the surveillance region. This modified version of the original filter has led to fairly good results where we have not been able to use the original version of the GM-PHD. Note this was also the case in [10] with a surveillance radar application.

These first results obtained on simulated data, with quite heavy clutter, are promising for this challenging application of passive surveillance. Note that slowly maneuvering targets have been correctly tracked with a single constant process noise filter. Of course this point could be enhanced by using a multiple model approach such as in [14] in case of “hard” maneuvers. Also note that we did not take advantage that we tracked surface targets. It could have been as well aerial targets.

Finally, though we did not carry out detailed analysis with simulations on different scenarios and perform Monte-Carlo simulations, we can believe that the GM-PHD filter proposed in [10] is a promising candidate for passive multitarget tracking in clutter that remains a difficult problem.

Future work will consist of a more detailed performance analysis of the proposed approach, in particular how to enhance the results at crossing points and how to take into account eventual occlusions.

References

- [1] C. Jauffret and Y. Bar-Shalom, *Target Motion Analysis in the Presence of False Alarms*, JASA, 94 (3), Sept. 1993, pp 1372-1375.
- [2] B. Ristic, M. Sanjeev Arulampalam, *Tracking a manoeuvring target using angle-only measurements: algorithms and performance*, Signal Processing, 83 (2003), pp. 1223-1238,
- [3] M. Sanjeev Arulampalam, B. Ristic, N. Gordon, T. Mansell, *Bearings-Only Tracking of Manoeuvring Targets Using Particle Filters*, EURASIP Journal on Applied Signal Processing, 2004:15, pp. 2531-2365, (2004).
- [4] D. Laneuville, *Bearings Only TMA on Manoeuvring Target: A Gaussian Mixture Approach*, IET Seminar on Target Tracking and Data Fusion, Birmingham, April 2008, pp. 129-136.
- [5] F. Dufour, M. Mariton, *Tracking a 3D manoeuvring target with passive sensors*, IEEE Trans. Aerospace Electronic, Systems 27 (4) (July 1991), pp. 725-739.

- [6] J. Welford, *Multi-Sensor Debris Tracking*, IET Seminar on Target Tracking and Data Fusion, Birmingham, April 2008, pp. 15-18.
- [7] R. Mahler, *Multitarget Bayes Filtering via First-Order Multitarget Moments*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 39, No. 4, pp. 1152-1178, October 2003.
- [8] B.-N. Vo and W.-K. Ma, *The Gaussian Mixture Probability Hypothesis Density Filter*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 54, No. 11, pp. 4091-4104, 2006.
- [9] M. Vihola, *Rao-Blackwellized particle filtering in random set multitarget tracking*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 43, No. 2, pp. 689-705, 2007.
- [10] J. Houssineau and D. Laneuville, *PHD filter with diffuse spatial prior on the birth process with applications to GM-PHD filter*, Proc. 13th International Conference on Information Fusion, Edingburgh, July 2010.
- [11] D. Clark, K. Panta and B. Vo, *The GM-PHD Filter Multitarget Tracker*, Proc. 9th International Conference on Information Fusion, Florence, July 2006.
- [12] E. A. Wan and R. van der Merwe, *The Unscented Kalman Filter for Nonlinear Estimation*, Proc. Of IEEE Symposium 2000 (AS-SPCC), Lake Louise Alberta, Canada, Oct. 2000.
- [13] D. Schumacher, B.-T. Vo and B.-N. Vo, *A Consistent Metric for Performance Evaluation of Multi-Object Filters*, IEEE Transactions on Aerospace and Electronic Systems, Vol. 54, No. 8, pp. 3447-3457, 2008.
- [14] A. Pasha, B.-N. Vo, H.D. Tuan and W.-K. Ma, *Closed Form PHD Filtering for Linear Jump Markov Models*, Proc. 9th International Conference on Information Fusion, Florence, July 2006.