The Gaussian Mixture Cardinalized PHD Tracker on MSTWG and SEABAR’07 Datasets

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Abstract – In this paper, we apply a Gaussian Mixture Cardinalized PHD tracker to several real and simulated datasets from the MSTWG (Multistatic Tracking Working Group) library from NURC, TNO and ARL:UT. We also report our analysis on the SEABAR’07 sea experiment.

Keywords: Cardinalized Probability Hypothesis Filter, CPHD, Multistatic Active Sonar, Sensor Fusion, Target Tracking, Anti-Submarine Warfare (ASW).

1 Introduction

The cardinalized probability density (CPHD) filter [7], a higher order PHD filter that also propagates the number of targets distribution, is attracting increasing attention. The CPHD filter is a nonlinear/non-Gaussian filter in its most general form. However, under the usual linear/Gaussian assumptions [1] closed form equations exist [14], obviating the need for a particle filter implementation. In this work, we implement the Gaussian-mixture CPHD (GM-CPHD) filter on real and simulated sonar data. The GM-CPHD filter gives the estimated number of targets in any given volume of surveillance space at every scan. But is not a tracker per se, hence we propose a track management scheme to augment it to serve as a tracker, as explained in the next section.

A multi-laboratory initiative was established in the end of 2004 – the Multistatic Tracking Working Group (MSTWG) – whose aim is to foster interaction among researchers in sonar and radar multi-sensor tracking, and to compare complementary approaches to fusion and tracking using common datasets. FUSION 2008 marks the third special session in a conference for the working group, following previous gatherings at FUSION 2006 and OCEANS 2007; the reader is referred to [9, 10] for details. To date, the MSTWG has offered up three datasets for common analysis, courtesy of Nato Undersea Research Center (NURC) [4], the Netherlands Organization for Applied Scientific Research (TNO) [13], and Applied Research Laboratory, University of Texas (ARL:UT) [5]; the ARL:UT dataset includes a second version as discussed in [6]. Here, we provide analysis results for all three datasets (we use the second version of the ARL:UT dataset), and we introduce a new scenario that was created by a recently developed sonar simulator from University of Connecticut.

Additionally, in October 2007, the University of Connecticut participated in SEABAR07, an international sea trial led by NURC, where the GM-CPHD tracker was applied to active sonar data; we report here our analysis on one run of this experiment as well.

2 The GM-CPHD Tracker

The Cardinalized Probability Hypothesis filter is a recursive filter that propagates both the posterior likelihood of (an unlabeled) target state and the posterior cardinality density (probability mass function of number of targets) [7]. Under the assumption of linear Gaussian dynamics, and the state independence of the probability of detection and the probability of survival, closed form filter equations are given in [14]. In that work, the posterior PHD surface is approximated by a Gaussian Mixture, and it is shown that after the update step it remains a Gaussian mixture, hence instead of propagating the whole surface, the weight, mean and the covariance of each mode in the mixture are propagated. This form is called Gaussian Mixture Cardinalized Probability Hypothesis Density (GM-CPHD).

In this analysis, we employ the GM-CPHD filter with a linear motion model, and a nonlinear measurement model where range, bearing and range rate (when available) form the measurement. Hence, our implementation is based on an Extended Kalman-like first order linearization of the following measurement model:
where \( w \) is the additive Gaussian noise, the target state consists of its position and velocity, \( X_t = [x \ y \ \dot{x} \ \dot{y}]' \) and \( r_{tr} \) is the range between the target and the receiver. Our implementation is capable of processing both Doppler-sensitive (e.g., a constant frequency pulse – CW) and Doppler insensitive waveforms (e.g., a linear frequency modulated pulse – LFM). For LFM waveforms, the range rate measurement, \( \dot{r} \), is insignificant and hence ignored.

The GM-CPHD filter provides an estimation for the number of existing targets and their states at every time instant that measurements arrive. However, a tracker implies more: there must be “tracks” that indicate targets’ location (and velocity) over time. These tracks would be the final output displayed on the radar/sonar screen. In its original form the GM-CPHD filter is not able to provide this. We propose a track management logic that overcomes this deficiency. The resulting algorithm, the GM-CPHD tracker, hence becomes a candidate for evaluation in the Multistatic Tracking Working Group (MSTWG), one of whose aims is to compare tracking algorithms utilizing the same data sets and common performance metrics. There are similar efforts: Clark et al. [11] proposed a tree-structured track management scheme for Gaussian Mixture PHD filter and it can also be applied to the GM-CPHD filter. One difference of this approach is that the merging step, a scheme aiming to reduce the computational load, is removed from the algorithm to simplify the track management logic.

Gaussian Mixture CPHD implementation requires pruning and merging to limit the number of modes in the mixture, hence limiting the computational load. Pruning is discarding the modes with extremely low weights. Merging, on the other hand, combines two or more Gaussian modes that are located very close to each other such that a single mode is sufficient to represent both. The combined mode simply has the weight that is the summation of all the weights of the merged modes, and its moments are calculated by matching the moments of the merged modes.

### 2.1 Track Management

The track-management logic we use is given below. It is a set of policies that deal with events such as track initiation, track deletion, update, merging, and spawning. The logic is designed based on the fact that in the GM-CPHD filter each mode at time \( k-1 \) creates a set of offsprings at time \( k \). This gives us the opportunity to assess a connectivity-over-time for the CPHD surfaces. Some of the Gaussian modes carry a track ID (based on the track initiation test), and these IDs are copied to their offsprings in the next iteration.

The track management rules are as follows. The numbers in parentheses indicate the values used in our implementation for corresponding parameters.

1. **Track Initiation**
   - If the last 3 connected modes have average weight > w-initiation (0.85)
     * ASSIGN A NEW TRACK ID

2. **Track Merging**
   - If sum of the weights < w-merge (1.7)
     * KEEP THE TRACK ID OF LARGEST WEIGHTED MODE
   - else
     * KILL MERGING TRACKS AND ASSIGN A NEW TRACK-ID TO THE MERGED MODE

3. **Track Update**
   - A track is updated by the largest weight mode of all modes with the same track ID
   - A track is updated backwards (use accumulated information)
     * UPDATE THE TRACK IN ITS MOST LIKELY PATH

4. **Spawn (at current time \( k \))**
   - Among all modes with the same track ID, if the last common parent mode is at a scan earlier than \( k-4 \)
     (a) BREAK THE CONNECTION FROM THE LAST COMMON MODE ON, and
     (b) ASSIGN A NEW TRACK ID TO THE SEPARATED BRANCH

5. **Track Deletion**
   - If a mode has weight < w-ID-limit (0.05)
     * DROP THE TRACK ID

To evaluate the behavior of the track-management logic, we apply the algorithm to a set of benchmark scenarios. The first scenario consists of two targets crossing each other. The tracks for each target are well established before they cross, and it can be seen in figure 3 that the tracks are successfully resolved after crossing.

The second benchmark scenario includes two main events. The target on the left hand side in figure 2 spawns a new target (a torpedo?) at the 10th scan, whereas at the 30th scan a new target appears in the scene (identified as target 3). The tracker creates three tracks: the new-born target is identified, and the split from target 1 is identified as a new
target as well. Considering the track spawn case in the track management scheme described above, the spawned target is not declared until scan 14, since the rule checks for a common parent at 4 – this being another parameter of the management scheme – previous scans. Between scans 10 and 13 both targets carry track ID 1, this track being updated with the mode that has larger weight.

The last benchmark scenario demonstrates joining (merging) targets. In this case, the two identified targets (1 and 2) come so close to each other that the Gaussian modes representing these targets merge into one. In this case, the track management logic decides to terminate both tracks and immediately declares a new track (track 3). The mode associated with track 3 has weight (approximately) 2, suggesting that there are two targets.

3 MSTWG - NURC Dataset

This tracking scenario (see [4]) consists of 3 ships equipped with Low Frequency Active Sonar equipment. One ship is a monostatic platform (ship 1) and the other two ships provide bistatic capabilities with an additional transmitter (ship 2) and receiver (ship 3). This yields 4 multi-static source-receiver pairs. Figure 4 shows the tracks of each ship.

The scenario duration is 180 minutes with each ship (simultaneously) transmitting at 60-second intervals. A scan of measurement data is defined by a unique source-receiver-ping triple. Each scan consists of 200 individual measurements, given in x-y coordinates.

The GM-CPHD tracker parameters are set as in the following:
• Probability of detection, $P_d = 0.8$.
• Process noise standard deviation = $0.007m/s^2$ (for nearly constant velocity model [1]).
• Probability of survival $P_s = 0.95$.
• Average number of false alarms = number of measurements.
• Direct blast feasibility filter = 2 seconds buffer.

The tracks are declared “true tracks” if their average position rms error is less than 1000 meters. The measurement set for each scan was further thresholded such that only measurements exceeding 13.5 dB post-processing SNR were passed to the GM-CPHD tracker. This means that the tracker processed 836 measurements per scan (mean of 21 measurements per scan). The GM-CPHD tracker creates in total 4 tracks, 3 of which are very short false tracks; the target is detected in the $15^{th}$ minute, and the track holds until the end of the scenario resulting in no fragmentation, i.e. the fragmentation rate is 1. Figure 6 shows these tracks, where the true track is marked with dark (red) color. The two of the false tracks are near the coordinates (-20000km, -4000km), and the third false track appears at the end of the scenario just above the target.

Figure 5: NURC Dataset. Position rms errors of the true tracks. The detection threshold is 13.5 dB.

The position root-mean-square (rms) error over time for the true track is given in figure 5. On average it is 304.6 meters, and only at the end it increases, possibly due to nearby false measurements while the target detection is missed.

4 MSTWG - TNO Dataset

The scenario (see [13]) consists of two ships, each hosting a transmitter and receiver. This results in four unique source receiver pairs. The zigzagging target passes by two fixed clutter points as figure 7 illustrates. The scenario duration is 180 minutes with the source transmitting at 60s intervals. This yields a total of 720 scans of data. Each scan of data consists of 56 – 183 measurements (mean of 111 measurements per scan). In this analysis, only the top 10 measurements (by SNR amplitude) were used in the track estimation. Figure 8 plots these measurements for all scans. Since the receivers are line arrays, there is an ambiguity in the direction of arrivals, and both the true and ambiguous bearings of the measurements appear in the measurement set.

The GM-CPHD tracker successfully detects the target at the beginning, as well as the two clutter points labeled in Figure 7. At the time the target makes the second turn (at the clutter point 1), the two tracks, the clutter track and the moving track exchange their associated measurements, and
Figure 8: TNO Dataset. Top 10 percent of the pings - sorted by SNR.

Figure 9: TNO Dataset. The red tracks are the true tracks, and the green tracks are false.

Figure 10: TNO Dataset. Position rms errors of the true tracks.

5 MSTWG - ARL:UT Dataset

The dataset is based on a segment of the DEMUS 04 sea trial, performed in the Malta Plateau region in September 2004. There was one source and two receivers. The two-hour scenario has two artificially injected targets: one fast (14kts) and one slow (4.2kts). The dataset includes one contact file every two minutes for each of two receivers and for both FM and CW waveforms, for a total of 240 contact files. Each scan of data consists of 20 measurements, given in x-y coordinates.

The tracker is able to detect and track both targets. The fast target is detected in the 14th minute, hence achieving a track detection ratio of 0.89 (see Table 1). The slow target, on the other hand, is detected 100% percent of the time. The

Figure 11: ARL/UT Dataset. Red tracks are true tracks, whereas the green tracks as false tracks created by the tracker.

Figure 12: ARL/UT Dataset. Position rms errors of the true tracks.
fragmentation rate seems higher than expected from Figure 11. There are some short false tracks due to clutter near the target location. The “true track” declaration test (average rms error < 1000 meters) declares these false tracks as true, hence a misleading fragmentation figure.

There seems to be a large number of “false” tracks; however, it is likely that these are due to other targets (surface ships, fixed sea-bottom features) in the area. In Figure 12, the position rms errors for both the slow and the fast targets are given. The fast target rms errors have large values between 45-60 minutes. This is due to the misclassification of the two clutter tracks (see the red “horns” near the origin in figure 11) as “true tracks”.

Figure 12: ARL/UT Dataset. Position rms errors of the true tracks.

6 SEABAR ’07

The SEABAR07 scientific sea trial was held in October 2007 on the Malta Plateau, and featured the deployable multistatic system (DEMUS) suite of one source and three receiver sonobuoys. The target is an echo repeater towed by a NURC research vessel. We focus on a run that featured the full suite of DEMUS equipment of one source (BTX) and three receivers (RX1, RX2, RX3) for a total of 416 contact files (half LFM, half CW) over a 90 minute period. This constitutes 6 source-receiver-waveform triplets, providing both Doppler-sensitive (CW) and Doppler-insensitive (LFM) detection opportunities. The scenario and the wide view of the tracker’s output are given in Figure 13.

The target makes two sharp turns as indicated by the dashed line in figure 14. The GM-CPHD tracker is fed by the strongest 10 contacts for each scan (i.e., for each source/receiver/waveform triplet). The other tracker parameters are the same as before.

The red tracks indicate that the tracker is able to detect and track the target (target is detected 98% of the time). The

Figure 13: SEABAR Experiment. The source is located at the origin, the three receivers are indicated by circles. The target associated tracks are red, and the false tracks are green tracks.

Figure 14: SEABAR Experiment. The target track (blue-dashed) in figure 13 is enlarged. The red tracks are target associated tracks from the output of the GM-CPHD tracker.
target track has 4 different segments, meaning during the run it is terminated 3 times and then re-initiated. There are three major (false) track (green tracks in Figure 13) sources in the area: the one in the north is a oil platform, and the other two are either surface ships or sea bottom features. Hence even though the false alarm rate appears to be 8.7 false tracks per hour, it is because of the fragmentation of tracks in these three regions.

7 MSTWG - UCONN Sonar Simulator

The University of Connecticut has recently developed a sonar simulator and made available to the work group. Its main aim is to provide the researchers the ability to conduct Monte Carlo analyses. The same scenario can be run multiple times with different noises hence the tracker performance can be evaluated for different target detections and clutter realizations. The main features of the simulator are:

1. GUI-supported or configuration-file-based scenario creation.
2. Aspect dependent target SNR.
3. False alarms are formed in angle/delay space, hence it provides higher density clutter near the receiver.
4. False alarms can be sampled from three different distributions: Rayleigh, Log-normal, and K-distributed.

The simulator provides a trade-off between the fidelity and the flexibility for data creation. The scenario we use consists of two platforms traveling east with constant speed. Each has one transmitter and one receiver and observes the two targets as well as the other ship. The targets travel east following the tracks shown in Figure 15.

The GM-CPHD tracker is fed the top (highest amplitude) 20 contacts at each scan and is able to create tracks for both targets (see Figure 16). The target in the south has low observability for the period before it makes the maneuver. Its aspect ratio is low at that time, hence its track dies and immediately after the maneuver the track is initiated again.

We performed 20 Monte Carlo runs with this scenario and the position root-mean square error is plotted in Figure 17. The second target becomes unobservable between minutes 20 and 28, as the first target’s track is initiated at minute 5.

8 Summary

In table 1 a set of performance metrics are listed for the scenarios analyzed. T-PD is the track detection ratio defined as ratio of the total (non-overlapping) duration of the true tracks and length of the ground truth. FAR is the number of false tracks per hour, and FRAG gives the fragmentation for the target tracks; for example, in TNO dataset FRAG being
Figure 17: Position rms errors for the two targets in Figure 15 for 20 Monte Carlo runs.

Table 1: Metrics of Performance for the analyzed datasets.

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<th>FRAG</th>
<th>RMS</th>
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References


