GM-CPHD and MLPDA Applied to the SEABAR07 and TNO-Blind Multi-static Sonar Data

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Abstract – *The Gaussian Mixture Cardinalized PHD (GM-CPHD) Tracker was applied to the SEABAR07 and to the "blind" TNO dataset from the MSTWG (Multistatic Tracking Working Group). The Maximum-Likelihood Probabilistic Data Association (MLPDA) batch tracker was applied to the TNO dataset only. The tracking results (plots and MOPs) are given.*

Keywords: CPHD, MLPDA, Multistatic Active Sonar, Sensor Fusion, Target Tracking.

1 Introduction

The new TNO-Blind dataset was created by Dr. Pascal de Theije for the MSTWG, and presents the challenge of discovering the number of targets present in the interest region and their tracks. The SEABAR07 datasets, also the subject of study by many members of the MSTWG, present the challenge of real sonar data obtained in a sea trial that took place in October 2007 on the Malta Plateau. In this paper we present some results of the application of the GM-CPHD tracker to both, and, since it is a new effort just beginning, of the MLPDA tracker to the former.

2 GM-CPHD

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 the number of targets) [8]. Under linear Gaussian dynamics and the assumption of state independence for the probability of detection and the probability of survival, closed form filter equations are given in [11]. In that work, the posterior PHD surface is approximated by a Gaussian Mixture and is shown to remain a Gaussian Mixture after the update step, hence the propagation of the whole surface can be replaced by the propagation of the weight, mean and covariance of each mode in the mixture. In common with other similar trackers such as the MHT, the number of Gaussian "modes" could increase exponentially with the number of scans, and as such track-management (pruning, merging, etc.) is necessary to make the approach practical.

In our analysis, we employ the GM-CPHD filter with a linear motion model and a nonlinear measurement model in which range, bearing and range rate (when available) form the measurement. Our implementation is thus capable of processing both Doppler sensitive (i.e., a constant frequency pulse - CW) and Doppler insensitive waveforms (i.e., a linear frequency modulated pulse - LFM). For LFM waveforms, the range rate measurement ($\dot{r}$) is not significant and hence ignored. In its original form the GM-CPHD filter is not able to provide scoreable tracks, so a track management scheme was devised in [5, 9]. This is a set of policies dealing with events such as track initiation, update, merging, spawning and deletion.

At present, we feed into the tracker only the top 10 (highest amplitude) contacts per waveform/receiver at each scan; this is perhaps a weakness of our GM implementation of the PHD filters, one that deserves further attention. The issue is that the number of sonar contacts per scan can be in the hundreds, and in principle each deserves to be explored with its own mode – for a manageable number of modes we require relatively few contacts per scan. The parameters of the GM-CPHD tracker were set as in the following:

- Probability of detection of target, $P_d = 0.7$.
- Probability of death of target, $P_{death} = 0.05$.
- Birth probability = 0.001.
- Process noise variance = $0.00005\ m^2/s^2$.
- Two-dimensional position/velocity kinematic model.
- Track initiation weight threshold = 0.85.
- Tracks merging weight threshold = 1.7.
- Maximum number of targets = 30.

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14. ABSTRACT
The Gaussian Mixture Cardinalized PHD (GM-CPHD) Tracker was applied to the SEABAR07 and to the ?blind? TNO dataset from the MSTWG (Multistatic Tracking Working Group). The Maximum-Likelihood Probabilistic Data Association (MLPDA) batch tracker was applied to the TNO dataset only. The tracking results (plots and MOPs) are given.

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Adjustments were made when deemed necessary. For a detailed explanation of the above parameters, please refer to [11].

3 MLPDA

A wide filter bandwidth is good in the sense that it offers robustness; however, a large bandwidth allows noise to enter, and in target tracking this noise is usually in the form of clutter. As such, the maximum-likelihood probabilistic data association (MLPDA) estimator – perhaps the ultimate approach to finding targets that are buried deeply in clutter [2] (successful tracking at less than 6dB post-signal processing SNR) – dials the bandwidth as low as it can by searching only for target trajectories that are parametrically defined: for us, that means straight-line trajectories. With the set of measurements $Z = \{Z_i\} = \{Z_{ij}\}$ for the jth contact Z_{ij} of the ith ping, we have the conditional likelihood

$$p_h(Z|x) = \prod_i p_k(Z_i|x) \qquad (1)$$

in which $k \in 0, 1$ depending on whether or not a target is present. Moreover, assuming that we have Poisson clutter (each clutter contact has a uniform pdf, and the number of clutter points for the ith ping has a Poisson pmf $\rho(\cdot)$ with mean λV, in which V is the surveillance volume). One's MLPDA task is to maximize (1) with respect to x. It is usually simpler to maximize the likelihood ratio (defined according to [10]):

$$\frac{p_1(Z_i|x)}{p_0(Z_i|x)} = \qquad (2)$$

$$(1 - P_d) + \frac{P_d}{\lambda} \sum_{j=1}^{m_i} \mathcal{N}(Z_{ij}|H_{ij}x; \Sigma_{ij}) \frac{f_1(a_{ij})}{f_0(a_{ij})}$$

in which λ is the clutter density, P_d is the probability of detection, and the last term is the likelihood ratio of the amplitude return conditioned on a threshold exceedance. The MLPDA technique seems first to have appeared in [6], and to have been refined – particularly, to use features – in [7]. It was previously applied to NURC data in [12]. A multi-target MLPDA was developed in [1]; our formulation here looks sequentially for single targets, with previously-associated measurements excised, and with the process stopped when a discovered track does not exceed the likelihood threshold.
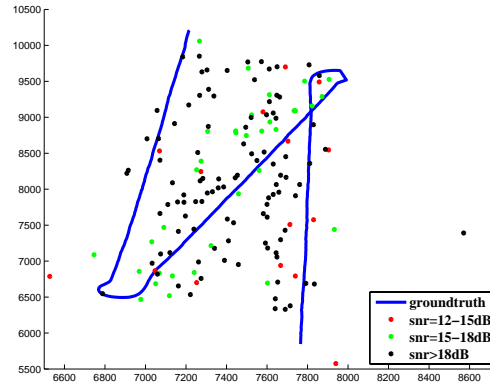
4 SEABAR07

4.1 Description

The SEABAR07 scientific sea trial featured the deployable multistatic system (DEMUS) consisting of one source (BTX) and 3 receiver sonobuoys (RX1, RX2, RX3). The receivers are able to provide both Doppler-sensitive (CW)
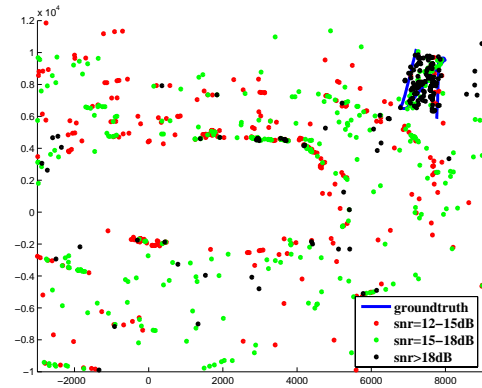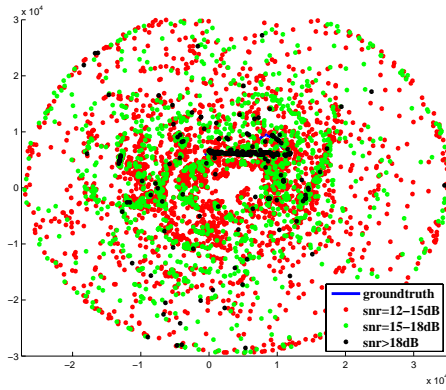

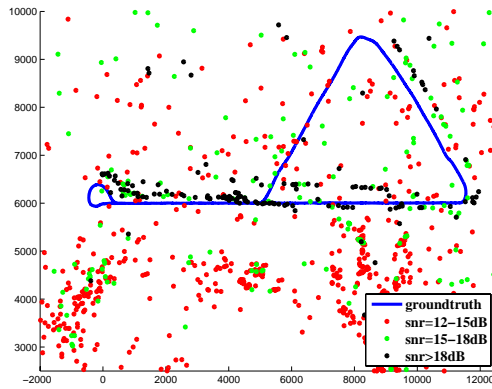(a) A01 RX2 (FM and CW) Contacts

(b) Detail of a)

Figure 1: A01 RX2 Contacts.

and Doppler-insensitive (LFM) contacts. The target was an echo repeater towed by a NURC research vessel. The scenarios include maneuvers, target births and in A07, a moving source. We present results obtained using GM-CPHD on the SEABAR datasets A01, A05, A06 and A07. Neither the tagged and SNR-adjusted datasets were available to us at the time our results were formed, so we report on the original datasets. These results include an Echo Repeater (ER) delay of 2.5sec, which the tracker adjusts for; however, in some runs (A05-A06), the ER delay underwent some unexplained transients, and these will be seen in the accompanying results. Also, please note that the results presented here are in meters, referenced to the transmitter at the origin.

In the A01 set all 3 receivers worked in this run and the target performs interesting maneuvers. The top ten contacts coming from the RX2 receiver (FM and CW), differentiated by SNR, are shown in Figure 1. In the un-zoomed contact plot for the joint run A05/A06, (Figure 2a), it is interesting to observe the indications of some accidental targets not part of the sea trial such as an oil platform, surface ships and sea bottom features. This is responsible for the

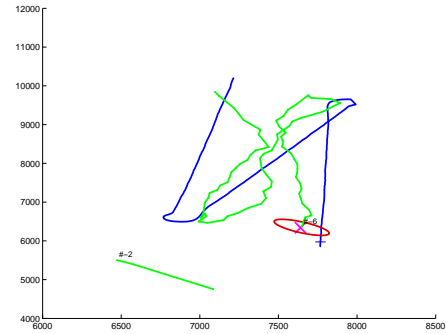(a) A05-A06 RX3 (FM and CW) Contacts

(b) Detail of (a)
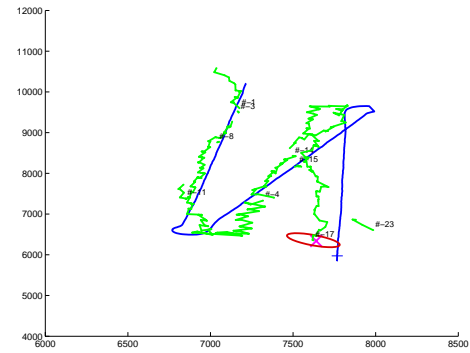
Figure 2: A05-A06 RX3 Contacts

(a) A01 RX2 (FM)

(b) A01 RX1/2/3 (FM & CW)

Figure 3: A01 results. The tracks are in green, and the ellipses indicate active Gaussian-mixture modes at the last scan.

high number of false tracks of this dataset. In the zoomed contact plot (Figure 2b), it is clear that the ER delay fluctuated during A05 (see the "jumps" in the horizontal portion of the triangle); apparently, the delay remained elevated for the whole of A06 (witness the offset).

4.2 GM-CPHD Results

Comparing the two parts of Figure 3 it is clear that sensor and waveform fusion significantly improves the tracking. All MOPs except the fragmentation indicate better results in the case of using all available sensors. (In the interest of space, we present only a few plots; but, for almost all other cases, the results are quite good, and indeed it is clear that when FM is used all portions of the track are followed successfully as supported by the measures of performance reported.) The MOPs (Figure 7(a)) also show that the fusion of the Doppler-sensitive CW with the highly-resolving (but perhaps overly sensitive to fixed clutter) FM reduces the number of false tracks. Another inference from the MOPs is that the use of multiple sensors increases both PD and fragmentation. The latter indicates that further work on approaches to fusion is necessary.

Examples of tracking results for the A05 and A06 runs are shown in Figures 4 and 5 – there is an offset in the latter that is known, but we preserve it in this plot so that it can be noted. In the MOPs (Figures 7(b) and (c)) the important FAR reduction associated with the addition of CW is again observed.

The tracking results for the A07 dataset were problematic: the target was tracked only during the midpoint of its trajectory (Figure 6b). From the examination of the actual contacts (Figure 6a), the reason for this is clear: there are none to represent the beginning and the end portions of the true track. In order to exclude the possibility of this being an artifact of the limitation to the top ten contacts, we have attempted to run the GM-CPHD with far more modes and contacts, and little improvement was observed.

5 TNO-Blind

5.1 Description

The TNO Blind dataset features three sensors in 2D Cartesian space (Figure 8) with the following character-
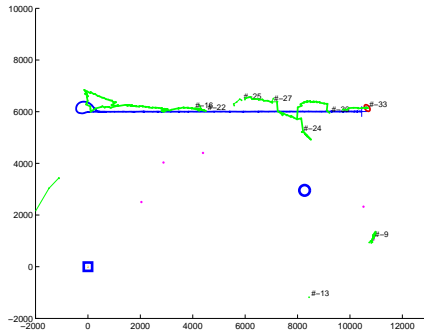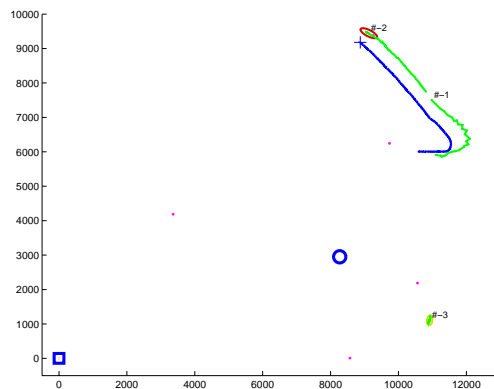
Figure 4: A05 RX3 (FM and CW) results.

Figure 5: A06 RX3 (FM and CW) results.

(a) A07 RX2 (FM and CW) Contacts
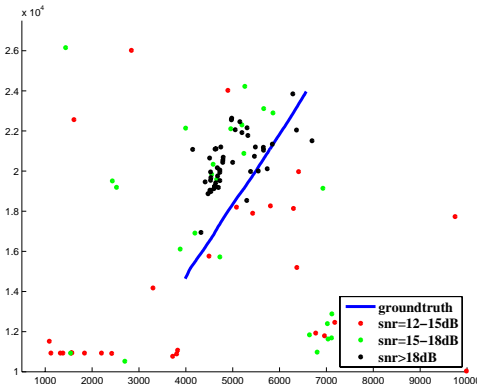

(b) A07 RX2 (FM and CW)

Figure 6: A07 Results

istics:

- Sensor 1 is bistatic and an FM sensor, giving 180 pings at a pulse repetition time of 60s.

- Sensor 2 is monostatic and a CW sensor, giving 210 pings at a pulse repetition time of 50s.

- Sensor 3 is bistatic and both an FM and a CW sensor, giving 113 pings at a pulse repetition time of 90s. The odd pings are FM contacts, the even pings are CW contacts.
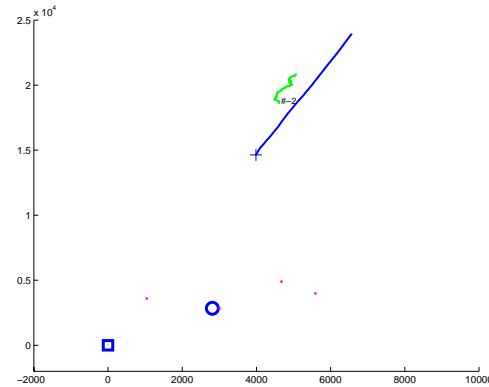
The top ten contacts available from all the sensors differentiated by SNR can be seen in Figure 9. RMS registration errors were taken into account for the following parameters: sound speed ($2m/s$), receiver heading (1°), bearing estimate (1°), sensor position ($20m \times 20m$), time ($0.001s$ FM and $0.1s$ CW) and Doppler ($0.5m/s$).

5.2 GM-CPHD Results

We submit Figures 10, 11, 12 – the individual sensors' tracking results – along with fused results in Figures 13

and 14. It can be seen that the GM-CPHD detects (albeit intermittently) all 4 of the targets present and is able to maintain the track when the targets maneuver. However, it is clear that there is room for improvement, especially in terms of fragmentation. Presumably there is further development work to be done on track management; it is also clear that fusion of contacts from multiple sensors is not always an unmitigated benefit to our present incarnation of the CPHD.

We usually evaluate the tracker's performance by looking at several MSTWG metrics of performance (MOPs): fragmentation (FRAG), probability of detection (PD), false alarm rate (FAR) and distance root mean square error (RMSE). It should be pointed out that PD calculates the track detection ratio, i.e., the sum of the durations of all true tracks divided by the total scenario duration. At present the MOPs are calculated (see Figure 15) only for the "given" first target.

The fusion of the Doppler-sensitive CW with the highly-resolving (but perhaps overly sensitive to fixed clutter) FM and the use of multiple sensors are beneficial because they increase both PD, but unfortunately, they also increase

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	FRAG	PD	NO_OF_FALSE TRACKS	FAR (per hour)	RMS (position)
RX1 –FM	1	0.83	9	18.00	305.70
RX1 – CW	1	0.50	4	8.00	317.70
RX1– FM&CW	3	0.86	4	8.00	314.90
RX2 – FM	1	0.92	27	18.19	359.40
RX2 – CW	2	0.90	15	10.10	363.90
RX2 – FM&CW	2	0.93	18	12.10	330.20
RX3 – FM	4	0.71	17	11.45	418.70
RX3 – CW	4	0.68	12	8.08	584.30
RX3 – FM&CW	4	0.83	17	11.40	325.00
RX2RX3 – FM	3	0.94	36	23.50	311.20
RX2RX3 – CW	4	0.93	21	14.10	313.50
RX2RX3 – FM&CW	4	0.94	13	8.70	285.90
RX1RX2RX3 – FM	4	0.94	32	21.56	314.00
RX1RX2RX9 – CW	5	0.95	20	13.40	369.70
RX1RX2RX3 – FM&CW	7	0.96	14	9.40	293.60

(a) A01

	FRAG	PD	NO_OF_FALSE TRACKS	FAR (per hour)	RMS (position)
RX2 - FM	2	0.61	75	45.45	130.51
RX2 - CW	3	0.54	14	8.48	322.73
RX2 - FM&CW	2	0.70	15	9.09	165.11
RX3 - FM	4	0.84	114	69.09	284.41
RX3 - CW	6	0.40	55	33.33	506.30
RX3 - FM&CW	7	0.84	26	15.76	410.61
RX2RX3 - FM	10	0.72	131	79.39	205.79
RX2RX3 - CW	7	0.37	37	22.42	348.72
RX2RX3 - FM&	7	0.71	48	29.09	157.53

(b) A05

	FRAG	PD	NO_OF_FALSE TRACKS	FAR (per hour)	RMS (position)
RX2 - FM	0	0.00	14	22.11	N/A
RX2 - CW	0	0.00	1	1.58	N/A
RX2 - FM&CW	0	0.00	14	22.11	N/A
RX3 - FM	1	0.81	18	28.42	463.83
RX3 - CW	0	0.00	3	4.74	N/A
RX3 - FM&CW	2	0.82	2	3.16	492.42
RX2RX3 - FM	0	0.00	26	41.05	N/A
RX2RX3 - CW	0	0.00	4	6.32	N/A
RX2RX3 - FM&	0	0.00	8	12.63	N/A

(c) A06

	FRAG	PD	NO_OF_FALSE TRACKS	FAR (per hour)	RMS (position)
RX2 - FM	1	0.26	12	9.73	749.46
RX2 - CW	1	0.38	10	8.11	651.14
RX2 - FM&CW	1	0.24	2	1.62	660.77

(d) A07

Figure 7: GM-CPHD SEABAR MOPs.

Figure 8: Scenario Setup

Figure 9: Contacts Differentiated by SNR

fragmentation. The latter indicates that further work on different approaches to fusion is to be done. In order to exclude the possibility of this being an artifact of the limitation to the top ten contacts, we have attempted to run the GM-CPHD tracker with far more modes and contacts, and little improvement was observed.

In Figure 16, we are looking at the SNR of the measurement coming from Sensor 1 that is closest (distance-wise) at each scan to the true position of target 1 at that scan. Some of these measurements are very good contacts and some can be false alarms. The shaded areas correspond to scans for which the GM-CPHD created a track for the known target (Figure 10). As expected, the contacts with high SNR are likely to come from the target and the GM-CPHD uses them for the formation of tracks. This information is to be incorporated into the GM-CPHD in the future.
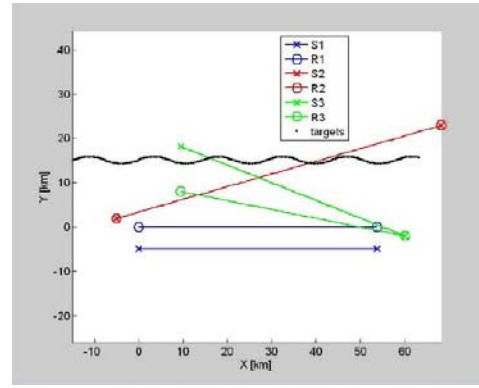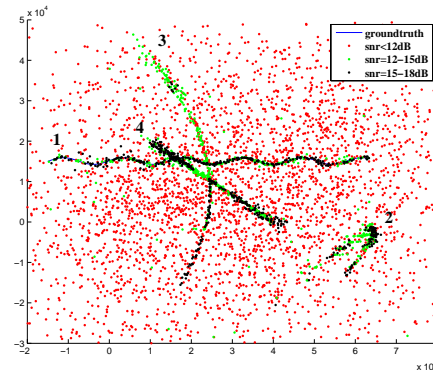
5.3 MLPDA Results

Some results of applying the MLPDA to the TNO-Blind challenge dataset are shown in Figures 17 and 18 – the former uses a high threshold (-70) to declare a track, the latter ten log-likelihood units lower. All data and all sensors are used in this work, which is an improvement over the GM-CPHD results presented previously. With the exception of the "hairpin" in the lower right, all tracks are well represented. The reason for the choppy appearance is perhaps clear from Figure 19: the quantization of the azimuthal angles does indeed produce such an effect. The MOPs are included for the lower threshold in Table 1 – these ap-

Target	Frag	Dup	PD	RMSE
1	1	6	.92	89.2
2	3	4	.64	175.3
3	1	3	.63	107.0
4	1	13	.92	67.6

Table 1: MOPs for MLPDA on TNO-Blind data, lower threshold. There were 8 false tracks.
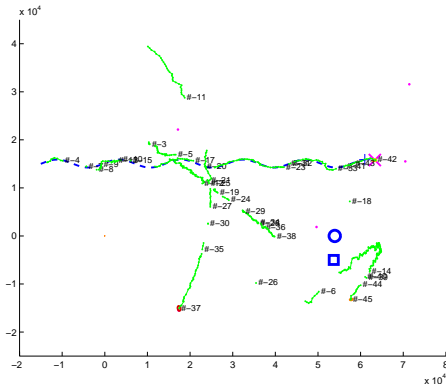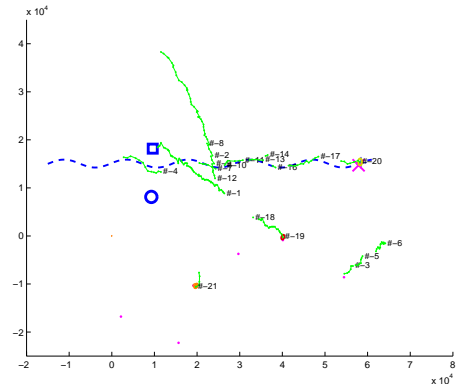
Figure 10: GM-CPHD Tracks with Sensor 1

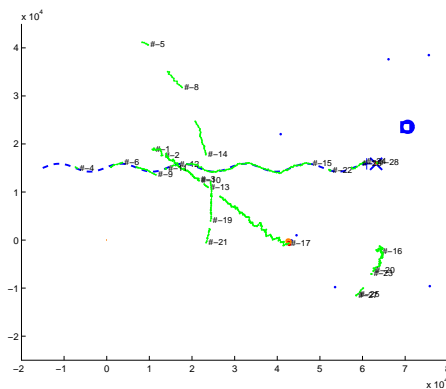Figure 12: GM-CPHD Tracks with Sensor 3
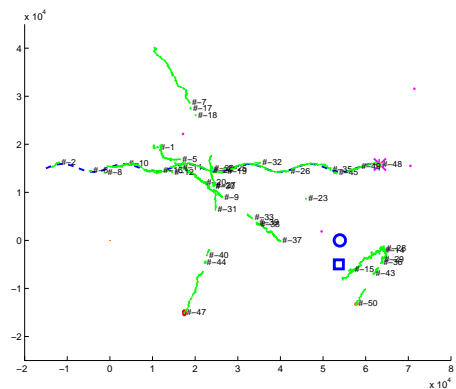

Figure 11: GM-CPHD Tracks with Sensor 2

Figure 13: GM-CPHD Tracks with Sensors 1 and 3

pear to be extremely promising. Note that although the MLPDA looks for straight-line trajectories, due to the finite batch-length that it uses these are in fact only straight line segments. As such, the MLPDA-derived tracks can be (or appear) curved, and the absence of a more sophisticated model is felt most strongly only for the challenging "hairpin" trajectory.

6 Summary

Most treatments of these data have used a "traditional" MHT target tracker, although we have seen others as well. A fielded system would probably use the MHT; we do have an MHT, but we would prefer to offer an alternative and exploratory perspective, and accordingly have proffered the MLPDA and GM-CPHD. We are pleased that our results are competitive, but must note that both GM-CPHD and MLPDA efforts are ongoing, and more-recent results with these will be made available on request.

Two GM-CPHD concerns we have identified are track fragmentation and GM mode-placements for initialization. As regards the former, present efforts center on incorpo-

ration of sensor-ID information for robust mode-linking, initiation and termination of tracks. Mode placement is a concern for a GM-CPHD in sonar data: when false alarms are few it is an easy task to assign a mode to each, but in the sonar situation, with hundreds of contacts per scan, this is not an option. Conversely, the MLPDA has no issues at all with deep clutter, and indeed we feel that it may eventually become the algorithm of choice for VLO tracking. Present research on the MLPDA centers on track linkage, and also on means to adapt its parametric modeling of target motion – most suite for straight-line tracking – to targets such as these that execute structured (but not necessarily straight) trajectories.

Acknowledgement

Figure 14: GM-CPHD Tracks with Sensors 1, 2 and 3

	FRAG	PD	NO_OF_FALSE TRACKS	FAR (per hour)	RMS (position)
Sensor 1	14	0.70	31	10.68	439.73
Sensor 2	7	0.65	21	7.23	264.32
Sensor 3	8	0.29	13	4.48	685.36
Sensors 12	19	0.98	33	11.06	267.06
Sensors 13	13	0.98	37	12.40	335.77
Sensors 23	12	0.86	34	11.4	329.63
Sensors 123	20	0.98	56	18.77	268.36

Figure 15: MOPs for Known Target

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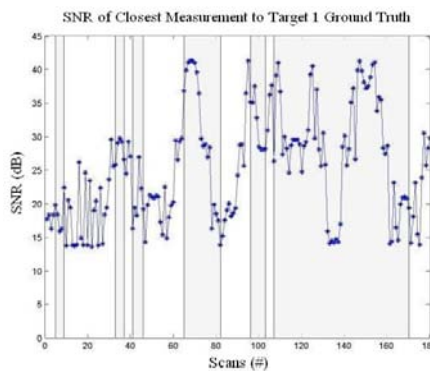
Figure 16: SNR of measurement of sensor 1 closest at each scan to the sinusoidal target
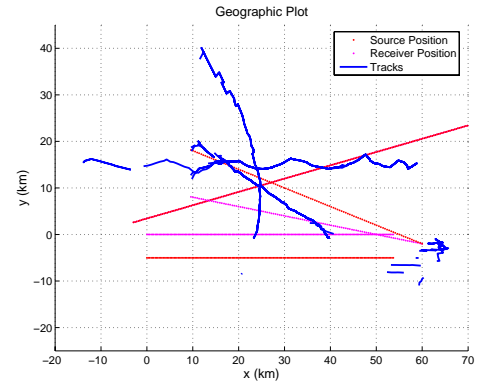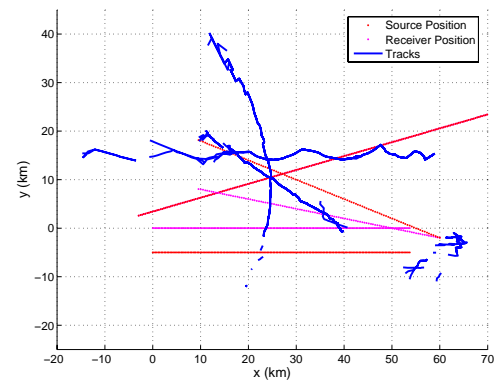

Figure 17: MLPDA Tracks at high threshold.
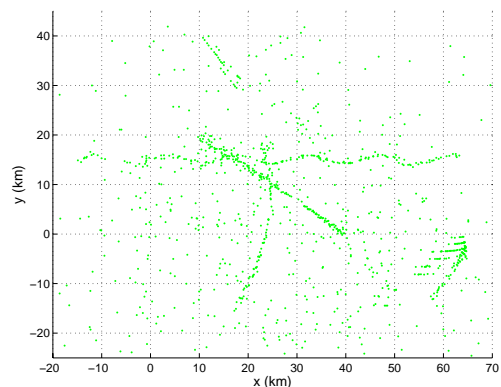

Figure 18: MLPDA Tracks at lower threshold.

Figure 19: Measurements from sensor 1.

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