Abstract—This paper presents tracking results on the PACsim data set using a framework based on the JPDA algorithm with a posterior distribution preprocessing step. The dataset is a multistatic simulation designed to approximate real-life data. In this paper, we extend the posterior distribution preprocessing technique to include feature data and compare tracking results with and without feature information. Results show that the inclusion of feature data in the preprocessing stage can improve tracking performance. This work also explores the benefits of more extensive parameter tuning for the harder tracking scenarios included in the dataset.

I. INTRODUCTION

This paper presents results of a Joint Probabilistic Data Association (JPDA) [1] based tracker on a new multistatic sonar dataset. Multistatic sonar tracking has several unique challenges when compared to other domains. It is characterized by a low probability of detection ($P_d$), high clutter rate and (often) inaccurate sensors. To overcome these issues, a posterior distribution preprocessing step is used to combine contacts from multiple receivers into a form which is more amenable to tracking in a PDA framework. We expand a previously proposed preprocessing approach to include feature data.

In previous work a sonar tracking algorithm was adapted to the acoustic propagation environment [2], [3] to improve tracking results. Results for the PDA Filter with Amplitude Information with Target Strength (PDAFAIwTS) on the TNO Blind data set and the SEABAR '07 sea trial were presented in [4]. The TNO blind data set was created by researchers at TNO Defence, Security and Safety (The Hague, The Netherlands) for use by the Multi-Static Tracking Working Group (MSTWG). The SEABAR '07 sea trial was an experiment conducted by the NATO Undersea Research Lab on the Malta Plateau [5], [6]. JPDA with posterior distribution preprocessing was then developed and tested on the Metron data set with mixed results [7].

Recently, the PACsim dataset was created by Doug Grimmlet to be used by members of the MSTWG and will be the focus of this paper [8]. The PACsim dataset includes a simulated feature measurement with each contact, with the purpose of testing feature aided tracking algorithms. This paper extends posterior distribution preprocessing to include the feature data in the preprocessing step, and show that it can improve performance.

Section II will summarize the PACsim data set. Section III of this paper will review the mathematical basis for the JPDA algorithm. Section IV will summarize the posterior distribution preprocessing step and its extension to include the new feature data. Section V will show the tracking results from the PACsim data set before the truth was revealed, and Section VI will discuss the latest tracking results knowing the truth. Section VII will summarize the paper and discuss areas of continued work.

II. PACSIM DATA SET ANALYSIS

The PACsim data set was created by Doug Grimmett for the MSTWG. It is a simulated data set with three distinct scenarios (A, B and C). When distributed, the dataset contained ground truth for only Scenario A. This scenario was a simple tracking task, provided as a “sanity check” for ensuring that the data was correctly loaded. In addition, the inclusion of ground truth allowed for the tuning of tracking and preprocessing parameters. We present two distinct sets of results on the dataset: one in which the trackers have been tuned only on Scenario A and then applied to the other two scenarios and one where truth was known for all the datasets and tuning was done to maximize performance on each individual scenario. We will refer to the former set of results as Blind results and the latter set as Optimized results. The latter set is included as a best-case scenario for the algorithms presented in this paper.

The ground truth plots for Scenarios A, B, and C are shown in Figures 1, 2, and 3 respectively. These plots are from the source document for the data set [8]. There is one target in Scenario A and Scenarios B/C have 4 targets. All three scenarios include fixed clutter points.

The sensor layout for the simulations is based on distributed underwater sensors with few sources and many receivers. The green circles are the receivers and the red boxes are the sources. The sensor layout is the same for all the scenarios (5 sources and 16 receivers). The ping interval is 60 seconds for a duration of 481 pings (8 hours). The ping schedule follows a preset list which cycles through all the sources sequentially and repeatedly. There are Frequency Modulated (FM) and Continuous Wave (CW) transmissions simulated (alternating each ping for each source), and in this paper all contacts are used in the tracking algorithms.
The contact measurements were generated using the following parameters for all three scenarios:

- 8 hours durations, 7696 scans, 481 pings
- Bearing error is normally distributed with mean $0.0^\circ$ and standard deviation $4.0^\circ$
- FM waveform: Time difference of arrival (TDOA) error is normally distributed with mean $0.0$ s and standard deviation $0.1$ s
- CW waveform: Time difference of arrival (TDOA) error is normally distributed with mean $0.0$ s and standard deviation $0.4$ s
- Bistatic Doppler error is normally distributed with mean $0.0$ knots and standard deviation $0.4$ knots (CW only)
- No blanking region is included in the simulations.

CW and FM pings each have their own benefits: FM pings result in better range resolution, and CW pings allow for the measurement of bistatic Doppler of the contacts. The Doppler measurement has been shown to be useful in track initiation [9], contact classification [10]–[12] and contact fusion [13]. For these reasons, CW pings have the potential to greatly improve tracking results. However, in the case of the PACSim dataset, we found that the CW pings had a much lower $P_d$ than the FM pings across all the scenarios, as listed in Table I.

<table>
<thead>
<tr>
<th>Target</th>
<th>CW</th>
<th>FM</th>
<th>FM</th>
<th>FM</th>
<th>FM</th>
<th>FM</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.21</td>
<td>0.47</td>
<td>0.47</td>
<td>0.47</td>
<td>0.47</td>
<td>0.47</td>
</tr>
<tr>
<td>B</td>
<td>0.14</td>
<td>0.15</td>
<td>0.10</td>
<td>0.01</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>C</td>
<td>0.08</td>
<td>0.02</td>
<td>0.09</td>
<td>0.01</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

**TABLE I**

*Probability of detection for CW and FM pings across Scenarios A, B, and C. Note the extremely low probability of detection for the CW pings.*

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### III. TRACKING AND TRACK MANAGEMENT

The process of tracking contains many interacting subsystems. For contact to track association, we use the JPDA algorithm described in [1]. JPDA is a modification of PDA to account for the presence of multiple targets. Track management is done using a *sequential probability ratio test* (SPRT) with a fixed confirmation threshold and a sliding window ($W$) for track deletion. At every time $k$, the current score is stored. If at time $k + W$ the score has dropped by more than the deletion threshold, the track is deleted.

For the **Blind** results, the parameters for confirmation threshold, deletion threshold, and window length were chosen by optimizing on Scenario A, which includes ground truth. These parameters were then kept constant for Scenarios B and C.

For the **Optimized** results, the parameters were optimized on each of the scenarios individually, while knowing the true
target paths.

A. Additional Tracking Details

- Tracking architecture is centralized: all contact data for a single ping is aggregated and processed at once.
- The gate size and the probability of detection parameters also play a role in the performance of the tracking algorithm. The values for each simulation run will be specified with the results.
- The number of maxima chosen after the posterior distribution preprocessing is also an input parameter that can be set. The preprocessing will be discussed in the next section, and the number of maxima was chosen to be 50 for all the results in this paper. Including more than 50 maxima did not appear to improve the tracking results, but resulted in greatly increased runtime.

IV. POSTERIOR DISTRIBUTION PREPROCESSING WITH FEATURE DATA

We found in initial testing of the PACsim dataset that using the PDA, PDAFAI, and the PDAFAIwTS algorithms did not produce very good results. There were many false tracks, so many that even if the true targets were tracked, they were indistinguishable. This is due to the large number of false contacts and the low probability of detection. Recently, it has become common to apply a pre-tracking contact fusion step [7], [14], [15]. The contact fusion step decreases the amount of clutter presented to the association step, which results in decreased runtime and memory usage. In this work, we expand on the posterior distribution preprocessing technique described below [7], with the addition of a term for feature information.

The posterior distribution over position $c$ given the $j^\text{th}$ bearing measurement, $b_{ij}$, and the $j^\text{th}$ bistatic range measurement, $r_{ij}$ for the $i^\text{th}$ receivers, $P(c|b_{ij}, r_{ij})$. The error statistics for the $i^\text{th}$ receiver are used in the formulation. $I_i$ is an indicator variable which indicates whether or not the true contact was actually detected.

$$P(c|b_{ij}, r_{ij}, I_i = 1) = \frac{1}{(2\pi\sigma_b\sigma_r)^{-1}} \exp \left( \frac{-(B_i(c)b_{ij} - \bar{b}_{i1})^2}{2\sigma_b^2} + \frac{-(R_i(c) - r_{ij})^2}{2\sigma_r^2} \right),$$

where $B_i(c)$ is a function which maps position $c$ to bearing for $i^\text{th}$ receiver, $R_i(c)$ is the bistatic range at $c$ for the $i^\text{th}$ receiver, $\sigma_b^2$ is the bearing variance, and $\sigma_r^2$ is the bistatic range variance.

For each receiver $i$, the posterior distribution given that the true contact was detected is calculated by summing over all $j$ contacts for each receiver, with normalizing constant $\gamma$,

$$P(c|\bar{b}_i, \bar{r}_i, I_i = 1) = \gamma \sum_{j=1}^{n} P(c|b_{ij}, r_{ij}, I_i = 1).$$  

Each receiver’s probability of detection surface $P_{d_i}(c)$ is the probability that a contact at $c$ will be detected. The total probability of a contact being at $c$ is calculated in Equation (2), where $P(c|I_i = 0)$ is the probability that a contact is at $c$ and not detected. We chose $P(c|I_i = 0)$ as a small constant, $10^{-25}$.

This value could be tweaked to be location dependent in a scenario where additional information is known (bathymetry, for example).

$$P(c|\bar{b}_i, \bar{r}_i) = P(c|\bar{b}_i, \bar{r}_i, I_i = 1) P_{d_i}(c) + P(c|I_i = 0)(1 - P_{d_i}(c)).$$  

The complete posterior distribution is calculated:

$$P(c|\bar{b}_{1..m}, \bar{r}_{1..m}) = \prod_{i=1}^{m} P(c|\bar{b}_i, \bar{r}_i).$$

The top 50 local maxima of the posterior distribution are then calculated and sent to the JPDA tracking algorithm. These maxima are simply found through exhaustive search. It is noted that there are other techniques for approximating the maxima of a distribution. The authors are currently exploring some of these techniques [16], including a Gaussian mixture approximation. As stated earlier, choosing to use 50 maxima is somewhat arbitrary, however when more maxima were chosen the tracking results were not significantly different and resulted in greatly increased computational requirements. When fewer than 50 were chosen the results were negatively affected some of the time. An example of the posterior distribution is shown in Figure 4. The log of the distribution is plotted for ease of viewing. The 50 maxima are marked with black plus signs. Note that the posterior distribution is high near all the true target locations (black plus signs in white circles), and a local maximum of the surface is often close to the true target location.

A. Inclusion of Feature data

The posterior distribution preprocessing step described above focuses on the use of position measurements to combine
contact data. In this work, we extend it to include any feature data, $z_{ij}$. For each contact, the class-conditional likelihood ratio, $\alpha_{ij}$ is calculated:

$$\alpha_{ij} = \frac{P(\zeta_T|z_{ij})}{P(\zeta_0|z_{ij})},$$

where $\zeta_T$ is the target class and $\zeta_0$ is the clutter class.

The class conditional likelihood ratio is then used to scale the posterior distributions for each contact in equation (1):

$$\tilde{P}(c|\bar{b}_i, \bar{r}_i, I_i = 1) = \gamma' \sum_{j=1}^{n} \alpha_{ij} P(c|b_{ij}, r_{ij}),$$

where $\gamma'$ normalizes the posterior distribution.

In cases where there are multiple classes of interest, the class conditional likelihood ratio is calculated for each of the possible classes and then either the maximum or mean of the values can be used. In Scenarios B and C, neither method was better than the other.

V. Blind Tracking Results

The truth for Scenario A was known a priori and was used to provide feedback on how well the tracking algorithms were performing on a baseline scenario and allow for tuning of tracking parameters. The truth for Scenarios B and C was provided after initial results were presented, and was not used to tune any tracking parameters in the reporting of the results in this section. The parameters tuned were: the number of maxima found in the posterior distribution, the fineness of the grid at which the posterior distribution is estimated, the initial state and covariance estimates for the extended Kalman Filter, the process noise for the extended Kalman Filter, the track confirmation threshold and the track deletion threshold.

The MSTWG metrics calculated for Scenarios A, B, and C are based on the metrics in [17] developed for the MSTWG. The posterior distribution preprocessing step provides a different set of contacts than the originals that do not include the associated truth flags. For this reason, the only metrics reported are: track fragmentation (Frag), track probability of detection (TPD), track localization error (TLE) and track false alarm rate (TFAR).

Figures 5 (feature data is not used) and 6 (feature data is used) show the tracking results for Scenario A of the PACsim data set using the JPDA algorithm with the preprocessing. These results were obtained using the following parameters: confirmation threshold = 15, deletion threshold = -3, deletion window = 5, gate = 3, EKF process noise scale = $4 \times 10^{-4}$. These parameters were tuned on Scenario A and used for both Scenario B and C. The target is tracked reasonably well although the confirmed track (red line) is not continuous through the corners. Features for target contacts are drawn one of two Gaussian distributions with mean of either 6 or 3 and standard deviation of 10. Features for clutter contacts are drawn from a Gaussian distribution with mean 0 and standard deviation of 10. The feature data does affect the tracking results, but for Scenario A it is difficult to make any conclusions.

Figures 7 through 10 are the tracking results for Scenarios B and C. Plots are included for simulations with and without feature data included in the tracking algorithms. The tracking results for Scenario B showed two targets and two fixed clutter points. Including the feature data improved the tracking results, which can be clearly seen in comparing Figures 7 and Figures 8. The two targets that are tracked have fewer fragments and tracking probability of detections is improved. This will be
more clearly seen in the following section where metrics are reported.

Scenario C proved very difficult to track using the parameters tuned on Scenario A. As expected, the fixed clutter points are appropriately tracked, however none of the other confirmed tracks are from a true target. This is due to the increased clutter rate in Scenario C as well as the much lower probability of detection for both the CW and FM pings, as included in Table I.

A. Metrics

The metrics and plots presented for Scenario B are from simulation runs before the truth data was known and the tracking parameters were not changed. The metrics were calculated based on the methods described above. Table II shows the per-target metric results for Scenario A. Table III shows the metric results for the single targets in Scenario B. Scenario C is not included in this section due to there being no correct target tracks. Metrics for Scenario C will be presented for the Optimized tracking results in the next section.

For targets 1 and 2 in Scenario B, including feature data results in increased TPD and decreased Fragmentation. For target 2, the inclusion of feature data decreased the TLE. In this scenario, adding feature information is clearly helpful.

<table>
<thead>
<tr>
<th>Target</th>
<th>1</th>
<th>1F</th>
<th>2</th>
<th>2F</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPD</td>
<td>0.757</td>
<td>0.738</td>
<td>0.986</td>
<td>0.944</td>
</tr>
<tr>
<td>TLE</td>
<td>7.79 × 10⁴</td>
<td>7.54 × 10⁴</td>
<td>6.27 × 10⁴</td>
<td>6.24 × 10⁴</td>
</tr>
<tr>
<td>Frag</td>
<td>4</td>
<td>4</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

TABLE II

METRIC RESULTS FOR THE TARGET AND FIXED CLUTTER IN SCENARIO A. TRACK PROBABILITY OF DETECTION (TPD), TRACK LOCALIZATION ERROR (TLE), TRACK FRAGMENTATION (FRAG). "F" INDICATES RESULTS WHEN FEATURES WERE INCLUDED IN THE PREPROCESSING STEP.

<table>
<thead>
<tr>
<th>Target</th>
<th>1</th>
<th>1F</th>
<th>2</th>
<th>2F</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPD</td>
<td>0.812</td>
<td>0.830</td>
<td>0.536</td>
<td>0.701</td>
</tr>
<tr>
<td>TLE</td>
<td>9.16 × 10⁴</td>
<td>1.01 × 10⁵</td>
<td>1.31 × 10⁵</td>
<td>1.20 × 10⁵</td>
</tr>
<tr>
<td>Frag</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

TABLE III

METRIC RESULTS FOR TARGETS IN SCENARIO B. TRACK PROBABILITY OF DETECTION (TPD), TRACK LOCALIZATION ERROR (TLE), TRACK FRAGMENTATION (FRAG). "F" INDICATES RESULTS WHEN FEATURES WERE INCLUDED IN THE PREPROCESSING STEP.

VI. Optimized Tracking Results

After the truth was revealed, a quick analysis of the data showed that the CW pings in Scenarios B and C were of limited use. Recall Table I, a comparison of the probability of detection for all of the contacts broken down by ping type. The extremely low probability of detection for all the targets motivated the discarding of all the CW pings and tracking only on the FM data. To further improve results on Scenario C, all contacts which had an SNR measurement of less than 25dB were discarded. Results showed a large improvement in tracking of targets 1 and 2 in Scenario B and target 1 in Scenario C. Figures 11 and 12 illustrate the difference in tracking results and Table IV shows the metrics for the three tracked targets.

VII. Conclusion

This paper presents results on the PACsim dataset, showing the usefulness of including feature data in a posterior
distribution preprocessing step. Section V showed that by incorporating feature data, fragmentation could be reduced and track probability of detection increased. In addition, after the contact labels for the data were provided, results in Section VI showed that discarding the CW pings altogether could increase tracking performance. This was due to the extremely low probability of detection for CW pings, illustrated in Table I. Using the Blind tuning method, good results were achieved on the target in Scenario A and two of the targets in Scenario B. None of the approaches in this paper resulted in satisfactory tracking on several targets in Scenarios B and C, due in part to their low probability of detection. We plan to incorporate environmental modeling in future work to allow for the classification of contacts as target or clutter based on amplitude information. In addition, a clustering step could provide additional clutter rejection [13].
Target | B1 | B2 | C1  
TPD  | 0.942 | 1 | 0.94 |  
TLE  | 5.69 × 10^4 | 8.60 × 10^4 | 2.35 × 10^5 |  
Frag | 1 | 1 | 1 |  

**TABLE IV**  
METRIC RESULTS FOR TARGETS IN SCENARIOS B AND C AFTER DISCARDING CW PINGS. TRACK PROBABILITY OF DETECTION (TPD), TRACK LOCALIZATION ERROR (TLE), TRACK FRAGMENTATION (FRAG).

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