Multistatic Post-Track Classification using a Target Strength Function

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Abstract—The Specular-Cued Surveillance Web (SPECSweb) multistatic tracker effectively reduces false track rate through the use of two amplitude thresholds. A high threshold is used to identify the occurrence of high-strength specular detection cues for track initiation. A low threshold is used for selective extraction of additional detections for track extension forward and backward in time. This approach significantly reduces the node-to-fusion-center communication loading requirements as well as reducing the output false track rate. At the time of the specular-cued track initiation, a historical (back)-track is reconstructed and output. In some cases, there may still be false tracks at the tracker output. We demonstrate a post-tracking classification method based on the expected Target Strength (TS) function, which identifies and further reduces residual false tracks. Cylindrical targets exhibit aspect-dependent TS which produces variations in the SNR levels of detected echoes. The multistatic tracker output provides estimates of target heading and therefore also of target aspect angle. The level variations of contact-sets corresponding to track segments are correlated with the expected TS function to provide a classification score. The method is shown to have potential in reducing false tracks when applied to the PACsim simulated data sets of the Multistatic Tracking Working Group (MSTWG).

Keywords—multistatic sonar; classification; multi-sensor fusion; tracking; cueing; clutter

I. INTRODUCTION

A concept known as “SPEcular-Cued Surveillance Web (SPECSweb)” is being pursued to mitigate the data-rate overloading problem inherent in multistatic sonar systems. The SPECSweb multistatic tracker does this through an implementation of high and low amplitude thresholds. The high threshold is used to identify the occurrence of high-strength specular detection cues for track initiation. The low threshold is used for a selective, proximity-based extraction of additional detections for track extension backward (from the time of the specular cue) in time. This historical track data is then extended forward in time as new data arrives. This approach provides a robust, automated Anti-Submarine Warfare (ASW) detection and tracking method, resulting in a significant reduction in false track rates and communication link loading compared to conventional multistatic fusion methods. SPECSweb has already been shown to be very effective at reducing false tracks [1-3]; the work discussed in this paper shows that yet additional reductions are possible through a post-tracking classification method based on the Target Strength (TS) function.

There are several approaches to perform target classification together with sensor fusion and target tracking, as depicted in Fig. 1. The traditional approach has been to perform classification prior to the fusion/tracking processes. In this case, firm acceptance/rejection decisions for detection contacts are determined prior to using the information in tracking. This acts as a filter on the data being sent to the fusion algorithm. It is usually performed on individual contacts from a single (source-receiver-waveform) “scan”, and classifies each of them based on statistical properties or physical “features” extracted from the detection data during upstream signal and information processing. The potential disadvantage of this approach is that the classification process may not be accurate or robust enough, resulting in unacceptable risk of true target contact dismissal. In this approach, the success of tracking will be largely dependent on the effectiveness of the classification step, since it determines which of the data are made available to the tracking algorithm.

An alternative approach is to integrate the classification process directly into the tracking algorithm itself (sometimes referred to as “feature-aided tracking”). In this case, the classification feature information in addition to typical kinematic features may be used to more effectively form true target tracks. The feature information may be used to aid in track management and/or data association. Likelihood ratios may be formed on the classification feature information, and incorporated into track scores, which can be used as the basis to improve track initiation and termination. The feature information may also be used to improve data association decisions. The feature likelihood ratio may be incorporated into the contact weighting scheme of probabilistic data association (PDA) methods [4]. It may also be incorporated into track scores and thereby improve decisions among multiple track hypotheses (as in multi-frame assignment and MHT approaches) [5]. If there is a sufficient ability to predict the feature/attribute values, then the tracker state may be augmented to include the feature information [4, 6]. These methods assume that the feature statistics and their distributions (for target and non-target cases) are predicted well enough to be used in making tracking decisions. If the predictions are not precise enough, it is possible that tracking performance could be degraded rather than enhanced.

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A final approach to using feature information with tracking (and the one pursued in this paper), is to apply the classification method only after the tracking process has been applied. This allows the kinematic contact association and filtering to proceed without the influence of feature information, but then subsequently filters the tracker output based on the feature information. This is particularly well-suited to the SPECSweb tracking approach, where the initiation scheme already significantly reduces the number of false tracks formed. Also, SPECSweb provides a backtrack history of the target tracks that it outputs. The availability of additional contact features in the historical backtracks provides larger, more effective statistical sample-sets for making certain classification decisions than those made scan-by-scan. In some cases, the backtrack segment may be of sufficient duration to perform classification prior to reporting to the operator (at the time of the initiation cue). Residual false tracks that are identified may either be terminated and/or suppressed from the tracker output display. This track-before-classify approach has previously been demonstrated with the SPECSweb tracker in conjunction with a track quality (track stability) feature and other “generic” features available at the tracker’s output [7].

This paper explores the potential of a track classification approach to exploit the TS function, which is sampled by the spatially distributed multistatic sensors of the surveillance field over time. Cylindrically-shaped targets exhibit aspect-dependent TS which produces variations in the SNR levels of detected echoes. The multistatic tracker output provides estimates of target heading and therefore also of target aspect angle. The received level variations within contact-sets corresponding to tracked objects are correlated with the expected TS function to provide a classification score. A classification criterion can then be applied to the classification scores.

Section II of this paper describes the SPECSweb fusion/tracking algorithm. Section III describes the post-tracking TS classification method. Section IV shows results for the classification method when applied to the MSTWG PACsim data set. Section V provides conclusions.

II. SPECSWEB ALGORITHM DESCRIPTION

Detailed descriptions of the SPECSweb multistatic tracking algorithm and specular cueing approach are found in [1-3]. A brief description of the algorithm is included here. In the SPECSweb concept, it is envisioned that all single-sensor processing will be embedded on the receivers, including storage of all local output data. Each receiver collects the contacts corresponding to one source transmission as a single scan of “ping” data. Each sonar node (bistatic receiver processing a unique source-waveform) self-searches each processed (and locally stored) scan for contacts which exceed a high SNR threshold (HTH). The HTH identifies very strong echoes, which likely correspond to targets that are in the “specular condition”. When in the specular geometry, there is greatly increased target strength, as indicated by various models [8-9] and data analyses. The HTH normally rejects most of the false alarm clutter echoes, which have a lower distribution of amplitudes than do specular target echoes.

Contacts which cross the HTH are assumed to be “specular cues”, and (only) these are initially sent over the communication link to the multistatic fusion center for potential track initiation. There may be some increased track reporting latency using this approach. Evaluation metrics for studying the occurrence statistics of specular detection in multistatic fields have been developed [10].

Once a specular cue arrives at the fusion center, tentative reverse-time tracks are initiated. A cue is mapped to an x-y position in Cartesian coordinates, and this position, along with its associated error covariance, is then sent as a snippet request to other nodes. These nodes calculate the appropriate snippet boundary in their respective measurement spaces within which data association would be possible, according to a specified gating parameter. Any contacts found within the snippet gate, and above the standard low-threshold (LTH), are sent over the communication link for further processing. As track estimates are obtained, they themselves are used as the cues for selective data retrieval on prior scans stored on any of the nodes. The retrospective tracking (backtracks) continue until they meet a track termination criterion. Recovering track history in this fashion provides valuable contextual and track classification information.

The contacts belonging to a backtrack are then re-filtered in the forward-time direction, until the current time (of the initiating specular cue) is reached. At this point the track classification method may be applied on all the retrospective historical track data. Tracking and classification updates continue in the forward-time direction updating with measurements found within the retrieval snippets of future scans. A logic-based track management scheme (M-of-N initiation and K missed detections for termination) is used. The tracker is implemented as an extended Kalman filter (EKF) with nearest neighbor data association and a nearly constant velocity (NCV) motion model.

III. POST-TRACKING TS CLASSIFICATION

Cylindrically shaped targets will exhibit aspect-dependent target strength. Multistatic fields are generally composed of multiple bistatic source-receiver pairs each of which has a

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Figure 1. Approaches to tracking and classification (SP- signal processing; IP- information processing).
particular geometry relative to a target’s location, as depicted in Fig. 2. TS increases when a target presents beam or near-beam aspect to the sonar pair. ϑs and ϑr are the angle from the target to source and receiver, respectively. The bistatic aspect angle, ϑBA, is the angle from target’s heading, ϑt, to the bisector of the bistatic opening angle, β. The specular condition (or beam aspect) occurs when ϑBA is ± 90°. Fig. 3, shows an example output of a cylindrical TS model [8]. The enhanced TS around specular is evident in this function, and this will be the feature upon which we develop a classification approach.

Figure 2. The bistatic sonar geometry, showing locations of the source (red), receiver (red), and target (green).

Figure 3. An aspect-dependent TS function.

A. Estimation of Bistatic Aspect Angle at the Tracker Output

The bistatic aspect angle, ϑBA, can be computed as the angle from the target heading, ϑt, to the bisector of the opening angle, β, as follows:

\[
\theta_{BA} = \frac{\beta}{2} - \theta_t = \frac{\theta_s + \theta_r - \theta_t}{2}
\]

(1)

where \(x_s, y_s, x_r, y_r\), and \(x_t, y_t\) are the locations of the source, receiver, and target, respectively, and \(\dot{x}_t, \dot{y}_t\) are the x and y components of target velocity. At the output of the tracker we obtain estimates of the target state parameters and can compute a mean estimate of the bistatic aspect angle using (1). We assume we have knowledge of the positional errors of our system components, given by the following parameters:

\[
\sigma_{\dot{x}_s}, \sigma_{\dot{y}_s}, \sigma_{\dot{x}_r}, \sigma_{\dot{y}_r}, \sigma_{\dot{x}_t}, \sigma_{\dot{y}_t} .
\]

At the tracker output, we obtain error estimates of the tracked target positions \(\sigma_{x_s}, \sigma_{y_s}, \sigma_{x_r}, \sigma_{y_r}\), and velocities \(\sigma_{\dot{x}_s}, \sigma_{\dot{y}_s}, \sigma_{\dot{x}_r}, \sigma_{\dot{y}_r}\), from the target state error covariance matrix. The second order statistics in estimates of the bistatic aspect angle at the output of the tracker can be obtained through small error analysis as follows:

\[
\sigma_{\theta_{BA}}^2 = E[\theta_{BA}] = \\
+ \frac{1}{4\sigma_{ST}^2} \left[ (x_s - x_r)^2 (\sigma_{\theta_{BA}}^2 + \sigma_{\theta_{BA}}^2) + (y_s - y_r)^2 (\sigma_{\theta_{BA}}^2 + \sigma_{\theta_{BA}}^2) \right] \\
- 2(x_s - x_r)(y_s - y_r)(\sigma_{\theta_{BA}}^2 + \sigma_{\theta_{BA}}^2)
\]

(2)

where

\[
\sigma_{ST} = \sqrt{(x_s - x_r)^2 + (y_s - y_r)^2}
\]

\[
s_f = \sqrt{\dot{x}_t^2 + \dot{y}_t^2}
\]

This quantity is important to know as it tells us how certain we can be in the estimates of bistatic aspect angle that we obtain at the tracker output.

B. Gaussian Blurring of the TS Function

Given that the tracker’s estimation of bistatic aspect angle will be subject to error, we smooth (or blur) the TS function by that estimated error. We start by forming a discrete sampled Gaussian kernel, g, using a value for the bistatic aspect angle error \(\sigma_{\theta_{BA}}^2\) obtained by (2) as

\[
g[n] = \frac{1}{\sqrt{2\pi\sigma_{BA}^2}} e^{-\frac{n^2}{2\sigma_{BA}^2}} .
\]

(4)

This Gaussian kernel is then circularly convolved with the sampled TS function of Fig. 3, f, as follows:

\[
y[n] = (f * g) = \sum_{m=-N}^{N-1} f[m] g[(n-m) \mod N] .
\]

(5)

where N is the sample size.

Fig. 4 shows an example of a Gaussian blurring kernel (\(\sigma_{BA}=15^\circ\)), the original TS function, and the resulting blurred TS function obtained at the output of the convolution. We observe that although the narrow, high specular glint feature is...
washed out in the blurring process, there is still a double bumped TS enhancement around beam aspect (90° and 270°), of about 10 dB.

A normalized, circular cross-correlation is then performed between the sampled polynomial estimate and the blurred TS function to obtain the feature score. The correlation peak near the zero angle-lag is then extracted as a classification score. High classification (correlation) scores (at zero lag) are expected when the data-set is consistent with the TS function; low scores are expected when the data-set is not consistent. As additional data becomes available, the processing may be repeated, with the generation of a new score.

A history of scores is plotted as a time sequence, and high and low correlation thresholds are set. The maximum, minimum, and ending scores are considered with respect to these thresholds to determine a classification decision. If the ending score exceeds the high threshold a “target” determination is made; similarly, if the ending score drops below the low threshold a “non-target” determination is made. If the ending score is in between the two thresholds, a target decision is made if the maximum score exceeds the high threshold; likewise a non-target decision is made if the minimum score is lower than the low threshold. A “undetermined” decision is made if both thresholds are never crossed. A sliding window (with a user-specified maximum number of the most recent scans) may be used in the classification computation. This allows for classifications decisions to change over the course of a track, which may be composed of target and non-target segments.

IV. CLASSIFICATION RESULTS

The Multistatic Tracking Working Group (MSTWG) is an ISIF-affiliated international collaboration with the objective to test various multistatic tracking algorithms on common data sets. A truth-blind simulated dataset (referred to as the “PACsim” data set) was provided to the group for analysis in 2011. It was generated using the Passive-Active Contact Simulator (PACsim) [12]. Fig. 5 shows a diagram of the multistatic field which was simulated. It includes five sources and 16 receivers distributed over a surveillance region. Transmissions are made once a minute, cycling amongst the five sources and alternating between FM and CW waveforms. We now apply the track classification algorithm to this data set.

PACsim calculates mean detection SNRs of targets for each source-receiver-waveform scan using a sonar equation model. An aspect-dependent, bistatic TS model [8] is used (Fig. 4) for each point along target trajectories. Mean target SNRs are perturbed by a random signal fluctuation term. Measurements of arrival time, bearing, and Doppler are computed from the true target trajectories truth, with random errors added (drawn from normal distributions).

False alarm clutter is also simulated, by randomly generating measurements. The data set also contains a “generic” classification feature with contact scores being taken from a target or non-target distribution. These features were ignored in our analysis here, since they are not TS-related features, however, such features have been successfully exploited in other classification approaches [7]. Here we wish
to quantify the performance of the TS classification feature independently and isolated from the effects of other classification features which may be considered. Combining various classification features may provide even better and more robust performance.

Two PACsim scenarios are analyzed, “B” and “C”. Each scenario lasts 8.5 hours, with ~500 pings and 8000 measurement scans (16 scans/ping). The SPECSweb multistatic tracker (without TS classification) was run on the “blind” data without truth information being available, and these results are shown. Subsequent to this, the truth information was provided and utilized to achieve the results that are shown with the TS classification applied.

**A. Results for PACsim-B Dataset**

The SPECSweb tracker results (without classification) for the PACsim-B data are shown in Fig. 6. We see here that good results are achieved, even without classification. In this case, this was achieved under truth-blind circumstances. Two of four mobile targets are totally tracked. Another is mostly tracked, except for a leg between two target turns. The target entering the area from the south is not tracked at all; this is due to fewer detections made on this particular target. Two fixed (immobile) targets are also tracked, although with a large number of fragments, some of which falsely wander away from their correct locations (at (5000,5000) and (10000,-15000) ) by associating clutter to them. Other false tracks are not observed. Since there are not a large number of false tracks to classify using our approach, the tracker is re-run with suboptimum parameters, which increases the number of false tracks which are output as seen in Fig. 7, and is the input for TS classification.

Fig. 8 shows the tracked contact SNRs as a function of estimated bistatic aspect angle (1) for one of the complete true track segments (both backtrack and forward track) of Fig. 7. Each data sample is copied and mirrored about 180°, since port and starboard views may be collapsed. This creates a symmetric function and allows the TS shape to more quickly emerge when less data is available. With all this data available, a clear aspect-dependence is observed. A polynomial curve-fit (order 8) is made to the data, which produces a curve with similar shape (shown in red) to the blurred TS function (shown in blue). Here the blurred TS function was obtained assuming a value of $\sigma_{MA} = 15°$, which was the mean error estimate obtained from the track data using (2). A normalized circular cross-correlation is then performed with the two curves and a maximum correlation value of 0.91 was extracted as a classification score. Fig. 9 shows a similar plot for a false track segment. The polynomial curve-fit produces a flat-shaped curve which does not correlate well with the blurred TS function (of a cylindrical target). In this case the resulting correlation peak was 0.39.
The feasibility of using the TS correlation score for classification on the tracks in Fig. 7 is shown in Fig. 10. Each track segment’s entire data is input to the TS classification process and correlation scores are produced. Upper and lower correlation thresholds were selected and applied. Only tracks classified as true are displayed. It shows good tracking performance, with a much cleaner picture than that of Fig. 7, and similar to the results obtained originally with optimum tracking parameters and without classification (Fig. 6), but with those tracks originating from the fixed targets correctly eliminated from the display. However, this is a best-case scenario because we have the maximum amount of data available from each track to compute the classification score. In practice, we can’t wait for tracks to terminate before they are classified, and we therefore desire to determine the classification after each ping has been processed and tracks updated. With less track history we expect some degradation in performance because of the difficulty in obtaining good polynomial fits with sparse data.

Fig. 11 shows the results of the track classifier which updates its decision every ping, using a sliding window of the 78 most recent scans. Track segments classified as false are suppressed from the display. Track portions which are classified as true are shown in thick colored lines. Track portions with thin colored lines show segments where a classification decision was not yet declared but the track eventually becomes true. The results are slightly poorer overall than what was achieved using all the data. A section of a true target track is lost, some target track fragmentation is induced, and a false track segment remains. However, the benefit of allowing the track classification to change over the lifetime of the track (via the sliding window) has in some cases removed false track segments which are spawned from true target tracks. The result is once again a much cleaner picture than that obtained without TS classification (Fig. 7). Track numbers are shown where the tracks originate.
B. Results for the PACsim-C Dataset

The SPECSweb tracker results (without classification) for the PACsim-C data are shown in Fig. 12. In this case we observe a more challenging tracking scenario. Here one of four mobile targets is completely tracked, two others are only partially tracked, and one is not tracked at all. This case was found to be more challenging than the previous one because of the large increase in the observed false alarm (clutter) rate. Many track fragments originate from two fixed (immobile) fixed clutter features (-10000,15000] and [-5000,5000] m).

This result already contains a large number of false tracks to classify, and we directly use this tracker output for TS classification. Upper and lower correlation thresholds were selected and applied. Fig. 13 shows the classification results obtained on the track data of Fig. 12 when each track segment’s entire available data history is used; only true tracks are displayed. The results show a much cleaner picture than Fig. 12, with little loss in tracking performance on the mobile targets. There is slightly worse performance on the southern, curving track, and the beginning of the western track.

Fig. 14 shows the results of the “real-time” track classifier which is updating its decision every ping, using a sliding window of the 400 most recent scans. Track portions classified as false are suppressed from the display. Track portions which are classified as true are shown in thick colored lines. Track portions shown in thin colored lines correspond to periods where classification was not yet determined. The results are similar to what was achieved using all the data, but several missing true track segments are recovered here, due to the ability to have different classifications for different parts of a track. The result is a cleaner picture than Fig. 12.
V. CONCLUSIONS

A post-tracking classifier, exploiting a TS feature matching approach, has been described. This method is compatible with SPECSweb, and its exploits the data available in retrospective historical track segments.

Good tracking results have been obtained on the MSTWG PACsim blind data sets. In 3 of the 4 mobile targets of each case (B and C), the target was fully or partially tracked. The TS classifier has been shown to be effective in confirming output tracks for true (and cylindrical) targets. False tracks are also classified and reduced. The approach is more effective when more track history is available to it; it is less robust when little track history is available.

Future work will focus on more robust implementations of the TS post-tracking classifier by improving score computation with sparse data and improving classification decision methods using these scores. In addition, methods for reducing estimated target track heading error (and therefore estimated bistatic aspect angle) will be pursued to produce a less-blurred TS function for the pattern matching algorithm.

REFERENCES


