Clutter Reduction for ASW Using Automatic Aural Classification With a Coherent Source

FY2010 Report

Stefan M. Murphy
Paul C. Hines

Prepared for:
US Office of Naval Research
875 North Randolph Street, Suite 1425
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Defence R&D Canada warrants that the work was performed in a professional manner conforming to generally accepted practices for scientific research and development.

This report is not a statement of endorsement by the Department of National Defence or the Government of Canada.

Defence R&D Canada – Atlantic

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Acknowledgements

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# Table of contents

Acknowledgements .................................................................................................................................................. i  
Table of contents .............................................................................................................................................. iii  
List of figures ...................................................................................................................................................... iv  
1 LONG-TERM GOALS ....................................................................................................................................... 1  
2 OBJECTIVES .................................................................................................................................................. 1  
3 APPROACH ................................................................................................................................................... 2  
4 WORK COMPLETED ...................................................................................................................................... 3  
5 RESULTS ......................................................................................................................................................... 8  
6 IMPACT/APPLICATION ................................................................................................................................. 16  
7 RELATED PROJECTS ................................................................................................................................... 17  
8 REFERENCES .................................................................................................................................................. 17  
9 PUBLICATIONS .............................................................................................................................................. 18  
List of symbols/abbreviations/acronyms/initialisms ............................................................................................. 19
List of figures

Figure 1: Clutter09 Track 2.3.2-A. .................................................................................................. 3
Figure 2: Clutter09 Track 2.3.2-B. .................................................................................................. 4
Figure 3: Clutter09 Track 2.3.2-C. .................................................................................................. 5
Figure 4: Campo Vega oil rig viewed from NRV ALLIANCE during Clutter07 (a) and Clutter09 (b). Note the decrease in sea state from 2007 to 2009. ................................. 9
Figure 5: Sound speed profiles from XBT data collected by NRV ALLIANCE. The dashed line represents the profile from 2007 and the solid line is the 2009 profile. .................. 9
Figure 6: Performance obtained training the aural classifier using Clutter07 data and testing using the same data. The maximum $A_{ROC}$ value of 0.943 occurs at 17 features and 2 principal components. .......................................................... 10
Figure 7: Performance obtained training the aural classifier using Clutter07 data and testing using Clutter09 data. Maximum $A_{ROC}$ value of 0.903 occurs at 29 features and 3 principal components. .......................................................... 10
Figure 8: Classification performance increases as the minimum SNR is increased by removing low SNR echoes from the data set. .......................................................... 11
Figure 9: Tracks formed using data from Clutter09 2.3.2-C. Echo repeater track selected (highlighted red) and saved as training target echoes. .......................................... 12
Figure 10: All of the contacts displayed along with tracks formed using data from Clutter09 2.3.2-C. Clutter echoes surrounding the ER track (highlighted red) are saved as training clutter echoes. .......................................................... 13
Figure 11: Tracks formed from Clutter09 2.3.2-B data. .......................................................... 14
Figure 12: Classification results for training (left) and testing (right). .......................................... 15
Figure 13: Tracking solution refined when the aural classifier results are integrated. .............. 16
1 LONG-TERM GOALS

Clutter is the single biggest obstacle facing anti-submarine warfare (ASW) performance in the littorals because it (clutter) causes unacceptably high false alarm rates and generates large numbers of false tracks in current automated systems. This increases the workload on the ASW controller/team to an unacceptable level and increases the likelihood of missing real targets. The long-term goal is to develop a robust automatic classifier using aural-based features that can discriminate active sonar target echoes from unwanted echoes, thereby reducing false alarms and false tracks.

2 OBJECTIVES

The primary objective of the second year of the grant was to complete rigorous testing of the aural classifier using the temporally robust discriminators of targets and clutter identified during year one of the grant. The purpose of this testing was to obtain a thorough performance baseline for the classifier in anticipation of improvements to the classifier that will be investigated in year three of the grant.

Following the proof of concept completed in the first year of the grant, the secondary objective was to develop an integrated tracker-classifier methodology with a prototype implementation in the Integrated Tracker and Aural Classifier (ITAC) software to demonstrate the potential for improvement over conventional kinematic trackers.

A third objective was to do a preliminary investigation of the dependence of signal-to-noise ratio (SNR) on classification.
3 APPROACH

The active sonar experiments performed during the Clutter07 and Clutter09 sea trials were documented in the FY2009 report. In each experiment NRV ALLIANCE transmitted a series of 1-second LFM upsweeps from 600–3400 Hz and received echoes from surrogate targets (oil rig and wellhead of Campo Vega Oilfield) and geological clutter. A database containing a few thousand of these echoes was used to support training and testing of the aural classifier during the first year of the grant. Since the classifier uses target and clutter echo statistics during training, a larger number of echoes is desirable. To address this, approximately 32,000 additional target echoes are extracted from side beams to form an expanded database suitable for rigorous evaluation of the classifier.

To test the temporal robustness of the aural classifier, it is trained using target and clutter echoes from Clutter07 and tested using echoes collected two years later during the Clutter09 sea trial. The aural classifier has two main parameters with the potential to affect classification performance: the number of aural features used and the number of principal components used. To form a thorough performance baseline, all combinations of these parameters are tested.

In order to support the second objective (ITAC), an echo repeater was towed by ITN LEVANZO to approximate a target during the Clutter09 sea trial. Preliminary studies completed in year 1 of the grant showed the potential for tracking improvement by training the classifier in situ. In that demonstration the aural classifier was used to identify echoes from the Campo Vega oil rig that were interfering with the nearby echo-repeater track. The interfering echoes were manually removed and the tracks were recomputed, resulting in an improved track. In year 2, the ITAC software was further developed to add the capability of automatically integrating classification results into the tracker decision algorithm.

A preliminary investigation on SNR dependence was performed by monitoring classification performance as low SNR echoes were removed from both the training and testing databases.
4 WORK COMPLETED

During the Clutter09 sea trial, 3 experimental runs denoted (2.3.2-A, 2.3.2-B, and 2.3.2-C) were performed to support the objectives outlined earlier in the report: Track 2.3.2-A is a repeat of a track from Clutter07 and was designed to test the temporal robustness of the aural classifier. Tracks 2.3.2-B and C are two-ship tracking experiments in which NRV ALLIANCE towed a broadband source and a towed-array receiver, and ITN LEVANZO towed an echo repeater (ER). The experimental details for each of the tracks are presented below.

Figure 1: Clutter09 Track 2.3.2-A.

Track 2.3.2-A, shown in Figure 1, was completed over approximately 7 hours at a constant speed of 5 knots. Tracks are denoted using S#d where “S” denotes the ship (A=NRV ALLIANCE, L=ITN LEVANZO, and N=nominal straight line for reference), “#” denotes waypoint number, and “d” is the lower-case letter in 2.3.2-A, B, or C. The track run by NRV ALLIANCE is denoted A#a and is shown in blue. A series of 1 second, linear FM sweeps (LFM), from 600–3400 Hz were transmitted using NURC’s low-frequency (LF) and mid-frequency (MF) free-flooding ring sources. The pulse repetition rate was 60 s. The pulse was designed to have constant source level by compensating for the TVR of both sources. The crossover frequency for the sources was 1810 Hz. From 1800–1820 Hz, the LF source level was ramped down and the MF source level was ramped up so as to maintain a constant source level (214 dB re 1μPa @ 1 m) and provide a smooth transition between sources. The NURC cardioid towed array was the receiver. Pings transmitted on the even minutes (0 min, 2 min, …) were sequential LFM upsweeps 600–3400 Hz. Odd minute pings (1 min, 3 min, …) were parallel upsweeps 600–3400 Hz. Sequential means that
the sweep began on the LF source at 600 Hz and transitioned to the MF source at such time as the pulse reached the crossover frequency. Parallel means that both sources were started at the same time so the duration of the pulse was actually less than 1 second to maintain constant energy for both pulse types. For the parallel pulse, the duration was fixed by the MF source because it had the greater bandwidth. The parallel pulse was selected to examine whether aural classification is robust in the presence of a narrow band break in the pulse correlation. This would have significant payoff in that several (less-expensive) moderate-bandwidth sources could be used to generate the required bandwidth.

![Figure 2: Clutter09 Track 2.3.2-B.](image)

Track 2.3.2-B was designed to collect data with which to examine tracker-classifier integration and examine performance in a high clutter area. Sequential LFM upsweeps 600–3400 Hz (identical to even-minute pings of 2.3.2-A) were transmitted every 60 seconds at a source level of 214 dB re 1μPa @ 1 m. Track 2.3.2-B in shown in Figure 2. The track was run from the north to south (waypoint 1 to 3) and repeated on opposite course from waypoint 3 to 1. The NRV ALLIANCE heading was selected to be nominally parallel to the Ragusa Ridge, a source of significant clutter. The ITN LEVANZO track was designed to have echo-repeater returns arrive at NRV ALLIANCE co-temporally with clutter from the Ragusa Ridge. The course change in the ITN LEVANZO track was designed to test the tracker’s ability to maintain contact through a turn and test the aural classifier’s ability to reduce tracking errors by identifying the target echoes amongst the clutter.

Track 2.3.2-C was designed to collect data with which to compare classifier performance along a high-clutter and a low-clutter track (the north-south track and east-west track, respectively.) In addition, the tracking difficulty increases at each turn by increasing the turn rate. That is,
3 degrees per minute at waypoint 2, 5 degrees per minute at waypoint 3 and 9 degrees per minute at waypoint 4. This sequence was repeated along the low-clutter track at waypoints 7, 8, 9 (i.e., 3, 5, 9 degrees per minute, respectively). Sequential LFM upsweeps 600–3400 Hz (identical to even-minute pings of 2.3.2-A) were transmitted every 60 seconds at a source level of 214 dB re 1μPa @ 1 m. Track 2.3.2-C is shown in Figure 3.

![Figure 3: Clutter09 Track 2.3.2-C.](image)

**TASK 1: Database Refining and Expansion**

The procedure for extracting echoes from the data collected during the Clutter07 and Clutter09 sea trials was refined during the reporting period. Previously, the Doppler effect caused by the speed of advance of NRV ALLIANCE was not taken into account in the replica-correlation processing.

To train the classifier, an equal number of target and clutter echoes should be used; otherwise, classification can be biased toward the class with the larger number of echoes. Classification being biased by SNR is another concern. For example, given a target echo with high SNR and a low SNR clutter echo masked by noise, the classification could be based on the aural differences between signal and noise rather than the difference between target and clutter signal features. This is of particular concern for the Clutter07 and Clutter09 data since the surrogate target echoes typically have much higher SNR than clutter echoes. Both concerns can be met by choosing target and clutter echoes in such a way that the SNR distributions of both classes are similar. In doing so, SNR bias is avoided, and class populations are automatically equalized.
In the Clutter07 and Clutter09 experiments the number of target echoes is much less than the number of clutter echoes since at most one echo per transmitted ping is returned from each target. For example, in Clutter07, only 233 echoes from the Campo Vega oil rig and wellhead were detected, while over 40,000 echoes from clutter were received. To equalize the number of target and clutter echoes, a small subset of clutter echoes must be randomly selected from the original set of clutter echoes.

In order to increase the number of target echoes (and in turn the number of clutter echoes that can be used), a set of 18,919 off-beam echoes are included. These echoes are caused by signal leakage into side lobes of the receive array. Although these echoes are derived from the same physical echoes received from the targets, the beamforming and superposition on different background noise makes them aurally distinct and suitable for use as additional examples in training the classifier [1]. This method is very attractive because, as well as increasing the number of echoes, it provides a greater target echo SNR distribution since the off-beam target echoes have lower SNR than the main beam. This facilitates matching the target and clutter SNR distributions. The number of target echoes was increased by a factor of 82 (from 233 to 19,152 echoes), and after refining the selection of echoes to match the SNR distributions, 12,366 target echoes and 13,133 clutter echoes remained.

In summary, the number of echoes in the training database (Clutter07) was increased by a factor of 55. Not only is echo quantity greater, but quality is also improved. The individual echoes are Doppler corrected, and the refined collection of target and clutter echoes have similar SNR characteristics for unbiased classification. A similar expansion was performed for the Clutter09 database used for testing the aural classifier.

**TASK 2: Temporal Robustness Performance Baseline**

The aural classifier was trained using the refined and expanded Clutter07 database. Testing was then performed using the Clutter09 database, which was also refined and expanded. Two main parameters of the aural classifier were varied in order to observe the maximum performance possible. The $A_{ROC}$ performance metric indicated successful classification of the Clutter09 database, indicating temporal robustness. To evaluate SNR dependence, the performance metric was monitored as the range of echo SNRs used in the classifier was varied.

**TASK 3: ITAC Software Development**

There were two main components to this task: (1) developing and implementing an algorithm for integrating classification and kinematic tracking probabilities within ITAC; (2) developing the ITAC interface to improve user control of the aural classifier from within the application in order to facilitate testing and further development.

Perhaps the biggest challenge in integrating tracking and classification probabilities is to establish an appropriate weighting scheme for the individual components. The following scheme was developed as a demonstration for one possible method of blending the classification and tracking probabilities. In this scheme, a contact (detection) is classified as a target with a certain probability, $P_T$, and this value is used to determine one of four possible actions to take. First, if $P_T < 0.25$, there is a high probability that the contact is clutter (< 25% chance of being a target
and > 75% chance of being clutter), so the contact is designated as Clutter and is disabled from track association. Second, if \( PT > 0.75 \), there is a high probability that the contact is a target (> 75% target, < 25% clutter), so the contact is designated as a Target and is given priority for track association over contacts with lower target probabilities. Third, in the medium-low confidence regime where \( 0.25 < PT < 0.75 \), the decision to classify a contact as Target or as Clutter is not straightforward. In this regime, the contact probabilities are merged with the track association probabilities according to the following equation:

\[
P = P_A + PT(1.0 - P_A)
\]

where \( P_A \) is the probability of association calculated by the raw tracker, \( PT \) is the classification contact probability, and \( P \) is the merged probability. The forth action occurs if the echo classification features reside in the “tails” of the probability distribution of both the target and clutter training sets. (The tails of the distribution are currently taken to be greater than 1.5 standard deviations from the mean value.) In this scenario, the aural classifier returns “unknown” and the tracker relies entirely on the track association probability to form the track.

The second component involved improving the ITAC interface to allow users to easily train the classifier using contacts and tracks shown on the display. This is useful for selecting contacts in a track as targets for classifier training and also for selecting recent, spatially relevant clutter. This procedure of choosing a similar number of targets and clutter in the same spatial region is different from the approach described in Task 1 that matched the SNR distributions of targets and clutter from a widespread area; however, it is better suited for the limited number of contacts (i.e., in tracks) encountered in operation. The ITAC interface was also improved to allow users to select tracks for classification, and then to reprocess or recompute the tracks using the contact probabilities calculated using the classifier.

The recent improvements to the interface and capabilities of ITAC allow for three modes of operation.

**Operation Mode 1**: Rely on temporal robustness of the classifier (invariance to sound propagation and background noise) to classify contacts based on general differences between clutter and targets. These differences are determined from large data sets spanning large spatial regions and long periods of time. In terms of human cognition, this mode asks: “Based on my past experience, does this contact sound more like an echo from a manmade object, or from a geological object?” This operation mode uses general characteristics and does not rely on prior intelligence on the target of interest.

**Operation Mode 2**: Use a classifier trained with echoes from a specific, previously encountered target. This mode is useful if there is prior intelligence on the target. For example, “Does this contact sound like an echo from Target X that I’ve previously encountered?”

**Operation Mode 3**: Near-real-time (in situ) training, where contacts in a confirmed track are used as targets and a well-defined group of contacts is used as clutter. For example, “Does this contact sound more like an echo from the geological objects in this region, or like the target currently being tracked?”
5 RESULTS

Temporal Robustness: Experimental Differences

Using 2.3.2-A track data from Clutter09, and recalling that this repeated the experiment from Clutter07, the temporal robustness of the aural classifier was evaluated by training using the refined Clutter07 database and testing using the refined Clutter09 database. There are two main experimental differences between Clutter07 and Clutter09 2.3.2-A that trial the classifier’s temporal robustness.

First, the weather conditions differed considerably. During the experiment in Clutter07 the average wind speed was 15.2 knots, while the average wind speed during the Clutter09 experiment was only 3.8 knots. Photographs of Campo Vega from each experiment are shown in Figure 4 and a significant difference in sea state can be observed; Beaufort force 5–6 seas were present in 2007 whereas nearly calm seas (Beaufort force 1) were present in 2009. The difference in sea state leads to a decrease in ambient noise in 2009, and also an increase in surface reflections due to the decrease in roughness of the water-air boundary and an increase in air bubbles near the surface.

Second, although both trials occurred in the month of May, the sound speed profiles were dissimilar. The sound speed profiles are shown in the plot of water depth versus speed of sound in Figure 5. For reference, NRV ALLIANCE’s sources and receiver were towed at a depth of approximately 50 m during both sea trials. The profiles are calculated from expendable bathythermograph (XBT) data taken near the half-way points of the tracks (at approximately 13:00 UTC).

While the 2007 sound speed profile is nearly isospeed, the 2009 profile is downward refracting. The differences in the sound speed profiles and surface reflections contribute to different sound propagation conditions for each trial, which could alter received echo signals and the aural features that describe them.

Temporal Robustness: Aural Classifier Performance

In order to maximize classifier performance, all combinations of two adjustable parameters of the aural classifier are evaluated: the number of aural features used, and the number of principal components used. A metric named ‘discriminant score’ was used to rank the effectiveness of the classifier’s aural features to discriminate target from clutter in the training set. The number of features was varied by changing the number of top ranked features retained, and similarly the number of principal components was varied by changing the number of principal components used.
Figure 4: Campo Vega oil rig viewed from NRV ALLIANCE during Clutter07 (a) and Clutter09 (b). Note the decrease in sea state from 2007 to 2009.

Figure 5: Sound speed profiles from XBT data collected by NRV ALLIANCE. The dashed line represents the profile from 2007 and the solid line is the 2009 profile.

Receiver Operating Characteristic (ROC) curves are used to evaluate the classifier’s performance at all operating points, and the area under the ROC curve, $A_{ROC}$, is the summary statistic used as the single value performance metric. For an ideal classifier, $A_{ROC} = 1$, and in the case of random guessing, $A_{ROC} = 0.5$. Classifiers with $A_{ROC} > 0.9$ are considered to be very successful [2]. In order to evaluate the separability of the target and clutter echoes in the training set, the classifier is trained with the Clutter07 data set and then tested using the same echoes. Figure 6 plots $A_{ROC}$ increasing from blue to red as the number of top features used is increased along the horizontal axis, and the number of principal components used is increased along the vertical axis.
Figure 6: Performance obtained training the aural classifier using Clutter07 data and testing using the same data. The maximum $A_{ROC}$ value of 0.943 occurs at 17 features and 2 principal components.

A similar plot in Figure 7 shows the performance of the classifier when it is tested using data from Clutter09. The maximum $A_{ROC}$ value of 0.903 indicates successful classification of the Clutter09 data and therefore temporal robustness of the aural classifier.

Figure 7: Performance obtained training the aural classifier using Clutter07 data and testing using Clutter09 data. Maximum $A_{ROC}$ value of 0.903 occurs at 29 features and 3 principal components.
As echo SNR decreases, noise begins to dominate, and the ability of the classifier to distinguish between targets and clutter is reduced. To quantify this behaviour, low SNR echoes were removed from the Clutter07 and Clutter09 data sets for several thresholds, and the classifier was re-trained and tested at each threshold. The performance ($A_{ROC}$) of the classifier (using the top 5 features and 2 principal components) is plotted against the minimum SNR threshold in Figure 8.

![Figure 8: Classification performance increases as the minimum SNR is increased by removing low SNR echoes from the data set.](image)

As the minimum SNR threshold is increased, the classifier evaluation of $A_{ROC} > 0.95$ approaches ideal performance. Note that increasing the minimum SNR decreases the size of the data set since low SNR echoes are removed. At the high SNR thresholds, very few echoes remain in the data set, which is why there are fluctuations in the performance curve in this region.

The probability mass function (pmf) of the target and clutter echo SNR is not uniform, rather it resembles a normal distribution with a mean of 7.2 and standard deviation of 3.3. It is interesting to note that the plot in Figure 8 resembles the cumulative distribution function (cdf) of such a pmf. Since the largest numbers of lower SNR (i.e., SNR < 16 dB) echoes are removed at thresholds around the mean, it is logical that the performance increases most rapidly in this region, and slowly at the tails of the distribution. A linear relationship between performance and the minimum SNR(dB) threshold is therefore expected for a uniform SNR distribution.
**Improvements to ITAC**

The remainder of this section will document the present capabilities of one of the operating modes (Mode 2) of ITAC using screenshots from the application. Using data from Clutter09 2.3.2-C, the aural classifier is trained using signals from the ER as targets, and clutter surrounding the ER track. Contacts from Clutter09 2.3.2-B are then classified, and false tracks formed by clutter are dramatically reduced when the classification results are integrated.

Figure 9 shows the route of NRV ALLIANCE as the straight yellow line from east to west. The zigzag dashed line north of this represents ITN LEVANZO’s route, and the parallel track to the north of this (highlighted red) shows the track being formed by “echoes” from the ER towed by ITN LEVANZO. The ER echoes are generated by applying a modeled target response to the received LFM ping transmitted by NRV ALLIANCE. The ER echoes are transmitted with a six second time delay; this delay causes a shift of the ER track to the north of ITN LEVANZO. The echoes associated with the contacts that form the ER track are saved as a group and designated as the targets for training the classifier. The ellipses representing the position uncertainties of each contact in the ER track are shown in green, but most are hidden by the red line highlighting the track.

![Figure 9: Tracks formed using data from Clutter09 2.3.2-C. Echo repeater track selected (highlighted red) and saved as training target echoes.](image-url)
Figure 10 shows ITAC in clutter selection mode. In this mode, only ‘aged out’ contacts that were not used to form ‘confirmed tracks’ can be selected. For example, each new contact that does not become associated with an existing track forms a tentative track, and this tentative track transitions to a confirmed track if 4 additional contacts become associated with it. Any track that is not updated with a new contact over a maximum period of 10 minutes (in this case 10 pings) is aged out, or disabled. The clutter contacts selected are shown highlighted in red in Figure 10. These were selected by drawing a rectangular box encompassing the region surrounding the ER track. The reasoning for using this limited selection of clutter contacts is twofold. First, using clutter contacts from the same region as the target track ensures that the echoes are spatially relevant in that they undergo the same propagation through the same range as the target contacts. This avoids classification biasing by effects of sound propagation. Second, for training purposes, the number of targets and clutter echoes should be equal, and if the clutter region was not limited, the number of clutter echoes would greatly outnumber the target echoes.

Together, the echoes from the ER track and clutter surrounding it form a training dataset for the aural classifier.

Figure 10: All of the contacts displayed along with tracks formed using data from Clutter09 2.3.2-C. Clutter echoes surrounding the ER track (highlighted red) are saved as training clutter echoes.
Next, the Clutter09 2.3.2-B data is processed in a new ITAC display, as shown in Figure 11. By experimental design, the delay from the echo repeater causes the echoes to line up with a large number of false alarms from the Ragusa Ridge. These false alarms form a large number of false tracks and it is very difficult to distinguish the ER track.

![Figure 11: Tracks formed from Clutter09 2.3.2-B data.](image)

As can be seen in the background of Figure 12, all of the tracks in Figure 11 were selected (highlighted red). The tracks were classified using the aural classifier trained with the training set from 2.3.2-C described earlier and shown in Figures 9 and 10. The left window in Figure 12 displays the data used to train the classifier, where each echo has been converted to a 2-dimensional coordinate using Principal Component Analysis. The red ‘T’s represent ER echoes and the blue ‘C’s represent clutter echoes. A decision boundary is automatically drawn, separating the two classes and forming target and clutter regions shown in light orange and blue, respectively. The right window shows the unidentified echoes (green ‘U’s) being tested. A large number of these echoes fall in the clutter region and therefore will not be considered by the tracker.
Using the classification probabilities and the merging policy (see Eq.1 and surrounding text), the tracker disables the contacts classified as clutter and recomputes the tracks. The result is shown in Figure 13. A single, clean, ER track is revealed; it was previously hidden within a large number of false tracks when the tracker had no access to classification information.
The aural classifier has been proven to be a powerful tool for clutter reduction. It can be used for this purpose even when trained in different environmental conditions and time periods: a performance measure of $A_{ROC} = 0.903$ was achieved when the classifier was trained with Clutter07 data and tested with Clutter09 data. This performance baseline will be used to mark classification improvements expected in future efforts.

With its modular design, ITAC is a test bed for new algorithms for integrating tracking and classification. It has operation modes that support training the classifier in advance with previously acquired data, and also in near real-time with incoming data. The current integration algorithm is very simple, but was used to demonstrate a significant reduction in false tracks. With the inception of the new Integrated Classification and Tracking (ICAT) TTCP Key Technical Area in MAR-TP9, new algorithms should emerge which can be implemented in ITAC for testing.
7 RELATED PROJECTS

1. Characterizing and Reducing Clutter for Broadband Active Sonar, Joint Research Program, NATO Undersea Research Center.


8 REFERENCES


### List of symbols/abbreviations/acronyms/initialisms

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td>ASW</td>
<td>Anti-submarine Warfare</td>
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<tr>
<td>cdf</td>
<td>Cumulative distribution function</td>
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<tr>
<td>ER</td>
<td>Echo repeater</td>
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<tr>
<td>ITAC</td>
<td>Integrated Tracker and Aural Classifier</td>
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<td>ITN</td>
<td>Italian Navy</td>
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<tr>
<td>LF</td>
<td>Low-frequency</td>
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<td>LFM</td>
<td>Linear Frequency Modulation</td>
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<td>MF</td>
<td>Mid-frequency</td>
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<td>NRV</td>
<td>NATO Research Vessel</td>
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<tr>
<td>NURC</td>
<td>NATO Undersea Research Center</td>
</tr>
<tr>
<td>ONR</td>
<td>Office of Naval Research</td>
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<tr>
<td>pmf</td>
<td>Probability mass function</td>
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<tr>
<td>ROC</td>
<td>Receiver Operating Characteristic</td>
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<tr>
<td>SNR</td>
<td>Signal-to-noise ratio</td>
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<tr>
<td>UTC</td>
<td>Universal Time, Coordinated</td>
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<tr>
<td>XBT</td>
<td>Expendable Bathythermograph</td>
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**Clutter Reduction for ASW Using Automatic Aural Classification With a Coherent Source: FY2010 Report**

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This report presents the results from the second year of a three year research grant from the US Office of Naval Research (ONR). The project’s aim is to develop a robust classifier using aural-based features that can discriminate active sonar target echoes from unwanted clutter echoes. A secondary objective is to develop an integrated tracker-classifier methodology with a prototype implementation in the Integrated Tracker and Aural Classifier (ITAC) software to demonstrate the potential for improvement over conventional kinematic trackers. The role of signal-to-noise ratio (SNR) in echo classification is also considered.

During the first year of the project, an experiment was conducted in NRV ALLIANCE as part of the NURC Clutter09 sea trial. This enabled temporal robustness of the aural classifier to be examined by training the classifier using data collected during a 2007 field trial (Clutter07) and testing on data collected during Clutter09. In classifying the Clutter09 echoes, a performance metric of $A_{ROC} = 0.903$ was achieved, which is indicative of a very successful, and temporally robust classifier.

In order to support the second objective (ITAC), an echo repeater was towed by ITN LEVANZO to approximate a target during the Clutter09 sea trial. This data was used to test a classifier-tracker integration algorithm. In the algorithm, the contact-track association weighting for the tracking algorithm is adjusted based on the classifier decision; in the limit, the classifier can override the tracker entirely and reject a detection as being clutter, or confirm that a specific detection is the target of interest. Using the algorithm, the ITAC software demonstrated a large reduction in false tracks, revealing an echo repeater track that was hidden when the tracker had no access to classification information.

A preliminary investigation on SNR dependence was performed. Evidence suggests that if the SNR of echoes is distributed normally, classification performance increases linearly with an increase in the minimum SNR of echoes evaluated by the classifier.

ASW, sonar-echo classification, aural classification, tracking, integrated tracking and classification, joint tracking and classification, detection localization classification and tracking
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