Copy No. _____

Defence Research and Development Canada
Recherche et développement pour la défense Canada

DEFENCE R&D DÉFENSE

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

FY2009 Report

Paul C. Hines
Stefan Murphy

Defence R&D Canada – Atlantic

External Client Report
DRDC Atlantic ECR 2009-241
October 2009

Canada

This page intentionally left blank.

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

FY2009 Report

Paul C. Hines
Stefan Murphy

Defence R&D Canada – Atlantic

External Client Report
DRDC Atlantic ECR 2009-241
October 2009

Principal Author

Original signed by Paul C. Hines

Paul C. Hines

Project Manager/Aural Classification

Approved by

Original signed by Dan Hutt

Dan Hutt

Head/Underwater Sensing

Approved for release by

Original signed by Ron Kuwahara for

Calvin Hyatt

Chair/Document Review Panel

This report produced for Office of Naval Research Grant Number N00014-09-1-0426.

Abstract

This report presents the results from the first 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 aurally-based features that can discriminate active sonar target echoes from unwanted clutter echoes. A secondary objective is to examine the hierarchy (or more accurately, the interdependence) of classification and tracking to improve the integration of classification and tracking in future systems. During the first year of the project, an experiment was conducted on board *NRV Alliance* as part of the NURC Clutter09 sea trail. 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. The Fisher linear discriminant was used to rank the effectiveness of the classifier's aural features. One of the most useful metrics to rate classifier performance is the area under the Receiver Operating Characteristic (ROC) curve, A_z. The greater A_z, the better the classifier, with a value of $A_z = 1$ indicating ideal performance. The training ROC curve obtains a value of $A_z = 0.97$ and the testing data obtains a value of $A_z = 0.90$. These numbers are indicative of a very successful classifier. During the remaining two years of the research grant, tracker-classifier integration will be examined and the aural classifier will be tested more thoroughly using the Clutter09 data set.

Résumé

Ce rapport présente les résultats de la première année d'une subvention de trois ans octroyée par l'Office of Naval Research (ONR) des États-Unis. Le but du projet est d'élaborer un classificateur robuste utilisant des entités auditivement définies et permettant de différencier les échos de cible obtenus par sonar actif et le fouillis d'écho indésirable. Un objectif secondaire est d'examiner la hiérarchie (ou plus exactement, l'interdépendance) de la classification et du suivi afin d'améliorer l'intégration de la classification et du suivi dans les futurs systèmes. Au cours de la première année du projet, une expérience a été réalisée à bord du *NRV Alliance*, dans le cadre de la campagne en mer NURC Clutter09. Nous avons examiné la robustesse temporelle du classificateur auditif en l'entraînant avec les données recueillies lors d'un essai sur le terrain en 2007 (Clutter07) et le testant avec les données recueillies lors d'un essai sur le terrain en 2009 (Clutter09.) Le discriminant linéaire de Fisher a été utilisé pour classer l'efficacité des caractéristiques auditives du classificateur. L'un des paramètres les plus utiles pour coter la performance d'un classificateur est l'aire sous la courbe caractéristique de fonctionnement du récepteur (ROC), A_z. Plus la valeur de A_z est grande, meilleur est le classificateur, la valeur $A_z = 1$ correspondant au rendement idéal. La courbe ROC avec entraînement donne une valeur $A_z = 0{,}97$ et les essais avec les données donnent une valeur $A_z = 0{,}90$. Ces chiffres sont indicateurs d'un classificateur très performant. Au cours des deux dernières années de la subvention de recherche, l'intégration du modèle de suivi et du classificateur sera examinée et le classificateur auditif sera testé plus à fond à l'aide de l'ensemble de données Clutter09.

This page intentionally left blank.

Executive summary

Clutter Reduction for ASW Using Automatic Aural Classification With a Coherent Source
FY2009 Report

Paul C. Hines; Stefan Murphy; DRDC Atlantic ECR 2009-241; Defence R&D Canada – Atlantic; October 2009.

Introduction: This report presents the results from the first 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 aurally-based features that can discriminate active sonar target echoes from unwanted clutter echoes. A secondary objective is to examine the hierarchy (or more accurately, the interdependence) of classification and tracking to improve the integration of classification and tracking in future systems. As well as reviewing the project results to date, the future direction of the research is highlighted.

Results: The temporal robustness of the aural classifier was examined by training the classifier using data collected during a 2007 field trial (Clutter07) and testing on data collected during a 2009 field trial (Clutter09.) The Fisher linear discriminant was used to rank the effectiveness of the classifier's aural features. One of the most useful metrics to rate classifier performance is the area under the Receiver Operating Characteristic (ROC) curve, A_z. The greater A_z, the better the classifier, with a value of $A_z = 1$ indicating ideal performance. The training ROC curve obtains a value of $A_z = 0.97$ and the testing data obtains a value of $A_z = 0.90$. These numbers are indicative of a very successful classifier.

Significance: Military sonars must detect, localize, classify, and track submarine threats from distances safely outside their circle of attack. Active sonars operating at low frequencies are favoured for the long ranges they afford against quiet targets. However, in littoral environments, operational sonars frequently mistake echoes from geological features (clutter) with targets of interest. This results in high false alarm rates and degradation in sonar performance. Conventional approaches – using signal features based on the echo spectra or using signal features derived from physics-based models of specific target types – have had only limited success; moreover, they ignore a potentially valuable tool for target-clutter discrimination – the human auditory system. That said, even if aural discrimination is effective, discriminating targets from clutter is labour intensive and requires near-fulltime effort from the operator. Since future military platforms will have to support smaller complements, and near-future operations will have to accommodate additional mission-specific forces, automation of on-board systems is essential. The technique is well suited to autonomous systems since a much smaller bandwidth is needed to transmit a classification result than to transmit raw acoustic data.

Future plans: During the remaining two years of the research grant, tracker-classifier integration will be examined and the aural classifier will be tested more thoroughly using the Clutter09 data set.

Sommaire

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

FY2009 Report

Paul C. Hines; Stefan Murphy; DRDC Atlantic ECR 2009-241; R & D pour la défense Canada – Atlantique; Octobre 2009.

Introduction : Ce rapport présente les résultats de la première année d'une subvention de trois ans octroyée par l'Office of Naval Research (ONR) des États-Unis. Le but du projet est d'élaborer un classificateur robuste utilisant des entités auditivement définies et permettant de différencier les échos de cible obtenus par sonar actif et le fouillis d'écho indésirable. Un objectif secondaire est d'examiner la hiérarchie (ou plus exactement, l'interdépendance) de la classification et du suivi afin d'améliorer l'intégration de la classification et du suivi dans les futurs systèmes. Outre la présentation des résultats du projet à ce jour, nous décrivons l'orientation future de la recherche.

Résultats : Nous avons examiné la robustesse temporelle du classificateur auditif en l'entraînant avec les données recueillies lors d'un essai sur le terrain en 2007 (Clutter07) et le testant avec les données recueillies lors d'un essai sur le terrain en 2009 (Clutter09.) Le discriminant linéaire de Fisher a été utilisé pour classer l'efficacité des caractéristiques auditives du classificateur. L'un des paramètres les plus utiles pour coter la performance d'un classificateur est l'aire sous la courbe caractéristique de fonctionnement du récepteur (ROC), A_z. Plus la valeur de A_z est grande, meilleur est le classificateur, la valeur $A_z = 1$ correspondant au rendement idéal. La courbe ROC avec entraînement donne une valeur $A_z = 0{,}97$ et les essais avec les données donnent une valeur $A_z = 0{,}90$. Ces chiffres sont indicateurs d'un classificateur très performant.

Importance : Les sonars militaires doivent détecter, localiser, classifier et poursuivre les menaces sous-marines à des distances de sécurité à l'extérieur de leur cercle d'attaque. Les sonars actifs à basse fréquence sont préférables en raison de leurs longues distances de fonctionnement contre les cibles silencieuses. Toutefois, dans les environnements littoraux, les échos provenant d'éléments géologiques (fouillis, aussi appelé *clutter*) sont souvent confondus avec des cibles d'intérêt. Cela se traduit par des taux élevés de fausses alarmes et occasionne une dégradation du rendement des sonars. Les techniques classiques de traitement des signaux – utilisation des caractéristiques du signal basées sur les spectres des échos ou obtenues par des modèles physiques de types de cibles spécifiques – ont eu un succès limité et ne tiennent pas compte d'un outil de discrimination qui pourrait s'avérer précieux : le système auditif humain. Cela dit, même si la discrimination auditive est efficace, discriminer les cibles dans le fouillis d'écho demande beaucoup de travail et impose un effort quasi constant de la part de l'opérateur. Comme les futures plates-formes militaires devront compter sur des effectifs plus petits et les opérations dans un proche avenir devront accueillir des forces supplémentaire pour des missions spécifiques, l'automatisation des systèmes de bord est essentielle. La technique est bien adaptée aux systèmes autonomes, car une bande passante beaucoup plus étroite est nécessaire pour transmettre un résultat de classification que pour transmettre des données acoustiques brutes.

Perspectives : Au cours des deux dernières années de la subvention de recherche, l'intégration du modèle de suivi et du classificateur sera examinée et le classificateur auditif sera testé plus à fond à l'aide de l'ensemble de données Clutter09.

This page intentionally left blank.

Table of contents

List of figures

Acknowledgements

The authors wish to acknowledge experimental support from NRV Alliance during Clutter09 as well as support from the NATO Undersea Research Center (NURC). Field trials were carried out as part of a US-CA-NURC Joint Research Program.

This work is supported by the Office of Naval Research, Undersea Signal Processing (code 321).

This page intentionally left blank.

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 work load 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 aurally-based features that can discriminate active sonar target echoes from unwanted echoes.

2 Objectives

A primary objective during the first year of the grant has been to identify temporally and spatially robust aural discriminators that can be incorporated into an automatic aural classifier.

A secondary objective is to examine the hierarchy (or more accurately, the interdependence) of classification and tracking. That is to say, how does one integrate classification and tracking to optimize or at least improve current systems? For example, should one use a classifier to reduce the number of detections going into the tracker, or alternatively should all detections be sent to a tracker and then use a classifier to eliminate false tracks? This leads to a second question: How does one weight the relative confidence of inputs from the tracker and classifier if the two systems disagree?

3 Approach

In May 2007, the PI conducted a broadband auralization experiment on board NRV Alliance on the Malta Plateau – an area of the Mediterranean Sea between Sicily and Malta. This experiment was part of the Clutter07 sea trial which supported a NURC JRP. The Malta Plateau was selected as the experimental site because it has been well surveyed and is known to be rich in clutter objects, and because of the presence of the Campo Vega oil rig and its tending tanker which served as surrogate targets for the aural classification experiment. During an 8 hour period, NRV Alliance ran a track while transmitting a series of 1 s, linear FM sweeps (LFM), from 600-3400 Hz using NURC's low-frequency and mid-frequency free-flooding ring sources. The NURC cardioid towed array was the receiver. The resulting data set contains several thousand echoes from the two surrogate targets and a large number of clutter objects. These echoes represent an invaluable data set with which to examine aural classification using a coherent source. The aurally derived features identified in the analysis of these data have shown significant potential as a robust feature set for use in an ASW classifier [1,2]. However, the temporal and spatial robustness of the feature set has not been tested. That is to say, can one use the same feature set on echoes collected at other locations and times? To address this, the experiment was repeated in May 2009 during the Clutter09 sea trial in order to collect a data set with which to examine the temporal and spatial robustness of the feature set.

Sonar detection, classification, and tracking are interrelated activities. For example, an ideal single-ping classifier would reject all false alarms generated in the detector, pass only the target detections to the tracker which would in turn generate tracks for the targets of interest.

Alternatively, one could pass all detections to the tracker which would then reject all detections that could not be associated into a realistic track. Then the reduced set of detections which form potential tracks would be sent to the classifier for verification. The technical approach here is to integrate classification and tracking into a single tool to examine their interdependency using data collected during Clutter09. To support this, a partner in the experiment, NRL DC, provided a towed echo-repeater programmed to incorporate modeled target highlights into the echo to simulate a target transiting a clutter field. The echo-repeater was towed using ITN Levanzo. The resulting data will be used in support of the second objective – examining the interdependence of tracking and classification.

4 Work Completed

TASK 1, Training: Hiring a new scientist to support this research was inherent in the initial project proposal. Therefore, considerable effort was expended in developing expertise in aural classification and gaining experience in modifying existing aural classification code. Of course this is an ongoing requirement in research but it is fair to say that this aspect of the project has moved very rapidly and can be considered successfully completed within the context of the project.

TASK 2, Data Collection: Clutter09 provided a rare opportunity to collect an invaluable data set with which to accomplish the objectives stated above. During the trial 3 carefully orchestrated experimental runs denoted (2.3.2-A, 2.3.2-B, and 2.3.2-C) were performed as described below:

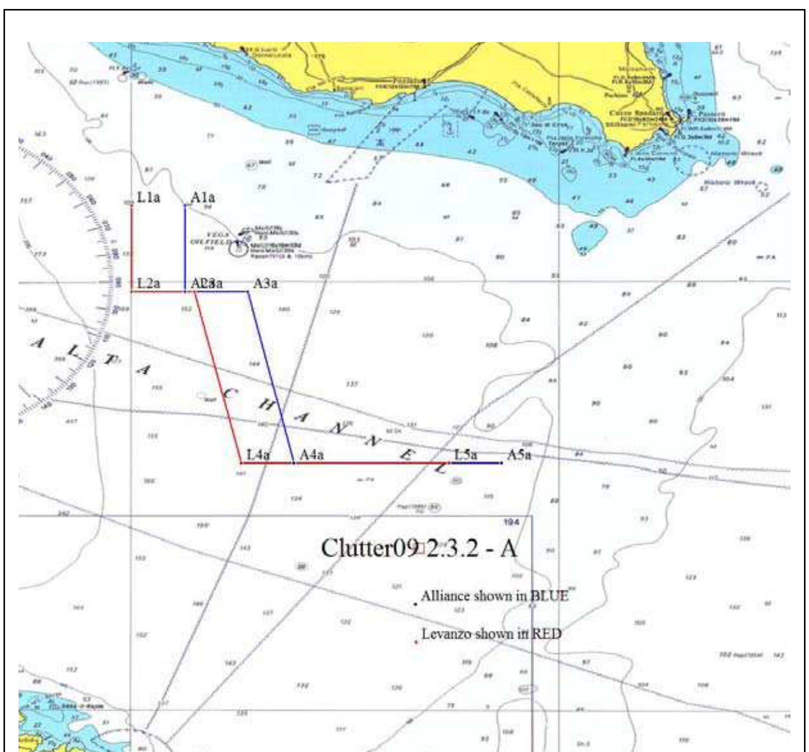

Figure 1. Clutter09 Track 2.3.2-A.

Track 2.3.2-A shown in Figure 1, was run during a period of approximately 7 hours at a constant speed of 5 knots. Tracks are denoted using S#d where S denotes the ship (A=Alliance, L=Levanzo, and N=nominal straight line for reference), # denotes waypoint number, and d refers to day A, B, or C. The track run by NRV Alliance is denoted A#a and is shown in blue. (The red track designated L#a, 3 nmi to the west of the Alliance track was planned as a work-up run for ITN Levanzo but circumstances precluded her participation during the run.) A series of 1 s, 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 up-sweeps 600-3400 Hz. Odd minute pings (1 min, 3 min, …) were parallel up-sweeps 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 cross-over frequency. Parallel means that both sources were started at the same time so the duration of the pulse was actually less than 1 sec 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. Track 2.3.2-A was essentially a repeat of the auralization track performed during Clutter07 and was designed to examine the temporal robustness of the aural classifier.

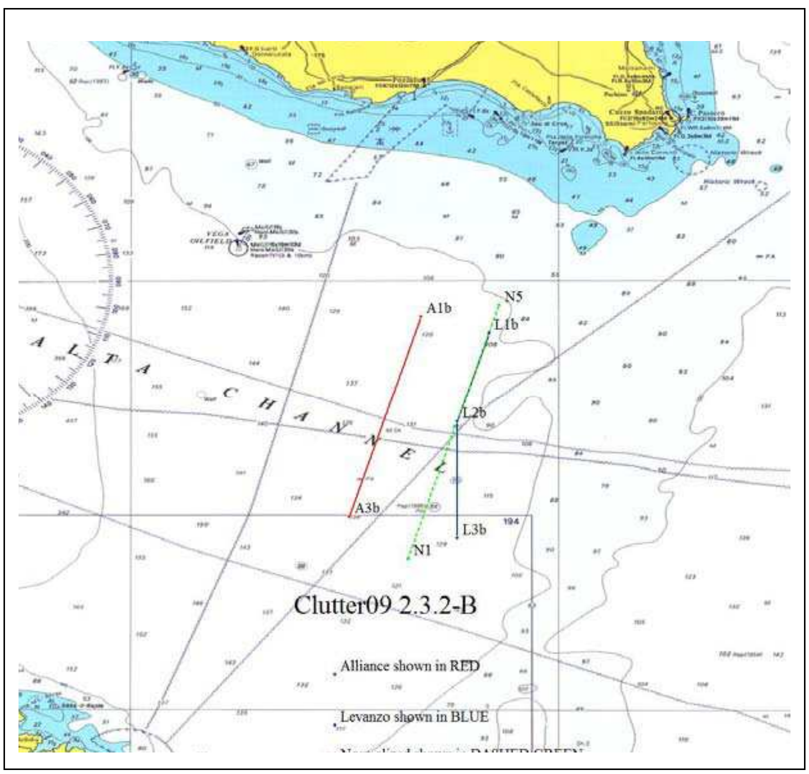

Figure 2. Clutter09 Track 2.3.2-B.

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 up-sweeps 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 from waypoint 3 to 1. The NRV Alliance heading was selected to be nominally parallel to the Ragusa ridge, the source of significant clutter. The ITN Levanzo track was designed to have echo-repeater returns arrive at Alliance cotemporally with clutter. The course change in the 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 echo amongst the clutter.

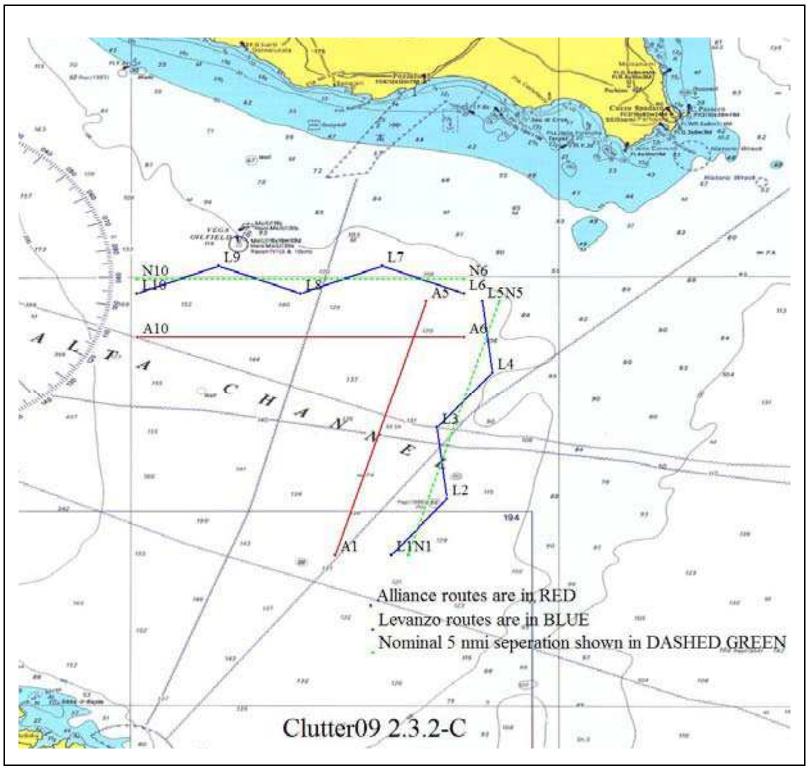

Figure 3. Clutter09 Track 2.3.2-C.

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 way point 2, 5 degrees per minute at way point 3 and 9 degrees per minute at way point 4. This sequence was repeated along the low-clutter track at way points 7, 8, 9 (i.e., 3, 5, 9 degrees per minute, respectively). Sequential LFM up-sweeps 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.

TASK 3, Developed Integrated Tracking and Aural Classification Software (ITAC): Detections from a simple energy detector tagged with relevant geospatial data, are input to a Kalman filter tracker within ITAC. The user can select a track and output the detections used to compose the track to the aural classifier. Detections classified as clutter are rejected and the track is recomputed.

TASK 4, Data Analysis: Initial data analysis has been performed on the Clutter09 classification and tracking runs. This includes performing detection and clustering of the data, generating .wav files for each of the detections, and performing preliminary tracking and classification using ITAC. To ensure a scientifically valid result when examining the temporal robustness of the aural classifier, the Clutter07 data has been reprocessed using the Clutter09 processing algorithms. Preliminary analysis has been completed in which Clutter07 detections were used to train the aural classifier which was then tested using the Clutter09 detections.

5 Results

To test the temporal robustness of the aural classifier, training was performed using data collected during Clutter07 and testing was performed on data collected during Clutter09. The Fisher linear discriminant was used to rank the effectiveness of the classifier's aural features to discriminate target from clutter in the training set and the 15 best features were selected. (Choosing 15 features represents a somewhat ad hoc compromise between good performance and high computation speed during this preliminary stage of analysis.) Two metrics are used to demonstrate the aural classifier's performance: principal component analysis (Figure 4 left panel) and the Receiver Operating Characteristic (ROC) curve (Figure 4 right panel). Referring first to the left hand panel of Figure 4, one must note that the features that make up the horizontal and vertical axes do not refer to specific aural features (e.g. loudness or duration) but rather, are an orthogonal, linear combination of the most important aural features used in the classification process.

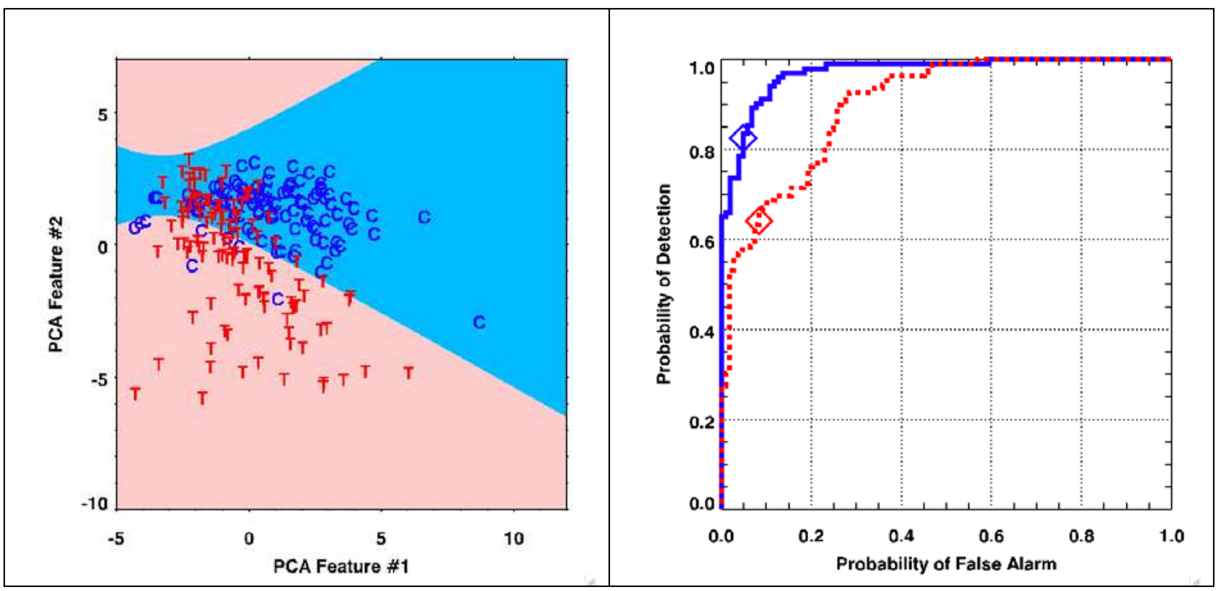

Figure 4. Performance obtained training the aural classifier using Clutter 07 data and testing using Clutter09 data. See text for discussion.

Essentially, the further the clutter points (C) separate from the target points (T), the better the classifier performs. If a red T lies on the red background, the classifier has correctly identified a target. Conversely, if a red T lies on the blue background, the classifier has missed a detection. Similarly, if a blue C lies on the blue background, the classifier has correctly identified a clutter echo but if a blue C lies on the red background it has allowed a false alarm. As well as demarkating the decision surfaces, the blue and red backgrounds graphically represent the ratio, R, of the probability of the echo being clutter to the probability of it being a target. Mathematically, this is written

$$P(C|X)/ P(T|X) = R \tag{1}$$

where X is the feature vector corresponding to the two PCA axes in Figure 4. The choice of where to set the boundary is determined by the cost associated with an error. In this example, we have set R = 1, corresponding to equal cost associated with a missed detection or a false alarm. By sweeping through all values of R one obtains the ROC curve. The ROC curve, shown in the right panel, plots the probability of detection vs. probability of false alarm; that is to say, the probability of correctly identifying a target vs. the probability of labelling a clutter echo as a target. The training data yields the solid line and the testing data yields the dashed line. The diamond plotted on the testing ROC curve corresponds to the decision surface shown in the left panel. One of the most useful metrics one can extract from the ROC curve is the area under the curve, A_z. The greater A_z, the better the classifier, with a value of A_z = 1 indicating ideal performance. The training ROC curve obtains A_z = 0.97 and the testing data obtains A_z = 0.90 indicative of a very successful classifier.

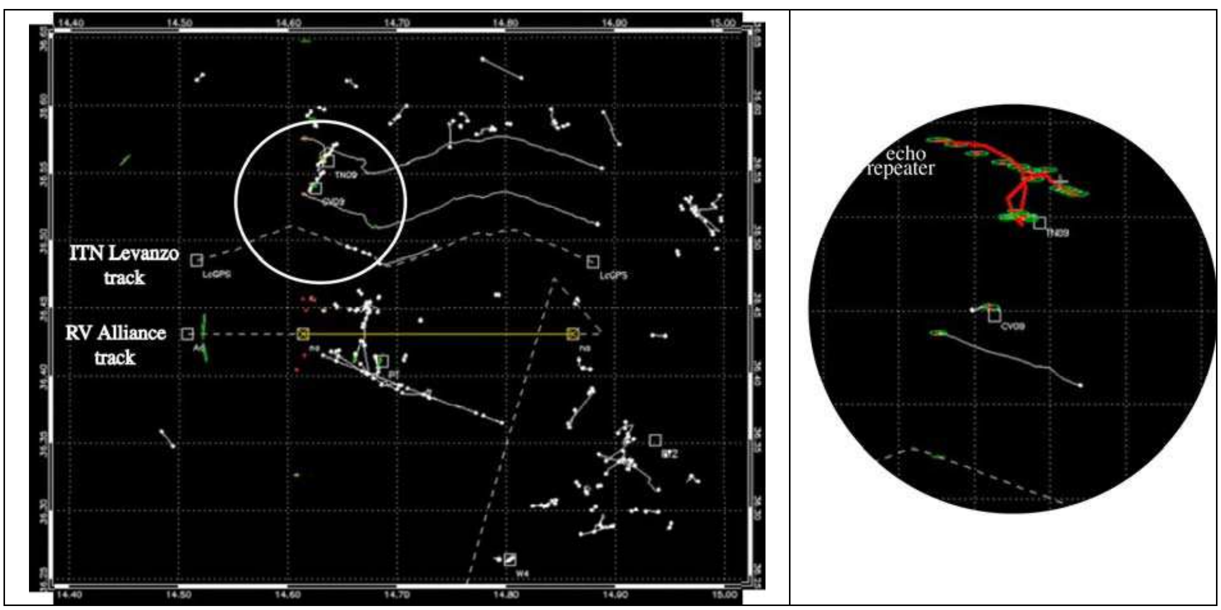

Figure 5. Sample of ITAC tracker output. The east-west lines to the north of Levanzo's track (left panel) are detections of the echo-repeater signals. The circled area, expanded in the right panel, shows tracker error (loop) that results from detections from the Campo Vega tending tanker. Note that only tracks (not individual detections) are displayed.

A preliminary examination of ITAC using data from Clutter09 (Experiment 2.3.2-C) has been completed and one possible application of the software has been examined. In this scenario, the tracker component is used to establish potential target tracks. When a track is confirmed, detections associated with that track are used to train the aural classifier. Once the classifier is sufficiently trained, future detections associated with the track are sent to the classifier for testing. Detections rejected as clutter are ignored when computing the track. This is demonstrated in Figures 5 and 6. As the target approaches the tending ship NE of Camp Vega, the tracker incorporates detections from the tending ship into the target track which results in an apparent loop in the target's course. The aural classifier correctly identifies these detections as clutter and the track is re-computed. Bottom panel of Figure 6 shows all detections rather than only established tracks.

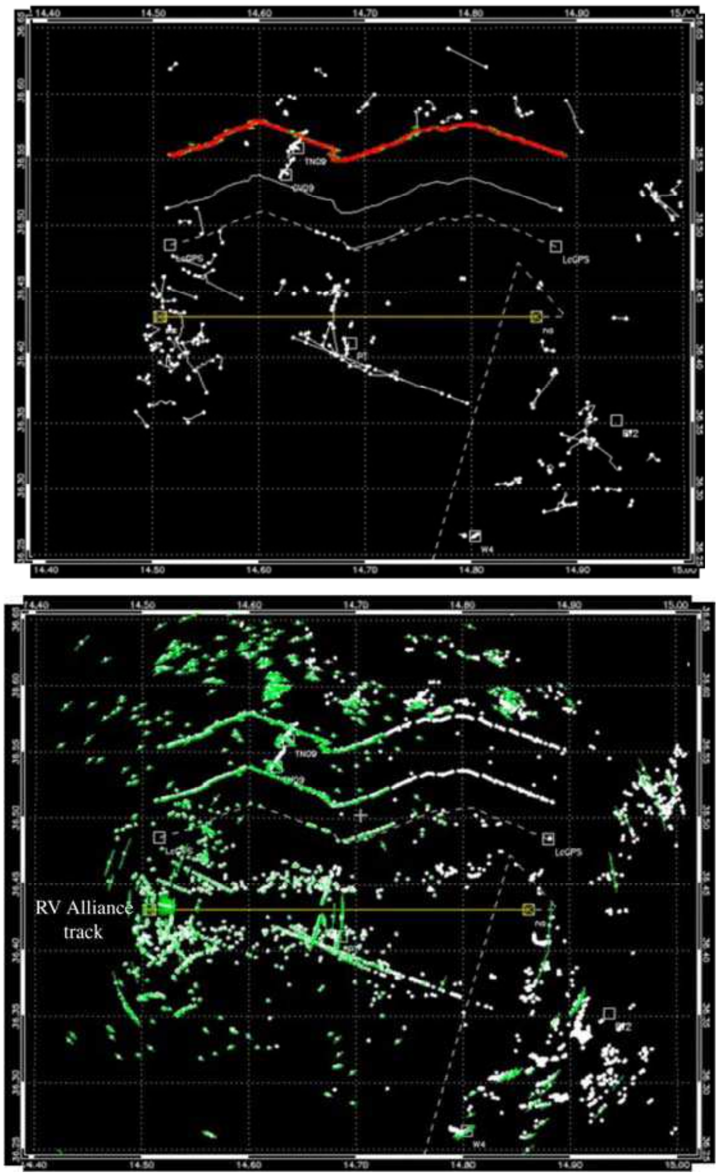

Figure 6. Corrected track (top) and all detections (bottom).

6 Impact/Application

Although, ITAC is still in the early stage of development, it has nonetheless been used to demonstrate in situ classifier learning as a technique to improve tracking. More generally, ITAC provides an opportunity to examine the interrelated roles of tracking and classification which could be used to guide the development of both.

Preliminary results indicate that within the experimental limits explored thus far the aural features are temporally robust and can be used for target classification. The aural classifier was trained using data collected in 2007 and subsequently tested using data collected at the same location in 2009. An area under the ROC curve of 90% was achieved on the test data which is representative of an excellent classifier.

7 Related Projects

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

2. *Automatic Clutter Discrimination Using Aural Cues*, Applied Research Program, Defence R&D Canada.

8 References

1. Hines, P.C., Young, V.W., Scrutton, J., Aural Classification of Coherent-Source Active Sonar Echoes, UNCLASSIFIED, Proceedings: International Symposium on Underwater Reverberation and Clutter, Leric, Italy, September, 2008, 9 pages.

2. Myers, V., Fawcett, J., Hines, P.C., Young, V.W., Reconstruction and Fusion of Perceptual Features for Automatic Classification of Sonar Echoes, UNCLASSIFIED, Proceedings: IEEE Oceans'08, Quebec, Canada, September, 2008, 7 pages.

List of symbols/abbreviations/acronyms/initialisms

ASW	Anti-submarine Warfare
ITAC	Integrated Tracker and Aural Classifier
NURC	NATO Undersea Research Center
ONR	Office of Naval Research
ROC	Receiver Operating Characteristic

This page intentionally left blank.

Distribution list

DRDC Atlantic ECR 2009-241

LIST PART 1: Internal Distribution by Centre:

3 Paul C. Hines
1 Stefan Murphy
3 DRDC Atlantic Library
1 H/US
1 Co-Chair/1C Thrust Advisory Group
1 GL/MEA
1 Senior Military Officer
1 Nicole Collison
1 Garfield Mellema

13 TOTAL LIST PART 1

LIST PART 2: External Distribution by DRDKIM

CFB Halifax, PO BOX 99000, Stn Forces, Halifax, NS B3K5X5
1 ADAC(A) – Commanding Officer
1 CFMWC – Commanding Officer
1 CFNOS – Commanding Officer
1 MOG5 – Commanding Officer
1 PSU HALIFAX – Commanding Officer
1 TRINITY – Commanding Officer

1 ADAC(P) – Commanding Officer
PO BOX 17000, Stn Forces, Victoria, BC V9A7N2

1 DRDKIM

1 Library & Archives Canada, Atten: Military Archivist, Government Records Branch

International
1 Dr. James Pitton
ONR Global
Edison House
223 Old Marylebone Rd.
London NW1 5TH

1 Dr. Keith L. Davidson
Undersea Signal Processing (321US)
Office of Naval Research
875 North Randolph Street, Suite 1425
Arlington, VA 22203-1995
USA

---

11 TOTAL LIST PART 2

24 TOTAL COPIES REQUIRED

DOCUMENT CONTROL DATA

(Security classification of title, body of abstract and indexing annotation must be entered when the overall document is classified)

1. ORIGINATOR (The name and address of the organization preparing the document. Organizations for whom the document was prepared, e.g. Centre sponsoring a contractor's report, or tasking agency, are entered in section 8.)

   DRDC Atlantic, PO Box 1012, Dartmouth, NS, B2Y3Z7

2. SECURITY CLASSIFICATION (Overall security classification of the document including special warning terms if applicable.)

   UNCLASSIFIED

3. TITLE (The complete document title as indicated on the title page. Its classification should be indicated by the appropriate abbreviation (S, C or U) in parentheses after the title.)

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

   FY2009 Report

4. AUTHORS (last name, followed by initials – ranks, titles, etc. not to be used)

   Hines, P. C.; Murphy, S.

5. DATE OF PUBLICATION (Month and year of publication of document.)

   October 2009

6a. NO. OF PAGES (Total containing information, including Annexes, Appendices, etc.)

   26

6b. NO. OF REFS (Total cited in document.)

   2

7. DESCRIPTIVE NOTES (The category of the document, e.g. technical report, technical note or memorandum. If appropriate, enter the type of report, e.g. interim, progress, summary, annual or final. Give the inclusive dates when a specific reporting period is covered.)

   External Client Report

8. SPONSORING ACTIVITY (The name of the department project office or laboratory sponsoring the research and development – include address.)

   Office of Naval Research, ONR Code 321US, 875 North Randolph St., Suite 1425, Arlington, VA, 22203-1995, USA.

9a. PROJECT OR GRANT NO. (If appropriate, the applicable research and development project or grant number under which the document was written. Please specify whether project or grant.)

   ONR Grant: N00014-09-1-0426

9b. CONTRACT NO. (If appropriate, the applicable number under which the document was written.)

10a. ORIGINATOR'S DOCUMENT NUMBER (The official document number by which the document is identified by the originating activity. This number must be unique to this document.)

   DRDC Atlantic ECR 2009-241

10b. OTHER DOCUMENT NO(s). (Any other numbers which may be assigned this document either by the originator or by the sponsor.)

11. DOCUMENT AVAILABILITY (Any limitations on further dissemination of the document, other than those imposed by security classification.)

   Unlimited

12. DOCUMENT ANNOUNCEMENT (Any limitation to the bibliographic announcement of this document. This will normally correspond to the Document Availability (11). However, where further distribution (beyond the audience specified in (11) is possible, a wider announcement audience may be selected.))

13. ABSTRACT (A brief and factual summary of the document. It may also appear elsewhere in the body of the document itself. It is highly desirable that the abstract of classified documents be unclassified. Each paragraph of the abstract shall begin with an indication of the security classification of the information in the paragraph (unless the document itself is unclassified) represented as (S), (C), (R), or (U). It is not necessary to include here abstracts in both official languages unless the text is bilingual.)

This report presents the results from the first 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 aurally-based features that can discriminate active sonar target echoes from unwanted clutter echoes. A secondary objective is to examine the hierarchy (or more accurately, the interdependence) of classification and tracking to improve the integration of classification and tracking in future systems. During the first year of the project, an experiment was conducted on board *NRV Alliance* as part of the NURC Clutter09 sea trail. 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. The Fisher linear discriminant was used to rank the effectiveness of the classifier's aural features. One of the most useful metrics to rate classifier performance is the area under the Receiver Operating Characteristic (ROC) curve, A_z. The greater A_z, the better the classifier, with a value of $A_z = 1$ indicating ideal performance. The training ROC curve obtains a value of $A_z = 0.97$ and the testing data obtains a value of $A_z = 0.90$. These numbers are indicative of a very successful classifier. During the remaining two years of the research grant, tracker-classifier integration will be examined and the aural classifier will be tested more thoroughly using the Clutter09 data set.

14. KEYWORDS, DESCRIPTORS or IDENTIFIERS (Technically meaningful terms or short phrases that characterize a document and could be helpful in cataloguing the document. They should be selected so that no security classification is required. Identifiers, such as equipment model designation, trade name, military project code name, geographic location may also be included. If possible keywords should be selected from a published thesaurus, e.g. Thesaurus of Engineering and Scientific Terms (TEST) and that thesaurus identified. If it is not possible to select indexing terms which are Unclassified, the classification of each should be indicated as with the title.)

Tracking, ASW, Anti-submarine Warfare, Clutter, Classification, Underwater Acoustics

This page intentionally left blank.

Defence R&D Canada

Canada's leader in defence
and National Security
Science and Technology

R & D pour la défense Canada

Chef de file au Canada en matière
de science et de technologie pour
la défense et la sécurité nationale

DEFENCE R&D DÉFENSE

www.drdc-rddc.gc.ca