CLASSIFYING CONTINUOUS ACTIVE SONAR ECHOES FOR TARGET RECOGNITION

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Abstract: *Classification and tracking are two important techniques for enhancing active sonar performance. Classification rejects unwanted clutter using echo analysis, and tracking provides a history of target motion while rejecting clutter that doesn't support realistic target motion. Continuous active sonar (CAS) has been proposed as an alternative to conventional pulsed active sonar (PAS), largely in order to provide tracking updates at a much higher rate than is possible with PAS. Unfortunately, these faster updates come at the cost of reduced classification performance, at least for CAS that uses linear frequency modulated waveforms. In this case, maximizing the update rate requires sub-band processing. Classification of echoes from these sub-bands is expected to be relatively poor, since the full bandwidth is favoured for classification. An alternate processing scheme for CAS uses full-band processing, which is typically used for PAS. This potentially maximizes classification performance rather than providing faster updates as in the sub-band approach. A risk of this scheme is the potential for complications in echo signals arising from coherence loss caused by the long duration of CAS waveforms. One facet of a recent Canada-U.S. sea trial, TREX13, focused on conducting experiments that allow direct comparison of the performance of CAS and PAS in shallow water. In this paper, DRDC's echo classification software was tested with sonar echoes from TREX13. The software, which was originally developed for PAS applications, was used to evaluate whether CAS echoes can be classified as accurately as PAS echoes.*

Keywords: *active sonar, continuous active sonar, detection, classification*

1. INTRODUCTION

Active sonar is required to detect underwater targets that are either silent or too quiet to reliably detect using passive sonar. Active systems, however, can be less effective in shallow littoral environments due to increased false alarms caused by echoes from the seabed in these areas. Two key methods of reducing clutter to improve target detection are classification and tracking. Classification rejects unwanted clutter using signal analysis, while tracking rejects clutter by removing localized contacts that don't support realistic target motion.

Continuous active sonar (CAS) is an alternative to commonly used pulsed active sonar (PAS). One of the potential advantages of CAS is that it can provide tracking updates at a much higher rate than is possible with PAS. PAS can achieve target detection at most once per ping repetition interval (PRI), which is typically on the order of tens of seconds in order to provide a useful search radius. CAS, on the other hand, can provide many detections within one PRI, potentially obtaining target detections at rates faster than once per second. Unfortunately, these faster updates come at the cost of reduced classification performance and/or reduced signal-to-noise ratio (SNR). In the case of swept waveforms, maximizing the update rate requires sub-band processing, or segmenting the CAS pulse and processing each segment as an individual matched filter. Classification of echoes from these sub-bands is expected to be relatively poor because higher bandwidth is favoured for classification. This dependence on bandwidth was confirmed to be the case for DRDC's aural classifier [1], which will be used for classifying sonar echoes in this paper.

An alternate processing scheme for CAS applies a matched filter with the full-band replica as is commonly used in PAS. This is the approach used in this paper. This potentially maximizes classification performance rather than providing faster updates as in the sub-band approach. A risk of this scheme is the potential for complications in echo signals arising from coherence loss caused by the long duration of CAS waveforms. In the simplest case, coherence loss would result in lower SNR, which tends to lower classification performance [2]. Of greater concern, however, is the potential for complicated changes on signal features. These changes are difficult to predict and could result in reduced classification capabilities for CAS.

In May 2013, the ONR-sponsored TREX13 sea trial was conducted off the coast of Panama City, Florida. DRDC's focus during the trial was conducting experiments that allow direct comparison of the performance of CAS and PAS in shallow water. This paper reviews two TREX13 experiments, and compares classification results of full-band PAS and CAS echoes from the experiments using DRDC's automatic aural classifier, which has not previously been tested on CAS data.

2. EXPERIMENTS AT SEA

2.1. Setup

The TREX13 sea trial was held within 8 km of shore in Panama City, Florida. University of Delaware's Research Vessel RV SHARP was positioned in a four-point mooring less than 3 km from shore at approximately 30.0599° N, 85.6811° W. The water depth was quite shallow at approximately 20 m over the trial area. The Five Octave

Research Array (FORA) of Pennsylvania State University's Applied Research Laboratory was positioned 70 m south of SHARP and oriented with a heading of 358°. An ITC 2015 source was positioned 20 m south of SHARP. It was verified that the CAS pulses transmitted by the ITC 2015 did not saturate FORA in this configuration. This is a requirement for CAS operation because pulse transmission and echo reception must occur simultaneously.

The two experiments considered in this paper took place on May 10th, 2013. The runs were each one-hour long with one hour in between. During the PAS run (trex13-r82), a 0.5 s LFM sweep from 1800–2700 Hz was transmitted with a 20 s PRI. A CAS run (trex13-r80) was also performed, where an 18 s LFM swept over the same band was transmitted with the same 20 s PRI. The 2 s down time in the cycle was required for processing time in an echo repeater system used during the trial, resulting in a nearly continuous 90% duty cycle.

DRDC's CFAV QUEST also participated in TREX13. During each run, QUEST travelled along either the 'clutter' or 'reverb' track, as depicted in Fig. 1. For the runs considered in this paper, QUEST started near SHARP, and opened at a constant speed of 5 kn at heading 240° along the clutter track. QUEST successfully operated an echo repeater that could repeat continuous transmissions with very low latency and impart a target impulse response on incident signals to simulate target echoes. Four echo repeater techniques were proposed in [3], and DRDC technical staff completed the hardware implementation of all four techniques for the trial. Some echo repeater signals are shown in the next section; however, early on during the trial it became apparent that the hull of QUEST also offered a strong echo, providing a target of opportunity. Furthermore, since this was the first attempt to compare CAS and PAS using the echo repeater, a simple ideal reflector was used for the echo repeater's impulse response for most of the trial rather than a target response. Therefore, the authors chose to focus on the echoes from QUEST's hull for the classification results presented in this paper. The data processing used to extract the QUEST echoes is presented next.

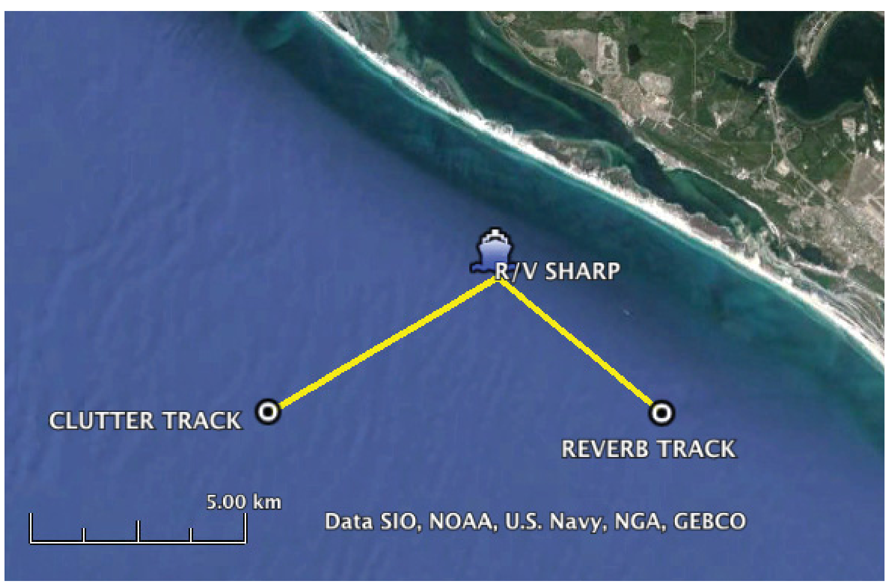


Fig.1: Setup of TREX13 trial area off Panama City, Florida.

2.2. Data Processing

After beamforming, the PAS and CAS data were each matched filtered using their respective full-band replicas. Note that CAS processing would normally employ some form of sub-band processing in order to increase the potential number of target detections per ping. This would reduce risk of coherence loss by reducing the processing bandwidth and time; however, the lower bandwidth and lower expected SNR of sub-band echoes would be expected to reduce classification performance based on previous results with DRDC's aural classifier [1,2]. Therefore, the full-band replicas were used for matched filtering.

An automatic detector was employed after matched filtering. 'Clutter-mitigation' images (see Fig. 2) were then formed by plotting each ping as a vertical column of pixels whose brightness was proportional to the enveloped, matched-filter outputs. A sequence of pings formed the horizontal extent of each image. Only the beam corresponding to QUEST's bearing from FORA is displayed for each ping. The clutter-mitigation images for the PAS and CAS runs are shown in Fig. 2(a) and (b), respectively. A clear trace of QUEST linearly increasing range from FORA can be observed. The echo repeater signal can be seen with a slight delay from QUEST, and only occurring every second ping cycle due to the echo repeater technique used for these runs. A delay had to be introduced in the echo repeater so that the low latency echo repeat would not coincide with the echo from QUEST. The traces in Fig. 2 were used to identify automatic detections that corresponded to echoes from QUEST and the echo repeater. Once identified, 1 s time-series snippets of un-enveloped, matched-filtered data were extracted for analysis using the classifier. Those echoes not associated with QUEST or the echo repeater were considered to be clutter; however, it is likely that echoes from vessels similar to QUEST were included in the clutter database which could reduce target-clutter discrimination. For example, in Fig. 2 other traces of moving objects can be observed, some of which likely correspond to other vessels and are captured during automatic detection.

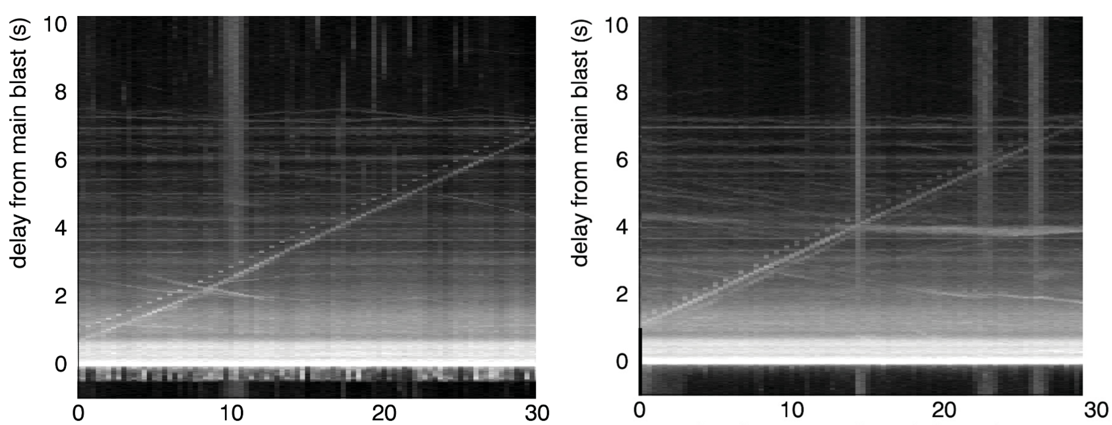


Fig.2: First half of the PAS run (a) and CAS run (b). The solid line is formed by echoes from QUEST and the dashed line is formed by the echo repeater signals, which were transmitted every second ping with the echo repeater technique used during these runs. Only half of the PRI is shown on the vertical axis.

In total, 120 PAS echoes were obtained from QUEST, with a mean SNR of 16.2 dB and standard deviation of 5.0 dB, with all statistics calculated from decibel values. There were 117 CAS echoes from QUEST with a mean SNR of 13.9 dB and standard deviation of 4.3 dB. In addition to the echoes from QUEST and the echo repeater, approximately 175,000 clutter detections were obtained with the detection threshold of 10 dB used. Most of these were not considered in this paper, as will be discussed in the next section. Detection was performed on enveloped matched-filter output, and these detections formed the centre of 1 s snippets extracted from un-enveloped matched-filter output. The snippets containing QUEST echoes formed the target database for training the aural classifier.

3. AURAL CLASSIFICATION RESULTS

3.1. Background

The aural classifier mimics the human auditory system by conditioning echo signals in a similar manner as the outer and inner human ear, and by simulating the cognitive process through representation of the echoes as perceptual features that are used by a Gaussian classifier to determine whether an echo should be designated as a target or clutter. Details on the aural classifier and the *aural features* it uses are published in [4], [5], and [6].

The classifier is trained by selecting a database of target and clutter echoes to form the *training dataset*. The training process uses discriminant analysis to formulate a combination of aural features that optimizes separation of the target and clutter echoes in the training dataset. The statistics of the training echoes determine how echoes in the *testing dataset* are classified. The testing dataset is typically independent of the training dataset to fully evaluate the classifier; however, in this paper, the same training data was used for testing. This removed the requirement to split the limited number of target echoes in the datasets into training and testing portions, which improved training statistics, and resulted in a measure of classification performance that represented the expected maximum achievable with that training configuration.

Previous work verified that the aural classifier performs better with signals of higher SNR [2], as is generally expected for signal classification. Given this SNR dependence, it was important to match the SNR distributions of the target and clutter classes to ensure that discrimination between classes was due to signal features and not a consistent difference in noise background. This was accomplished by forming SNR histograms for each class and removing echoes such that the histogram bin counts matched within 40%. Allowing some discrepancy in the SNR of the two classes allowed more echoes to be included, which improved statistics.

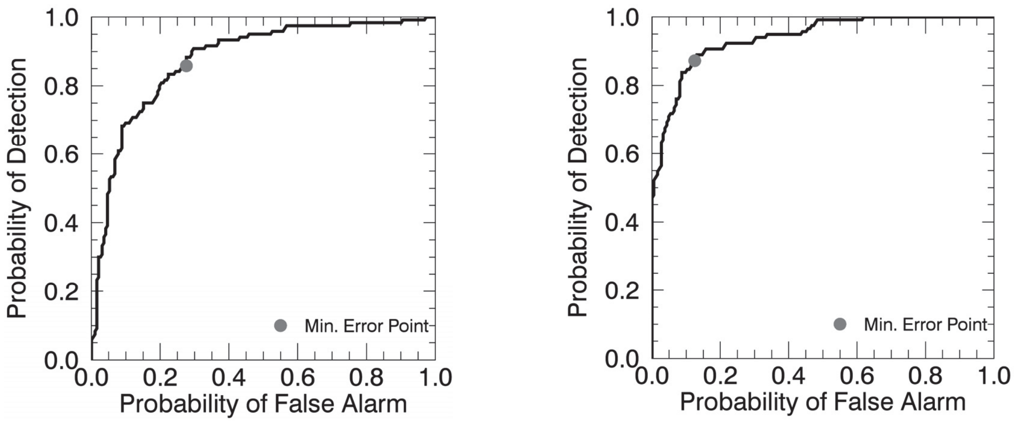
As in previous work [4,5,6], the area under the receiver-operating characteristic (ROC) curve (AUC) was used to evaluate classifier performance.

3.2. Classification Results

After matching the SNR distributions of the target and clutter training sets to within a reasonable approximation, the PAS dataset consisted of all 120 echoes from QUEST and 192 clutter echoes. This data was used to train the classifier and generate a training ROC curve, shown in Fig. 3(a). The AUC value for the curve was 0.88, with probability of detection, PD = 0.86, and probability of false alarm, PFA = 0.28 at the minimum-error-rate operating point [7]. AUC values above 0.8 indicate excellent discrimination [8].

The procedure was repeated for the CAS data, forming a training dataset with the 117 QUEST echoes and 184 clutter echoes. The resulting ROC curve shown in Fig. 3(b) has AUC = 0.94, indicating outstanding discrimination [8], with PD = 0.87 and PFA = 0.13 at the operating point.

Given that previous experimental validation used 2800 Hz of bandwidth (600–3400 Hz) [5], the results obtained using 900 Hz of bandwidth (1800–2700 Hz) are very promising. The interesting result of higher performance with CAS than PAS was unexpected and warranted preliminary analysis.



(a) (b)

Fig.3: ROC curve for the QUEST/clutter training dataset for the PAS run (a) and the CAS run (b).

3.3. Analysis of echoes

When using the aural classifier, preliminary analysis usually involves listening to the echo snippets to see if there are any obvious aural characteristics that could affect classification. In this case, the CAS echoes from QUEST had a distinct chirp sound, compared to broadband impulsive sound of the PAS echoes from QUEST, which sounded similar to PAS echoes previously examined by the authors. A spectrogram of a CAS echo from QUEST, extracted from un-enveloped, matched-filter output, is shown in Fig. 4(d), and is centred on the peak sample within the echo. The chirp effect can be observed in the QUEST echo, and even more clearly on the slightly delayed echo repeat, which starts just after 0.6 s. This phenomenon was not observed in PAS echoes, or in CAS echoes from stationary objects. It was therefore deduced that the effect is due to Doppler mismatch between the replica and Doppler distorted echo from QUEST, and that the effect is dependent on pulse length.

To further investigate the chirp phenomenon, the CAS replica was dilated in time to model 5 kn Doppler shift distortion. This distorted signal was then cross-correlated with the original CAS replica to observe the mismatch effect. A spectrogram of the cross-correlation is shown in Fig. 4(b), and is centred on the peak sample. The chirp caused by the mismatch is clearly visible, and closely resembles the experimental CAS matched-filter output displayed immediately below it in Fig. 4(d). The sweep rate estimated from the spectrogram is 8.0 Hz/ms.

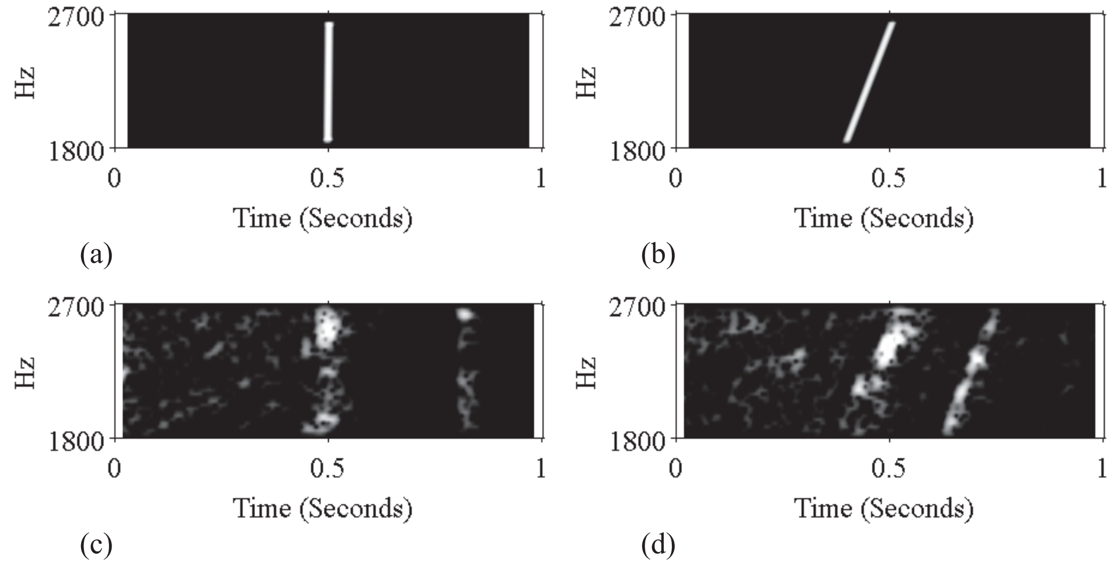


Fig.4: Spectrograms of un-enveloped matched-filter output for:
(a) modeled 5 kn Doppler distortion (PAS) (b) modeled 5 kn Doppler distortion (CAS)
(c) QUEST and echo repeater echoes (PAS) (d) QUEST and echo repeater echoes (CAS)

The same procedure was followed to examine if the effect of Doppler mismatch could be observed for the PAS case. The spectrogram of the PAS cross-correlation is shown in Fig. 4(a) with an example of a PAS echo from QUEST shown immediately below it in Fig. 4(c). The chirp effect is not observable on the scale shown in Fig. 4, which was chosen to match the CAS example to allow comparison; however, it is present and could be observed when closely zoomed on the PAS cross-correlation spectrogram with a compressed vertical axis. The estimated sweep rate is approximately 220 Hz/ms.

As the chirp effect is clearly audible, it can presumably affect the aural features, and it is therefore possible that the aural classifier is cueing on this signal feature, resulting in increased discrimination between QUEST echoes and clutter for the CAS case.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we observed that CAS, when processed identically to PAS using a full-band replica, produced echoes with comparable SNR to PAS echoes, even in the complex environment of 20 m littoral waters where coherence loss is expected to have the largest impact.

Discrimination between echoes from the hull of CFAV QUEST and clutter using automatic aural classification was possible using 900 Hz bandwidth, where experimental validation had previously been performed using a much higher bandwidth of 2800 Hz. Discrimination between QUEST and clutter echoes was observed to be higher with CAS than PAS. It is speculated that the aural classifier was cueing on features related to the chirp structure of CAS echoes, which was caused by Doppler shift distortion. The chirp phenomenon was clearly audible and consistent over the entire run because of QUEST's constant speed and heading. As observed in this paper, this phenomenon could be useful for discriminating moving targets from clutter.

The results presented in this paper are preliminary and further analysis is required to draw conclusions on the classification performance expected for CAS echoes compared to that expected for PAS echoes. Due to the heavy marine traffic during the trial, the PAS and CAS clutter datasets potentially contain different numbers of echoes from other surface ships in the area. High SNR clutter contacts were used to match the SNR distribution of QUEST echoes, which increases the likelihood that echoes from passing ships were in fact included in these clutter databases. This would likely have a large impact on classification because the echo features from other vessels would presumably resemble those of QUEST. In future analysis of the TREX13 data, AIS data and clutter-mitigation images will be used to identify echoes from moving vessels, which will avoid their inclusion in clutter datasets.

5. ACKNOWLEDGEMENTS

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REFERENCES

[1] **S.M. Murphy**, Classifying sonar signals with varying signal-to-noise ratio and bandwidth, *Proceedings of Meetings on Acoustic,* Vol. 19, Montreal, Canada, June 2013.

[2] **S.M. Murphy and P.C. Hines**, SNR dependence and temporal robustness of an automatic aural classifier, In *Proceedings of the 4th International Conference and Exhibition on Underwater Acoustic Measurements: Technologies and Results*, Kos, Greece, June 2011.

[3] **P.C. Hines**, "Experimental comparison of continuous active and pulsed active sonars in littoral waters," In *Proceedings of Underwater Acoustics 2013*, Corfu, Greece, June 2013.

[4] **V.W. Young and P.C. Hines**, Perception-based automatic classification of impulsive-source active sonar echoes, *J. Acoust. Soc. Am.*, 122 (3), pp. 1502–1517, 2007.

[5] **S.M. Murphy and P.C. Hines**, Examining the robustness of automated aural classification of active sonar echoes, *J. Acoust. Soc. Am.*, 135 (2), pp. 626–636, 2014.

[6] **C.M. Binder and P.C. Hines**, Automated aural classification used for inter-species discrimination of cetaceans, *J. Acoust. Soc. Am*, 135 (4), pp. 2113–2125, 2014.

[7] **R.O. Duda, P.E. Hart, and D.G. Stork**, *Pattern Classification*, 2nd ed., Wiley-Interscience (New York), pp. 20–124, 2001.

[8] **D.W. Hosmer and S. Lemeshow**, *Applied Logistic Regression*, 2nd ed., Wiley and Sons (New York), pp. 162, 2000.