LOW FREQUENCY ACTIVE SONAR NOISE REJECTION IN A MULTISTATIC SONAR SYSTEM

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Abstract The use of low frequency active sonar for ASW has repercussions on automated detection performance. Input data contain not only target returns, but also noise formed by returns from the environment. The detector may report a contact that is actually the result of environmental noise. Detecting noise is an undesirable behavior in modern sonar systems. Noise characteristics such as bottom returns, tonals, and onset of convergence zones can produce a multitude of false alarms as well as poorer detection performance and reduced operator confidence in the automated system.

In this study, noise rejection techniques are analyzed using data collected during the 92-3C Multistatic Sonar System (MSS) sea trials performed in 1992. Two techniques will be described and evaluated. The first is the conventional Bayesian Vector Classifier (BVC) method used during the MSS sea trials. The second is a modified BVC approach that uses post-sequential detection information. The two techniques are compared and the resulting effects on false alarm rate and probability of detection are discussed.

1. Introduction

It is important to automatically detect and track target-like contacts for improved operability in low frequency active processing. The data input to the information processor contain both target returns and noise returns such as returns from the environment. Noise can be caused by many things such as bottom features, tonals, and onset of convergence zones. Noise results in false alarms, poorer detection performance, and reduced operator confidence in the information processor algorithm. Detecting noise also produces additional CPU and memory load on the computer system.

One way to avoid detecting noise is to filter out the noise from the measurement data before the detector uses them. This process is called noise rejection. Noise rejection identifies and removes, on a ping-by-ping basis, nontarget-like sonar signals from the sonar data stream. In order to support a tactical system, noise rejection must be performed in-situ and in real time.

One question that needs to be answered is how to best perform noise rejection. The MSS uses a statistical approach to characterizing noise and target returns. There are various methods that can be used to obtain samples for the analysis. The at-sea method used a random noise sampling approach. Post-sea test analysis concentrated on choosing a sample based on the processing characteristics of the detector. Methods used are described in section 2 and results of the analysis are discussed in section 3. Recommendations for future work are presented in section 4.

2. Method

2.1 Functional Data Flow

Figure 1 shows the data flow of the MSS Information Processor system. Solid lines represent the real-time data flow. Dashed lines represent the off-line data collection mode of the Bayesian Vector Calculator. The Bayesian Vector Calculator computes a set of parameters which is then used by the BVC in real time to distinguish between noise and targets. The details of the data flow are described below.

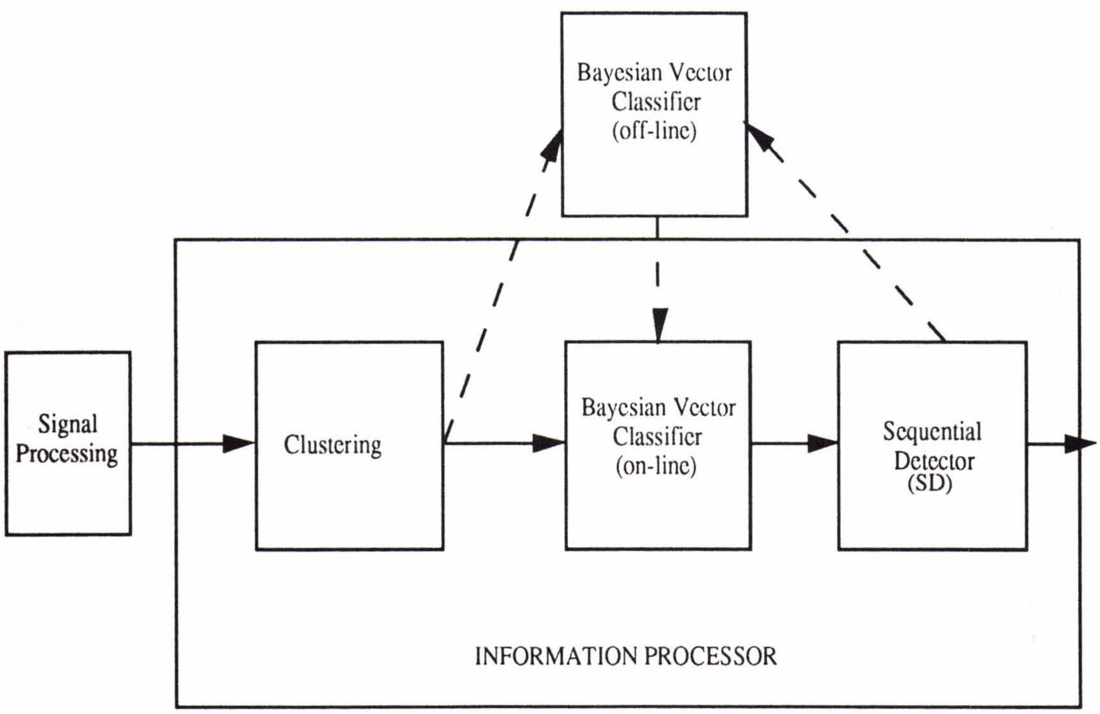

Figure 1. Information Processor Data Flow

The detector works on data provided by the signal processing subsystem. The Signal Processor provides data in the form of threshold crossings (TXMs). TXMs are packets of information containing Signal-to-Noise Ratio (SNR) data. The TXMs are further defined in terms of beam and time of arrival. There are two data paths for the TXMs: Hyperbolic Frequency Modulation (HFM) and Continuous Wave (CW).

Signal Processor input data for the HFM data path contain four channels. The information is space (beam number) and time (seconds) ordered. There are 64 beams that can handle a maximum of 128 samples per second on each of 4 channels. At maximum rate, 32,768 complex samples per second can be output from the Signal Processor. Each sample is then compared to a threshold in the Signal Processor. The threshold passes a percentage of the data (typically 1 percent of the data based on the SNR of the sample) to the Information Processor. This is done so that the Information Processor does not become overloaded.

Since the CW processor does not work on a per second basis, the CW Signal Processor input data rate per second is an averaged value. There are four channels for CW. The output of the normalizer for CW is nominally 17 Hz every 0.5 seconds given that 50 percent overlap data are used. This yields 34 bins per second. Thirty-four bins for 64 beams for 4 waveforms yields 8,704 samples per second. It should be noted that if 75 percent overlap was to be used, the data rate would be double. For the purposes of this paper, only HFM results will be analyzed.

A cluster is a collection of TXMs from the Signal Processor which are viewed as belonging together. TXMs are grouped together based on proximity in beam, time, and Doppler space (for CW only). The clusters represent energy in a beam/time/Doppler area. Calculations are performed to quantify the clusters in terms of time of arrival, beam and bearing, and Doppler (CW only) for the cluster. By using clusters, the data rate is reduced for downstream computation. Other processes perform calculations in cluster space viz. TXM space. Figure 2 shows the distinguishers calculated in the clustering process for the HFM waveforms.

$$\text{TOA Centroid} = \frac{\sum_{i=1}^{n} (A_i toa_i)}{\sum_{i=1}^{n} A_i} \equiv \bar{t} \quad :(\text{seconds})$$

$$\text{Bearing Centroid} = \frac{\sum_{i=1}^{n} (A_i MRA(beam_i))}{\sum_{i=1}^{n} A_i} \equiv \bar{\phi} \quad :(\text{radians})$$

$$\text{Beam Centroid} = \frac{\sum_{i=1}^{n} (A_i beam_i)}{\sum_{i=1}^{n} A_i} \equiv \bar{\text{B}} \quad :(\text{beams})$$

A = Amplitude TOA = Time of Arrival MRA = Maximum Response Angle of a Beam

Figure 2. HFM Cluster Distinguishers

Due to environmental and processing effects on the incoming sonar data, TXMs from a physical object (in space) may be noncontiguous. This causes gaps to occur between the TXMs from an object. The clustering process must allow for the gaps or objects will be broken into multiple clusters. It is undesirable for a target to be broken into more than one cluster since this affects characteristics, such as extents. Improper gap sizing may cause some of the target clusters to be removed as noise clusters. To be able to handle gaps, the clustering process uses gap parameters. Parameters are operator adjustable for time gaps, beam gaps, and Doppler gaps (CW only).

Noise filtering is performed once clustering has occurred. Clusters that have the characteristics of noise are removed from the data path. To accomplish this, clues are used that attempt to distinguish between target returns and noise returns. The BVC, as used during the MSS sea trials of 1991 and 1992, contains four clues for distinguishing targets and nontargets. The clues are defined below. Table 1 presents the BVC clue equations.

1) Energy Density - A measure of the total energy (amplitude) per beam/time area in the cluster,

2) Effective Time Duration - A measure of length of time extent of the cluster,

3) Crossing Density - A measure of the number of TXMs (threshold crossings) per beam/time area in the cluster, and

4) Effective Beamwidth - A measure of the bearing extent of the cluster.

The BVC is the process which decides which signals are target-like and should be passed on, and which signals are nontarget-like and should be removed from the sonar data stream. The BVC Calculator and extraction tools are off-line programs that allow an experienced operator to create a feature vector and covariance matrix. The BVC calculator creates a file called the BVC parameter set. This file contains the feature vector and covariance matrix used to statistically separate target sonar data from noise data.

A feature vector and covariance matrix are created based on predefined clues for historical signals using the clue equations shown in table 1. Separate feature vectors and covariance vectors are created for both target and nontarget signals. A cumulative density function (CDF) is plotted for the target and nontarget signals (see figure 3). A classification feature score is chosen at the desired noise rejection / target acceptance level. A typical level would be setting a score based on a 90 percent rejection of noise clusters. At this level, figure 3 shows a loss of 20 percent of the target returns. Given these settings the BVC score would be 0.1. This score is then used by the on-line BVC for classifying signals as target-like or noise-like. If the signal exceeds the threshold, it is declared to be target-like and passed on. If the signal is below the threshold, it is declared to be noise-like and removed from the data.

Table 1. BVC Clue Equations

Target Discriminant Name	Symbol	Definition	Where:
Energy Density	ε	$\varepsilon = (\sum_{1}^{n} A) / (\alpha \gamma b)$	n = number of threshold crossings in cluster A = amplitude of threshold crossing α = Effective Time Duration γ = Effective Beamwidth b = degrees of bearing per beam for the cluster
Effective Time Duration	α	$\alpha = 2\sqrt{(\sum_{1}^{n} (t - \bar{t})^2 A) / (\sum_{1}^{n} A)}$	n = number of threshold crossings in cluster A = amplitude of threshold crossing t = time of arrival of threshold crossing $\bar{t}$ = centroided time of arrival for cluster
Crossing Density	χ	$\chi = n / (\alpha \gamma)$	n = number of threshold crossings in cluster α = Effective Time Duration γ = Effective Beamwidth
Effective Beam-width	γ	$\gamma = 2\sqrt{(\sum_{1}^{n} (B - \bar{B})^2 A) / (\sum_{1}^{n} A)}$	n = number of threshold crossings in cluster A = amplitude of threshold crossing B = beam of threshold crossing $\bar{B}$ = amplitude weighted mean beam for threshold crossings in cluster

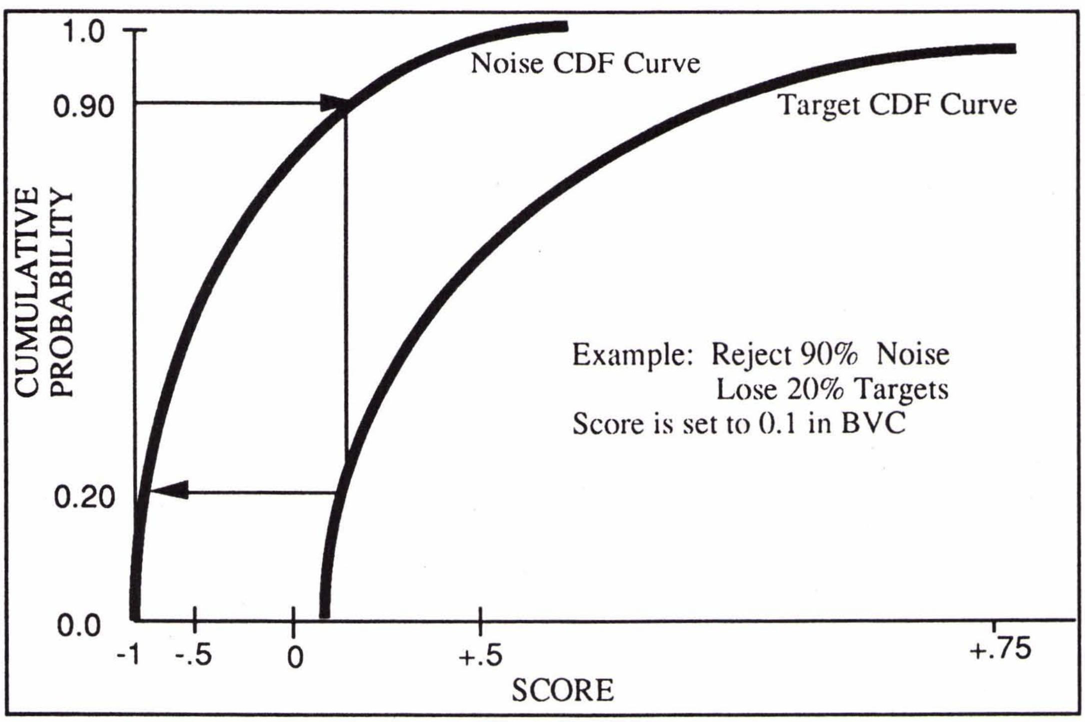

Figure 3. CDF Curves

2.2 Description of Run Geometries
The conventional BVC will be compared to a modified BVC by examining performance during five at-sea runs. The target used for the experiments was an echo repeater. The runs used for this analysis are:

RUN 1: The target was two CZs away from the source and one CZ away from the receiver. All vessels maintained a constant course and speed.

RUN 2: The target was two CZs away from the source and one CZ away from the receiver. The target changed course in a zigzag pattern.

RUN 3: The target was two CZs away from the source and one CZ away from the receiver. The target slowly changed bearing with respect to the receiver platform.

RUN 4: The receiver ship closed range to the target. The source remained two CZs away from the target. The receiver started two CZs away and closed to one CZ. One hour of data was taken from the two CZ area and one hour from the one CZ area.

RUN 5: The geometry was unknown during at-sea collection of data. The target changed course and speed during the event.

The ocean location was generally flat with small bottom features. Wind speed ranged from 8 to 17 knots. Sea state ranged from 1 to 2.

2.3 Conventional BVC Tuning Method
Conventional BVC training uses 10,000 random samples to estimate the noise background statistics. A window is defined around the target region for target sample extraction. This window is used to extract clusters in a specified beam and time window. The data sets are typically collected from the previous run. As an example, the run 1 data set is used for collection of statistics for the run 2 run because run 1 was the run previous to run 2. These data are then run through the off-line BVC calculator to obtain the BVC parameter set file used for noise rejection. The feature vector and covariance matrices were calculated using random noise samples.

2.4 Post-Sequential Detection BVC Tuning Method
The second approach to BVC tuning involved using only clusters that had passed through the sequential detector. In post-sea test analysis, it was observed that the sequential detector can be viewed as a noise filter in the sense that clusters must be observed on multiple pings before a track is formed. If a cluster is seen on one ping and then not on a consecutive ping, the sequential detector removes the cluster from the sonar data stream. Since the 10,000 random samples used by conventional BVC tuning include noise clusters that the sequential detector will reject anyway, the BVC is really doing too much "work." It would be more efficient to use the BVC to reject the specific noise clusters that the sequential detector would not reject. This would allow the BVC to become more discriminating in its definition of noise and target, because

only objects that look like noise and that pass the sequential detector would have to be removed. It is hoped that better statistical separation between noise and target energy could be achieved.

A file containing only clusters from tracks output from the sequential detector was used for training. A window was created for collecting data needed for training the BVC. The size of the target window may be set by the operator for training purposes. A small window was chosen to capture only the target returns and no side lobe returns. A larger window blocks out all echo repeater return clusters including side lobe returns for collection of the background noise data. All other clusters outside the large window are considered noise and are included in the noise cluster samples.

In addition, target pings from two separate tests were used. If the BVC set is trained solely on data from a specific run, there is a good chance that the values obtained will not be applicable to other runs. By combining different examples of target and noise values, a generalized BVC set can be created. The performance on a specific run is reduced, but the performance across all runs is better. Several different runs containing different target and noise data were combined to create a more general BVC set. For the purposes of this test, the first 20 pings of data from run 1 and run 4 were used as training samples for the post-sequential detection approach. The feature vector and covariance matrices were calculated based on post-sequential detection clusters.

2.5 Effect of Other Parameters on BVC Results

The same four BVC clues as defined in table 1 will be used during the five runs. It must also be noted that other parameters affect the noise rejection process. Parameters which affect performance include cluster, detection, and track age parameters. Cluster gap parameters affect the size of clusters generated. Separation between target clusters and noise clusters is reduced by setting the cluster gap sizes too small or too large. For this analysis, all other parameters were set to the same level so that a fair comparison can be made.

2.6 Data Analysis Procedures

For purposes of developing the training data, the MSS system is run in data collection mode. Data are collected and analyzed using the Off-Line Processor. Feature vectors and covariance matrices are developed to describe both target and noise returns. The at-sea BVC parameter set will be used for the conventional tuning part of the experiment. This set was created using the conventional tuning method as described below. A separate BVC parameter set will be created using the post-sequential detector training method. The BVC parameter sets will then be hosted on the Information Processor. The MSS system will be run using both BVC parameter sets. The effectiveness of each method will be measured in terms of target detection and noise rejection.

The system will be run first with the BVC turned off and the number of false alarms recorded. This is done to measure the maximum performance that can be achieved in terms of probability of detection. Environmental and processing losses may cause the target not to be seen on every ping. As an example, for 60 pings of data, the tracker may only receive 58 pings with target data. Since the BVC may also reject true target returns, running with the BVC off also gives a measure of the best probability of detection that can be achieved by the tracker. Turning the BVC off also measures the maximum number of false alarms that would be output from the system given that no noise rejection measures were taken.

Two metrics are defined for comparison of the methods - Percent Detected (PD) and Temporal Track Probability of False Alarm Rate (TTPFAR). Percent detected is defined as the number of pings that had a valid detection divided by the number of pings that target energy was available for detection. TTPFAR is defined as the total number of tracks the system creates per hour minus the number of tracks which represent the target. As an example, if there are 10 tracks created per hour and 2 are target tracks, the TTPFAR would be 8 false alarm tracks per hour.

3. Results

Table 2 summarizes the results of the study. A total of eight hours of data were analyzed. Two hours of ping data were analyzed from run 2, run 3, and run 4 runs, and one hour of ping data was analyzed from the run 1 and Run 5 runs.

For the run 1 test, both the conventional BVC method and the post-sequential detection training method yielded similar PD. The TTPFAR for the post-sequential detection method was three times that of the conventional method.

For the run 2 test, both the conventional BVC method and the post-sequential detection training method yielded similar PD for the first hour while the post-sequential detection method yielded better PD for the second hour. The TTPFAR for the post-sequential detection method had six more false alarms.

For the run 3 test, both the conventional BVC method and the post-sequential detection training method yielded similar PD for the first hour while the post-sequential detection method yielded slightly better PD for the second hour. The TTPFAR for the post-sequential detection method had nine more false alarms.

For the run 4 test, the post-sequential detection training method yielded much higher PD. The TTPFAR for the post-sequential detection method was three times that of the conventional method.

For the Run 5 test, both the conventional BVC method and the post-sequential detection training method yielded similar PD. The TTPFAR for the post-sequential detection method was slightly higher.

Table 2. BVC Tuning Method Comparison

	PD		**AVG PD**	**TTPFAR**		**AVG TTPFAR**	**# PINGS ANALYZED**
BVC SETS	TAPE 1	TAPE 2		TAPE 1	TAPE 2		
RUN 1							
BVC OFF	96.67			154			60
AT-SEA BVC	90			12			60
POST SD BVC	88.33			36			60
RUN 2							
BVC OFF	80	98.33	89.165	92	78	85	120
AT-SEA BVC	76.67	85	80.835	18	17	17.5	120
POST SD BVC	80	93.33	86.665	20	26	23	120
RUN 3							
BVC OFF	95	76.67	85.835	76	114	95	120
AT-SEA BVC	86.67	61.67	74.17	2	29	15.5	120
POST SD BVC	85	66.67	75.835	9	40	24.5	120
RUN 4							
BVC OFF	86.67	91.67	89.17	257	216	236.5	120
AT-SEA BVC	66.67	73.3	69.985	10	0	5	120
POST SD BVC	86.67	83.3	84.985	40	22	31	120
RUN 5							
BVC OFF	96.67			43			60
AT-SEA BVC	93.33			2			60
POST SD BVC	95			7			60
Total Avgs	8 hrs	data					
	pd	pfa					
BVC OFF	90.21	128.75					
AT-SEA BVC	79.1638	11.25					
POST SD BVC	84.7875	25					

An average was calculated for all the data tested. For the eight hours of data collected, turning the BVC off yielded a maximum tracker performance of 90.21 percent PD. It should be noted that, with the BVC turned off, the maximum amount of data available to the detector is being sent to the detector. The value of 90.21 shows that about 10 percent of the pings received do not have energy available for target detection. This could be due to environmental effects and/or processing losses occurring before the Information Processor. This 90.21 percent should be used for comparisons between noise rejection techniques because this is the "best" that they could achieve. Conventional BVC tuning yielded a 79.16 percent PD (11.05 percent below BVC off).

Post-sequential detection tuning yielded a 84.79 percent PD (5.42 percent below BVC off). Overall, the post-sequential detection method has a higher PD.

The TTPFAR results for BVC off are 128.8 false alarms per hour. The TTPFAR for conventional BVC tuning was 11.25 false alarms per hour, or a reduction in TTPFAR of a factor of 11. The TTPFAR results for post-sequential detection tuning were 25 false alarms per hour, or a factor of 5 reduction.

Results showed that there is still a trade-off between false alarm rate and PD even between alternate methods. If a higher false alarm rate is acceptable, then a higher PD rate can be achieved. Note that the cumulative performance (PD and TTPFAR) of the Information Processor is nonlinearly dependent on how the individual processor sections and parameters are set. As an example, the BVC was essentially set for an 80 percent PD and a 10 percent TTPFAR. The overall measured PD was 94.5 percent with a TTPFAR of 20 percent (accounting for the fact that with the BVC off, the PD was 90.21 and TTPFAR was 128). It is difficult to predict performance based solely on CDF curves. The effect of the entire processing string must be measured.

The post-sequential detection method of tuning the BVC used a single set of values across all runs and still achieved good performance. The conventional method had to be hand tuned during every run. A lower PD could be achieved by tuning the post-sequential detector method to the individual run environment.

4. Recommendations

The following are recommendations for further study of noise rejection techniques:

The post-sequential detection technique was tuned with 40 pings of data from two sets basically chosen by chance. Better selection of example target pings is recommended. In addition, a larger set of target pings should be used for tuning purposes.

A comparison should be made between using post-sequential detection tuning on an individual run and using the post-sequential detection technique for an average value.

The systems should be adjusted so that TTPFAR is the same for both methods and the resulting PD can be compared for a more definitive conclusion.

In-situ automatic tuning for background noise in a real-time system should also be explored. The run 4 had a much higher background noise floor in terms of TTPFAR. The BVC noise estimates used for this test may need to be different from those of the other runs.