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REVEAL: Receiver Exploiting Variability in Estimated Acoustic Levels FY07 Year End Report

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ABSTRACT

The long-term goal of the REVEAL project is to develop a signal processing structure that exploits available knowledge of the environment and of signal and noise variability induced by the environment. The research is directed toward passive sonar detection and classification, continuous wave (CW) and broadband signals, shallow water operation, both platform-mounted and distributed systems, and frequencies below 1 kHz.

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The ideas behind the REVEAL project were those of the late Leon H. Sibul, Professor of Acoustics and Electrical Engineering and Senior Scientist at the Applied Research Laboratory at Penn State. Leon was always interested in getting the physics of underwater acoustics into the signal processor, and he had a lot of ideas regarding how to do that. He was a great mentor to me and to the students. We are grateful for the opportunity to work for him and we miss his enthusiasm and leadership.

The late Dr. Nirmal Bose, HRB Professor of Electrical Engineering at Penn State, played a significant role in developing and injecting rigor into the project. He too is missed.

All of the credit for what we accomplished is due to the students who contributed so much of their time and energy: Jeff Ballard (MS Acoustics, 2007); Jeremy Joseph (MS Acoustics, 2009); Brett Bissinger, John Camin, Colin Jemmott, and Alex Sell.

OBJECTIVES

The primary FY07 objectives were to:

- Apply the maximum likelihood (ML) detector developed previously under the REVEAL project (Ballard et. al., 2006; Ballard, 2007) to detection and classification of sinusoids with random amplitude due to propagation through the ocean.
- Use data from the SWellex-96 experiment to investigate the statistics of sinusoids transmitted by different sources and propagated through the ocean to a horizontal hydrophone array.
- Investigate the ability of a rough surface PE acoustic propagation code to predict received signal parameter variability using ocean surface and volume parameter variability.

APPROACH

At-sea experience has shown that passive sonar systems often have difficulty distinguishing between targets of interest and interference or noise sources, especially in areas with high shipping traffic. The hypothesis underlying the REVEAL project is that passive sonar performance can be improved if the signal processor incorporates knowledge of the deterministic and random components of the received signal. An example is shown in Fig. 1, in which received signal variability is due to source variation and propagation through the ocean. The latter is due to temporal and spatial variation in the ocean parameters that effect acoustic propagation.

The relevant environmental parameters include water depth, sea surface condition, temperature and salinity (hence sound speed) in the medium, and bottom characteristics. There is nearly always some knowledge of these parameters, e.g. the mean or seasonally-averaged values, but other aspects such as the time or spatial dependence, or statistical moments of the parameters, may not be known. Lack of knowledge regarding a parameter distribution can be indicated by a uniform probability density function (pdf).



Figure 1: A possible application of the signal processing architecture under development in the REVEAL project is source depth classification based upon signal parameter probability density functions (pdfs) derived from knowledge of the ocean environment.

Monte Carlo simulation using an acoustic propagation code can make use of deterministic and stochastic ocean environmental models, range-dependent volume and bottom parameters, and even insitu measurements, to produce ensembles of received signals. The received signal ensembles can be processed to estimate stochastic representations of signal and noise parameters, i.e. pdfs. This is shown in Fig. 2. The benefit of the method is that received signal parameter statistics are directly related to environmental parameter statistics.



Figure 2: Available environmental information (models, in-situ measurements, probabilistic descriptions) is used with Monte Carlo simulation and an acoustic propagation code to produce received signal ensembles. The Maximum Entropy method is used to obtain pdfs for the received signal parameters.

The signal processing architecture developed under the REVEAL project incorporates statistical measures of received signal parameters into the signal processing algorithm in order to improve detection and classification performance. Specifically, a likelihood ratio (LR) detector/classifier is constructed to decide between hypotheses H_1 and H_2 using the computed signal parameter pdfs

$$p_{1}(\boldsymbol{\theta} | \mathbf{r}) = \frac{p_{1}(\mathbf{r} | \boldsymbol{\theta}) p_{1}(\boldsymbol{\theta})}{\int_{\boldsymbol{\theta}} p_{1}(\mathbf{r} | \boldsymbol{\theta}) p_{1}(\boldsymbol{\theta}) d\boldsymbol{\theta}}$$
Calculated using
knowledge of the
environment and
propagation modeling. (1)

Here $\Lambda(\mathbf{r})$ is the likelihood ratio and the likelihood functions are $p_{1,2}(\mathbf{r} | \boldsymbol{\theta})$. Building upon a derivation by Schwartz (1977), we require that the conditional likelihood function belong to the exponential class:

$$p_{1}(\mathbf{r} | \boldsymbol{\theta}) = K_{1}(\boldsymbol{\theta}) \exp\left[g_{1}(\mathbf{r}, \boldsymbol{\theta}) + B_{1}(\mathbf{r})\right]$$
(2)

where $K_1(\mathbf{\theta})$, $g_1(\mathbf{r}, \mathbf{\theta})$ and $B_1(\mathbf{\theta})$ are arbitrary functions. This is a somewhat expanded and less restrictive form than that of Schwartz. The conditional moment estimate is defined as

$$h_{1}(\mathbf{r}) \equiv \int_{\Theta} \left[\frac{\partial g_{1}(\mathbf{r}, \mathbf{\theta})}{\partial \mathbf{r}} \right] p_{1}(\mathbf{\theta} | \mathbf{r}) d\mathbf{\theta}$$
(3)

where the *a posteriori* pdf is calculated using the likelihood functions and signal parameter pdfs:

$$p_{1}(\boldsymbol{\theta}|\mathbf{r}) = \frac{p_{1}(\mathbf{r}|\boldsymbol{\theta})p_{1}(\boldsymbol{\theta})}{\int_{\boldsymbol{\theta}} p_{1}(\mathbf{r}|\boldsymbol{\theta})p_{1}(\boldsymbol{\theta})d\boldsymbol{\theta}}$$
Calculated using
knowledge of the
environment and
propagation modeling. (4)

We further define

$$G_{1}(\mathbf{r}) \equiv \int_{-\infty}^{\mathbf{r}} h_{1}(\boldsymbol{\zeta}) \, d\boldsymbol{\zeta} = \int_{-\infty}^{\mathbf{r}} \oint_{\boldsymbol{\Theta}} \left[\frac{\partial g_{1}(\boldsymbol{\zeta}, \boldsymbol{\Theta})}{\partial \boldsymbol{\zeta}} \right] p_{1}(\boldsymbol{\Theta} | \boldsymbol{\zeta}) \, d\boldsymbol{\Theta} \, d\boldsymbol{\zeta} \, .$$
(5)

where ζ is a variable of integration. With $G_2(\mathbf{r})$ similarly defined, the log likelihood ratio (LLR) becomes

$$l(\mathbf{r}) = \ln \Lambda(\mathbf{r}) = \ln \frac{p_1(\mathbf{r})}{p_2(\mathbf{r})} = G_1(\mathbf{r}) + B_1(\mathbf{r}) - G_2(\mathbf{r}) - B_2(\mathbf{r}) + \ell n \frac{C_1}{C_2}.$$
 (6)

Figure 3 shows a block diagram of the processor. Note that the $B_{1,2}(\mathbf{r})$ terms do not depend on the signal parameters and thus will often cancel out. This detector structure has been termed an "estimator-correlator" by Price (1956), and in application to ocean acoustic signal processing, the Estimated Signal Parameter Detector (Ballard, 2007). The only assumption is that the pdfs $p_{1,2}(\mathbf{r} | \boldsymbol{\theta})$ belong to the exponential class, which is much less restrictive than the Gaussian form.

BACKGROUND

There is a large body of literature discussing how to incorporate uncertainty into the analysis and synthesis of sonar signal processing systems. The principal approaches are linear system theory (Van Trees, 1971; Ziomek, 1981), the Bayesian approach (Sha and Nolte, 2005; Battle et. al., 2004), model-based signal processing (e.g. Candy, 2006), stochastic operator theory (Adomian, 1970, 1971a, 1971b; Sibul, 1979), dynamic stochastic modeling of uncertainty (Lermusiaux and Robinson, 1999; Lermusiaux, 1999; Lermusiaux, et. al., 2001), sequential estimation (Nolte, 1973; Proakis, 2004), the Maximum Entropy (MaxEnt) method (Jaynes, 1957, 1968, 1982; Kapur and Kesavan, 1992; Kapur, 1990; Burg, 1967), and wave propagation through random media (WPRM) (Flatté et. al., 1979; Lutz et. al., 2004; Uscinsky, 1977; Uscinsky et. al. 1983, 2002).



Figure 3: Block diagram of the processing structure developed under the REVEAL project.

Linear systems theory is a widely used classical approach in which signal propagation and scattering in a stochastic medium are modeled using random spreading functions that characterize how a single propagating pulse is spread in space, time and frequency. The mean square spreading functions are called scattering functions - they characterize the *average* spread of the pulse in space, time and frequency. Reverberation, propagation and target scattering functions have been used to characterize the average performance of matched filter detectors in high frequency sonars (Van Trees, 1971; Ziomek, 1981; Kay and Doyle, 2003). The spreading function paradigm is a good staring point for < 1 kHz frequencies, but critical examination is required before applying it to low frequency propagation and extending it to higher orders statistics (Sibul et. al., 2004). The linear systems approach is not limited to the active sonar processing; it is also an effective tool for analysis of signals for passive processing. Linear system theory can be used to model frequency shift and frequency spreading caused by randomly time and space varying propagation media. Continuous wavelet transform (CWT) techniques are also effective tools for characterization of time-varying systems for wideband signals (Weiss, 1996; Young, 1993). CWT approach leads to generalization of the narrowband spreading and scattering functions to the wideband signals (Sibul and Weiss, 2002).

An important aspect of modeling of random processes (signals) is computationally effective characterization of non-stationary stochastic processes that have been generated from stochastic signals that have propagated through randomly time-varying media. A class of non-stationary stochastic processes that have spectral representations is the class of *harmonizable processes* and its multidimensional generalization to *harmonizable random fields* (Loevè,1963; Cramér and Leadbetter,1967). These processes have two-dimensional spectral distributions that display the effects such as non-stationarity, spectrum shifts and spreading that are caused by time-varying systems. These results can be derived using linear system theory as previously discussed.

The Bayesian approach incorporates uncertainties in the environment, target and sonar as *a priori* pdf's, which are then incorporated into the signal processor (Haralabus et.al., 1993; Premus et. al., 1995; Richardson and Nolte, 1991; Battle et. al., 2004). The critical issue of the Bayesian approach is how to obtain valid a priori pdf's. Our approach is to obtain them using MaxEnt method (Jaynes, 1968, 1982; Kapur and Kesavan, 1982; Kapur, 1989; Burg, 1967).

The model-based processor (MBP), as investigated by Candy and Sullivan (Candy and Sullivan 1995a, 1995b, 1994; Candy 2006), is a version of the matched field processor that utilizes the normal-mode acoustic propagation model in state-space form. In this research, we do not consider matched field processing, but do incorporate several distinct advantages offered by the MBP: recursive implementation, inclusion of both noise and parameter uncertainties, relaxation of the assumption of stationary statistics, ability to estimate environmental parameters, and capability to monitor its own performance. Burkhardt (1992) has investigated robust adaptive processing for application to underwater acoustic array processing. His work is applicable to a wide class of robust signal processing techniques in uncertain acoustic channels. Williams (1989) has investigated robust signal subspace techniques for direction of arrival estimation in multipath environment.

Stochastic operator theory, dynamic modeling of uncertainty, and sequential estimation theory provide a theoretical formalism that is derived from fundamental physical principles and probabilistic characterizations of signals propagating through stochastic channels. In most cases, these approaches require more complete knowledge, e.g. a pdf, than is usually unavailable. The Maximum Entropy (MaxEnt) method uses the knowledge or data that is available, but is maximally noncommittal of what is unknown. The MaxEnt method is a well-developed scientific method that has been applied to many problems in physics, engineering, spectral estimation and Bayesian estimation. Our proposed application of this powerful method to signal processing in random/uncertain underwater channels is the first of this type.

Recently there has been renewed interest in exploitation of environmental information for improvement of performance of detectors, estimators and classifiers. Abraham and Willett used the Page test for improved detection of time-spread active echoes (Abraham and Willett, 2002). Sun, Willett and Lynch fused constant frequency and linear frequency modulated signals to improve detection of reverberation-limited targets (Sun et. al., 2004). Proakis (2004) showed that using a sequentially estimated channel impulse model for the acoustic multipath channel reduced the bit error rate of a communication system by an order of magnitude.

WORK COMPLETED

Application of the REVEAL processor to classify random amplitude sinusoids.

In FY05-06, the REVEAL LR detector (eqn (1)) was implemented for Gaussian signal and noise (Ballard, 2006; Ballard, 2007) and shown to be equivalent to the likelihood ratio test for Gaussian signal and noise presented by Van Trees (1968, Chapter 2, eqn 327). In FY07, the processor was implemented for classification of random amplitude sinusoidal signals embedded in exponential class distributed noise. Performance was evaluated for additive Gaussian noise, in which case the conditional likelihood function (eqn (2)) for M independent observations becomes

$$p_{1,2}(\mathbf{r} \mid A) = \left(2\pi \sigma_n^2\right)^{-M/2} \exp\left\{-\frac{1}{2\sigma_n^2} \sum_{i=1}^{M} \left[r_i - A\cos(\omega_o t_i + \phi)\right]^2\right\}$$
(7)

Here A is the unknown signal amplitude, ω_0 and ϕ are the signal frequency and phase, and σ_n^2 is the noise variance. Multiplying out the squared term and putting the result into (1) above yields an expression for the log likelihood ratio $l(\mathbf{r})$ similar to that given by Whalen (1971, Chap. 7)

$$l(\mathbf{r}) = \ln \left[\int_{\mathbf{A}} \exp \left\{ \frac{AV(\mathbf{r})}{\sigma_n^2} - \frac{A^2}{2\sigma_n^2} \sum_{i=1}^{M} \cos^2\left(\omega_o t_i + \phi\right) \right\} \frac{p_1(A)}{p_1(A)} \frac{dA}{dA} - \frac{1}{\log\left(\frac{AV(\mathbf{r})}{\sigma_n^2} - \frac{A^2}{2\sigma_n^2} \sum_{i=1}^{M} \cos^2\left(\omega_o t_i + \phi\right) \right\} \frac{p_2(A)}{p_2(A)} \frac{dA}{dA} - \frac{1}{2\sigma_n^2} \sum_{i=1}^{M} \cos^2\left(\omega_o t_i + \phi\right) \frac{p_2(A)}{p_2(A)} \frac{dA}{dA} = \frac{1}{2\sigma_n^2} \frac{1}$$

where $V(\mathbf{r}) = \sum_{i=1}^{M} r_i \cos(\omega_o t_i + \phi)$ is the coherent matched filter. In order to obtain an analytical

expression for $l(\mathbf{r})$, the density functions for the signal amplitude were taken to be Gaussian with the same mean but different variances, i.e. $p_1(A) \sim N(m, \sigma_1^2)$ and $p_2(A) \sim N(m, \sigma_2^2)$. The LR thus

amounts to a signal classifier. Defining the signal-to-signal ratio as $SSR = 10 \log \left[\frac{\sigma_1^2}{\sigma_2^2} \right]$, the

performance of the processor is shown in Fig. 4. The left panel shows $p_1(A)$ and $p_2(A)$ for different SSR values, while the right panel shows a receiver operating characteristic (ROC) curve for a 10 dB signal to noise ratio (SNR). Note that we have defined P_D as the probability of deciding H₁ when in fact H₁ is true, and P_{FA} as the probability of deciding H₁ when in fact H₂ is true. Fig. 4 shows that better performance is achieved when the SSR is increased, corresponding to greater differences between the pdfs of A under the two hypotheses. This is the desired result.

Analysis of SWellex-96 data.

A small portion of the SWellex-96 data were investigated in FY07 under the REVEAL project in order to address the question of whether received signal parameter statistics can be used to identify the source location. This is an important question because the LR processor defined in eqn. (8) can only distinguish between signals whose parameter pdfs are different. The Swellex-96 data have been investigated by several other researchers (Premus et. al., 2004; Booth et. al., 2000). The measurement was made in 200 m deep water just west of Pt. Loma, California between 30 April and 18 May 1996. Our interest was in Event S5, which included towed sources at 9 m and 54 m depth, transmitting CW signals simultaneously at particular frequencies between 100 Hz and 400 Hz, and two bottomed horizontal line arrays.

Figure 5 shows signal amplitude for two lines, one originating from the deep source and the other from the shallower source. The left panel shows that signals from the sources exhibit similar but not identical amplitude variations.



Figure 4: Performance of the REVEAL Likelihood Ratio processor under Gaussian noise and for sinusoids with known frequency and phase and Gaussian-distributed amplitude. The left panel shows $p_1(A)$ and $p_2(A)$ for various values of the amplitude variance ratio. (SSR = 10 log σ_1^2/σ_2^2). The right panel is a receiver operating characteristic (ROC) curve showing performance for different values of SSR.



Figure 5: Received signal amplitude, dB, for Event S5, Swellex-96 data. Depth of the shallow and deep sources was 9 m and 54 m, respectively. In the right panel, the amplitude has been corrected for cylindrical spreading.

A noise-free implementation of Eqn. (8) for the deep and shallow Swellex-96 sources is shown in Fig. 6. Kernel density estimates of the signal amplitude pdf were constructed using an acoustic propagation model for the 166 Hz (deep) and 163 Hz (shallow) sources. A likelihood ratio test was constructed by point-wise dividing the pdfs, as shown in Figure 6. Figure 7 shows the performance of the processor evaluated using samples from the Swellex-96 data. While these are not completely realistic simulations, they do indicate that there is sufficient difference between the deep and shallow amplitude pdfs to classify the signals with some degree of accuracy.



Figure 6: Likelihood ratio test constructed by point-wake dividing the kernel density estimates.



Figure 7: Results of the Likelihood Ratio test using the detector shown in Fig. 6 operating on samples constructed from the two distributions.

Rough surface PE.

In FY05-06, the method presented in Fig. 2 by which received signal statistics are calculated using knowledge of the environment, Monte Carlo simulation and the Range-dependent Model (RAM) (Collins, 1993) acoustic propagation model was demonstrated using acoustic and environmental measurements made in the Strait of Gibraltar in 1996 (Camin et. al., 2006; Tiemann et. al., 2001a, 2001b). The Strait of Gibraltar is a dynamic region from an oceanographic standpoint due to strong tidally-driven flow and the presence of internal waves. The acoustic measurements utilized broadband acoustic pulses transmitted 13 km across the strait hourly over several days and many tidal cycles, and significant variation in received signal pressure was measured. Monte Carlo simulation was carried out using sound speed fields derived from a time and space-varying mean sound speed model combined with a large number of sound speed measurements. The MaxEnt method was used to obtain range- and depth-dependent pdfs of rms received pressure. The predicted pdfs have been found to compare favorably with the measured pdfs, providing some validation for the method.

However, a limitation of the RAM code relative to our needs is that effects due to temporal variation and roughness of the ocean surface are not modeled. These important effects include time and frequency spread imparted to the propagating signal, both of which cause signal de-correlation. In FY07 we began running the rough surface PE code developed by Rosenberg (1999) by extending RAM to handle a rough air-water interface. The rough surface PE code has been shown to be able to predict frequency spread induced in the received signal by time-dependent variation of the ocean surface.

RESULTS

As discussed above, the log likelihood ratio processor was implemented for random amplitude sinusoids in noise whose pdf belongs to the exponential class. For Gaussian noise, the processor is equivalent to the result given by Whalen (1971, Chap. 7). However, the noise need not be Gaussian. If samples are available, the Maximum Entropy method can be used to obtain an exponential class pdf. Further, in order to obtain an analytical result, the signal amplitudes were taken to be Gaussian with identical means but different variances for the two source location hypotheses. The ROC curves shown in Figure 4 indicate that the processor is able to select the correct hypothesis with probability that depends upon the difference between the two signals variances.

In general, the processor must compute signal parameter pdfs using knowledge of relevant environmental parameters as discussed above (Monte Carlo simulation, an acoustic propagation model, the MaxEnt method). The linkage of the MaxEnt method, which produces an exponential class pdfs, with the LR or EC processor, which can achieve optimal performance using an exponential class conditional likelihood function, is an important result of this project. Further work is required to evaluate the processor for exponential but non-Gaussian noise distributions and for other signal parameters.

Regarding the Swellex-96 data investigation, as shown above in Figures 6 and 7, there does appear to be sufficient information in the amplitude statistics to distinguish between the deep and shallow sources. These results are encouraging, but very preliminary.

IMPACT/APPLICATIONS

The results of this research are expected to lead to new passive sonar detectors and classifiers that take advantage of knowledge of medium variability and uncertainty. The results are mainly applicable to passive processing. However, the active processor can be considered "*a detector matched to the estimated ocean*." These results could have significant impact on Navy sonar system applications.

RELATED PROJECTS

None.

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APPENDIX A: PUBLICATIONS

Peer Reviewed Journal Articles

Cotté, B., Culver, R. L. and Bradley, D. L. (2007). "Scintillation index of high frequency acoustic signals forward-scattered by the ocean surface," J. Acoust. Soc. Am. (accepted for publication).

Refereed Conference Proceedings

- Camin, H. J., Culver, R. L., Sibul, L. H., Ballard, J. A., Jemmott, C. W., Holland, C. W., and Bradley,
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- Ballard, J. A., Jemmott, C. W., Sibul, L. H., Culver, R. L., and Camin, H. J. (2006). "The Estimated Ocean Detector: Derivation and Predicted Performance under Gaussian Assumptions," Proceedings of IEEE OCEANS 2006, 18-21 September 2006, Boston, MA.
- Culver, et. al. "Application of the Maximum Entropy method to sonar signal processing," to appear in the proceedings of 27th Int. Workshop on Bayesian Inference and Maximum Entropy Methods, 8-13 July 2007, Saratoga Springs, NY.

Student Theses

Ballard, J. A. (2007). The Estimated Signal Parameter Detector: Incorporating Acoustic Variability into the Signal Processing to Detect Stochastic Signals Based on the Received Statistics, (Master of Science thesis, The Pennsylvania State University, State College, PA).

Professional Society Talks

- Culver, R. L. and H. J. Camin, "Environmental and signal models for acoustic propagation through a variable ocean," 153rd Meeting of Acoust. Soc. Am., Salt Lake City, UT.
- Jemmott, C. W., Ballard, J. A., Culver, R. L., and Sibul, L. H., "Probabilistic descriptions of lowfrequency passive sonar signal," 153rd Meeting of Acoust. Soc. Am., Salt Lake City, UT.
- Jemmott, C. W., Culver, R. L., Ballard, J. A. and Sibul, L. H., "The effect of non-Gaussian noise on detection of sinusoids in the ocean," 153rd Meeting of Acoust. Soc. Am., Salt Lake City, UT.
- Ballard, J. A., Jemmott, C. W., Culver, R. L. and Sibul, L. H., "The estimated ocean detector: Detection of signals with different parameters," 153rd Meeting of Acoust. Soc. Am., Salt Lake City, UT.
- Ballard, J. A., Culver, R. L., Sibul, L. H., Jemmott, C. W. and Camin, H. J., "The estimated ocean detector: Predicted performance for continuous time signals in random/uncertain oceans," 4th Joint Meeting of Acoust. Soc. Am. and Acoust. Soc. Japan, Honolulu, HI.
- Camin, H. J., Culver, R. L., Sibul, L. H., Ballard, J. A. and Jemmott, C. W., "Incorporating environmental variability in received signal statistics,"," 4th Joint Meeting of Acoust. Soc. Am. and Acoust. Soc. Japan, Honolulu, HI.

Invention disclosure submitted at Penn State for a "Classifier/Detector for Passive Sonar Signals with Different Parameter Distributions."

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DISTRIBUTION LIST

Distribution List for ARL Penn State Technical Report 09-012 titled "REVEAL: Receiver Exploiting Variability in Estimated Acoustic Levels FY07 Year End Report" by R. Lee Culver, dated 2 November 2009.

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