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REVEAL:
Receiver Exploiting Variability in Estimated Acoustic Levels
FY08 Year End Report

by
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14. ABSTRACT

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

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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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ACKNOWLEDGEMENTS

This work was supported by the Office of Naval Research through Grant Number N0014-07-1-0047. The content of the information does not necessarily reflect the position or policy of the Government, and no official endorsement should be inferred.

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 FY08 objectives were to:

- Apply the log likelihood ratio (LLR) receiver 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.
- Use data from the 1996 Strait of Gibraltar Acoustic Monitoring Experiment (SGAME) to evaluate the capability of the LLR to classify source depth using probabilistic environment and signal parameter descriptions.
- Compare the LLR developed under this project to the Kullback-Leibler divergence and other distance measures in terms of performance (Pd vs Pfa).
- Investigate the ability of a rough surface PE acoustic propagation code to predict received signal parameter variability using ocean surface and volume parameter variability.
- Investigate higher order whitening for exponential class (but non-Gaussian) processes that arise in conjunction with the LLR processor

APPROACH

At-sea experience has shown that passive sonar systems often have difficulty distinguishing targets of interest from interference or noise sources, especially in areas with high shipping traffic. As shown in Fig. 1, the shape of the received signal amplitude probability density function (pdf) is affected by source characteristics and propagation through the ocean. The hypothesis underlying the REVEAL project is that passive sonar performance can be improved if the signal processor makes use of predictions of received signal parameter statistics or pdfs. The received signal statistics must be predicted based upon knowledge of ocean volume and boundary parameter temporal and spatial dependence, as well as uncertainty in that knowledge.

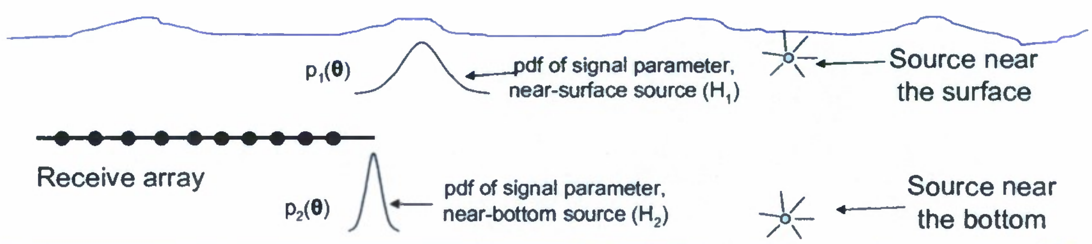

Figure 1: A possible application of the signal processing architecture under development in the REVEAL project is source depth classification based upon signal parameter probability density functions (pdfs) derived from knowledge of the ocean environment.

The relevant environmental parameters include the 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 time or spatial dependence, or statistical moments of the parameters, may not be known. Uncertainty characterizes the gap between knowledge and ground truth, and uncertainty regarding environment or signal parameter values is indicated by parameter pdfs.

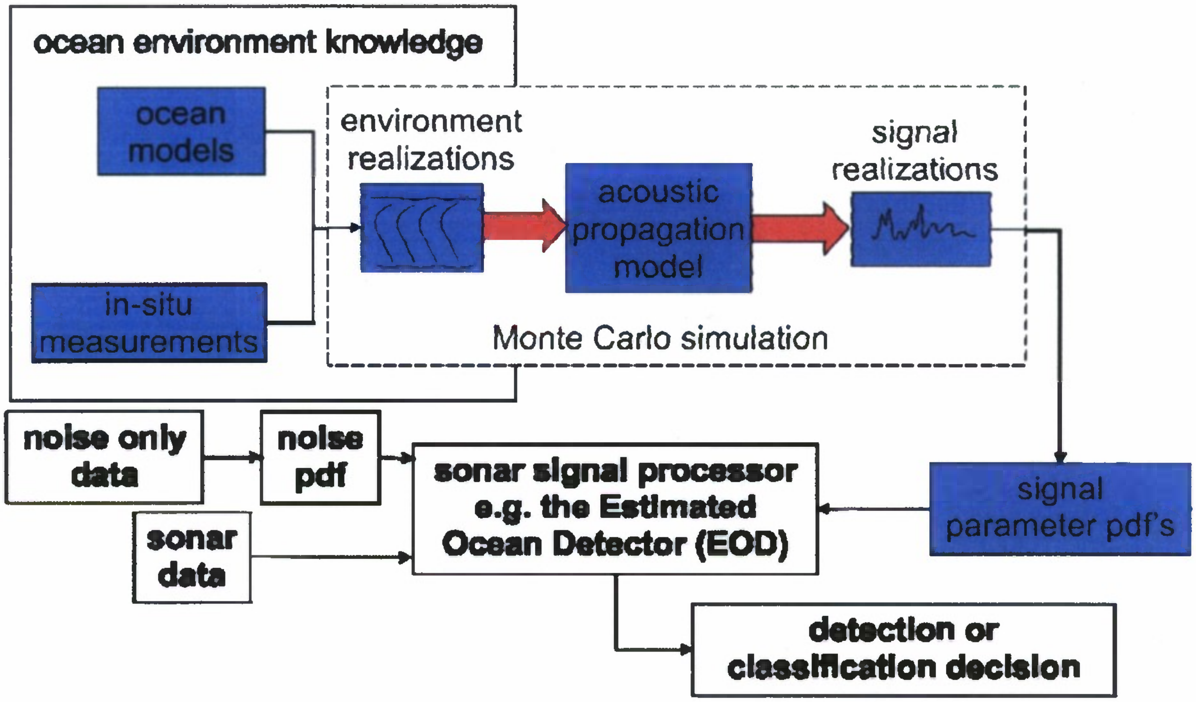

Figure 2: Available environmental information (models, in-situ measurements, probabilistic descriptions) is used with Monte Carlo simulation and an acoustic propagation code to produce an ensemble of received signals. Signal parameters are extracted from the ensemble, and probability density functions (pdfs) are estimated for the signal parameters. Noise only data are used to estimate the noise pdf. The signal processor utilizes these model-based inputs to classify sonar signals.

The vector *conditional moment* estimate is defined as

$$h_1(\mathbf{r}) \equiv \int_{\boldsymbol{\Theta}} \left[\frac{\partial g_1(\mathbf{r},\boldsymbol{\theta})}{\partial \mathbf{r}} \right] p(\boldsymbol{\theta} \mid \mathbf{r}, H_1)\, d\boldsymbol{\theta} \tag{3}$$

where the *a posteriori* pdf has been obtained using the likelihood functions and signal parameter pdfs:

$$p(\boldsymbol{\theta} \mid \mathbf{r}, H_1) = \frac{p(\mathbf{r} \mid \boldsymbol{\theta}, H_1)\, p(\boldsymbol{\theta} \mid H_1)}{\int_{\boldsymbol{\Theta}} p(\mathbf{r} \mid \boldsymbol{\theta}, H_1)\, p(\boldsymbol{\theta} \mid H_1)\, d\boldsymbol{\theta}} \tag{4}$$

Calculated using knowledge of the environment and propagation modeling.

We further define

$$G_1(\mathbf{r}) \equiv \int h_1(\mathbf{r}) \cdot d\mathbf{r} = \int\int_{\boldsymbol{\Theta}} \left[\frac{\partial g_1(\mathbf{r},\boldsymbol{\theta})}{\partial \mathbf{r}} \right] p(\boldsymbol{\theta} \mid \mathbf{r}, H_1)\, d\boldsymbol{\theta} \cdot d\mathbf{r}\ . \tag{5}$$

With $G_2(\mathbf{r})$ similarly defined, the log likelihood ratio (LLR) becomes

$$l(\mathbf{r}) = \ln \Lambda(\mathbf{r}) = \ln \frac{p(\mathbf{r} \mid H_1)}{p(\mathbf{r} \mid H_2)} = G_1(\mathbf{r}) + B_1(\mathbf{r}) - G_2(\mathbf{r}) - B_2(\mathbf{r}) + \ell n \, {}^{c_1}\!/_{c_2} . \tag{6}$$

Here $\Lambda(\mathbf{r})$ is the likelihood ratio. 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 $p(\mathbf{r} \mid \boldsymbol{\theta}, H_{1,2})$, also written $p_{1,2}(\mathbf{r} \mid \boldsymbol{\theta})$, belong to the exponential class. This is much less restrictive than a Gaussian assumption.

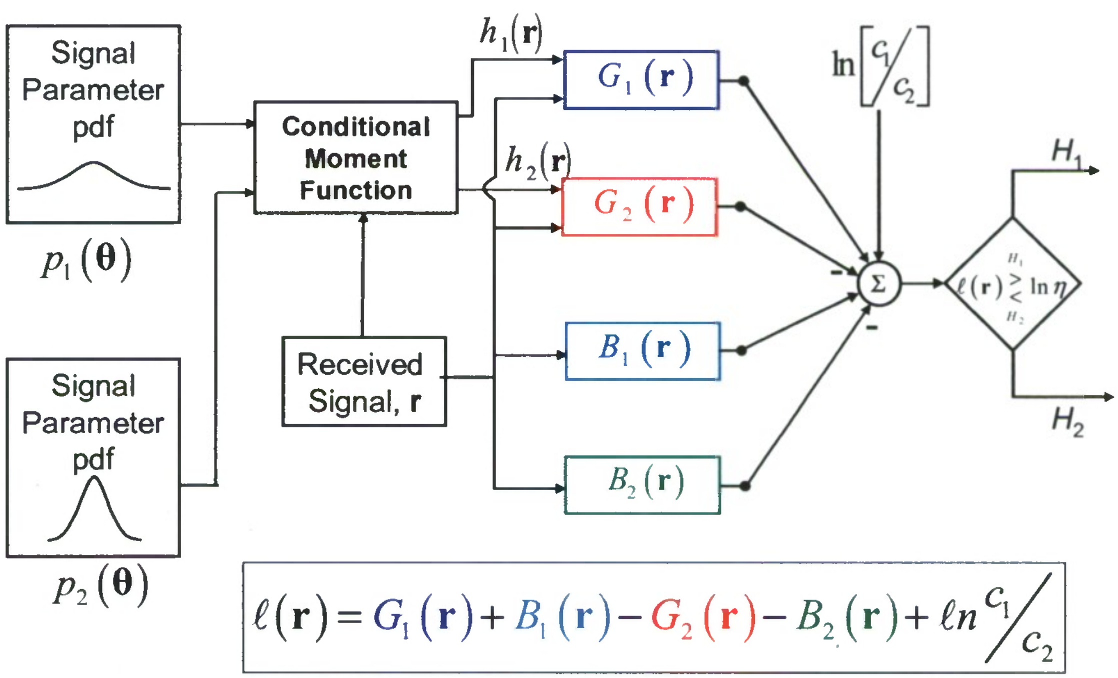

Figure 3: Block diagram of the processing structure developed under the REVEAL project.

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).

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 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* pdfs, 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 pdfs. 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 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 likelihood ratio (LR) detector (eqn (1)) was implemented for Gaussian signal and noise (Ballard et al., 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

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

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

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

Need these to proceed.

$$\ln\left[\int_A \exp\left\{\frac{AV(\mathbf{r})}{\sigma_n^2} - \frac{A^2}{2\sigma_n^2}\sum_{i=1}^{M}\cos^2(\omega_o t_i + \phi)\right\}\boxed{p_2(A)}\,dA\right] \underset{H_2}{\overset{H_1}{\gtrless}} \ln\eta \tag{8}$$

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. $p(A \mid H_1) \sim N(m, \sigma_1^2)$ and $p(A \mid H_2) \sim N(m, \sigma_2^2)$. The LR thus amounts to a signal classifier. Defining the signal-to-signal ratio as $SSR = 10\log\left[\sigma_1^2 / \sigma_2^2\right]$, the performance of the processor is shown in Fig. 4. The left panel shows $p(A \mid H_1)$ and $p(A \mid H_2)$ 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 H_1 when in fact H_1 is true, and P_{FA} as the probability of deciding H_1 when in fact H_2 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.

In FY08, Ballard's MS thesis was the basis for an article submitted it to the IEEE Journal of Oceanic Engineering. Comments were received from reviewers and the manuscript was revised and resubmitted. As of this writing, there has been no further communication from JOE.

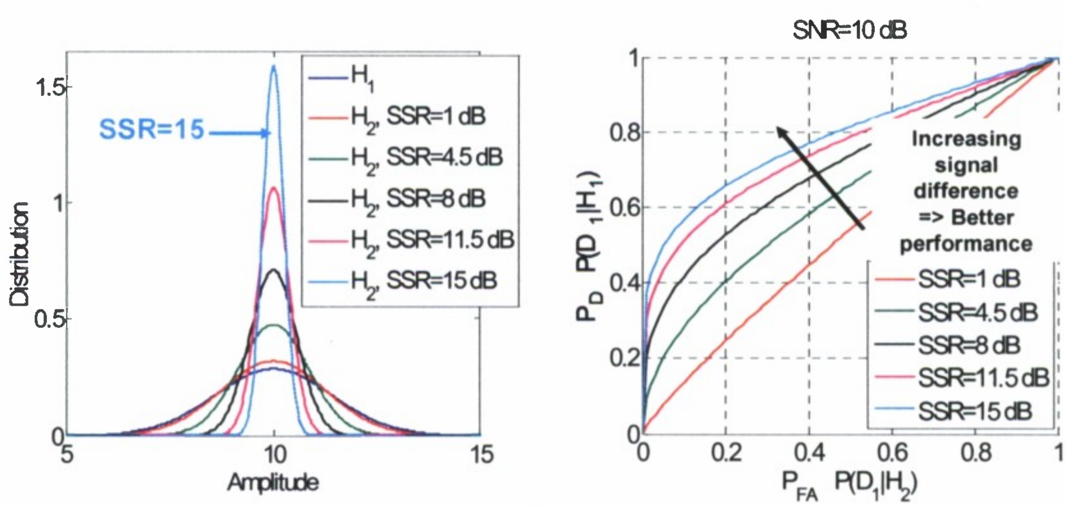

Figure 4: Performance of the REVEAL Likelihood Ratio processor under Gaussian noise and for sinusoids with known frequency and phase and Gaussian-distributed amplitude. The left panel shows $p_1(A)$ and $p_2(A)$ for various values of the amplitude variance ratio. (SSR = 10 log σ_1^2/σ_2^2). The right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

Investigation of other statistical processors to classify random amplitude sinusoids.
Two other approaches were investigated in FY08 for their ability to classify signals based upon signal statistics. The point of the comparison was (1) to gain better understanding of the REVEAL processor by comparing it with other processors and (2) to understand whether the REVEAL processor was providing better performance than other processors.
A histogram filter is a discrete implementation of a Bayesian inference filter (Thrun, et al., 2005). In FY08, a histogram filter was applied to a passive sonar target localization problem in which the source level and source velocity were known but the source initial position was unknown. Noisy measurements of received level were generated using an acoustic propagation model, from which transmission loss could be estimated. The prior distributions, which are used to design the classifier, were obtained from acoustic simulations with uncertain environmental parameters. The histogram filter is shown to localize the moving target broadcasting a tonal signal in shallow water using a single hydrophone, albeit with some unrealistic assumptions (known target velocity and source level). Future work may consider relaxing these assumptions. In addition, insight into the REVEAL processor and the histogram filter is being sought by putting the two processors into the same notation and the assumptions of each compared.

In parallel, target classification using statistical distance measures between pdfs was investigated. Statistical distance-based methods have previously been used in estimation problems (Beran, 1977; Novovicova et al. 1996). These methods can be adapted to classification applications which compare modeled pdfs to measured pdfs and offer a classification capability that is similar to that offered by the REVEAL processor. A family of statistical distance measures (Ali & Silvery, 1966) including the well-known Kullback-Leibler divergence, Hellinger distance and Battacharyya distance were evaluated and the Hellinger distance was chosen for classification purposes. A Minimum Hellinger Distance Classifier (MHDC) was constructed and tested on simulated acoustic data with positive results. The MHDC was then compared to the LR processor and it was found that the LR processor outperforms the MHDC when there is no significant data-model mismatch. It is believed that the MHDC will show robustness that the LR processor does not possess in exchange for its performance under ideal conditions (Lindsay, 1994). The issue of robustness to poor or erroneous models and application of the MHDC to real acoustic data will be considered in the future.

Application of the LLR Receiver to SWellex-96 data.
A small portion of the SWellex-96 data was investigated in FY07 and FY08 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.

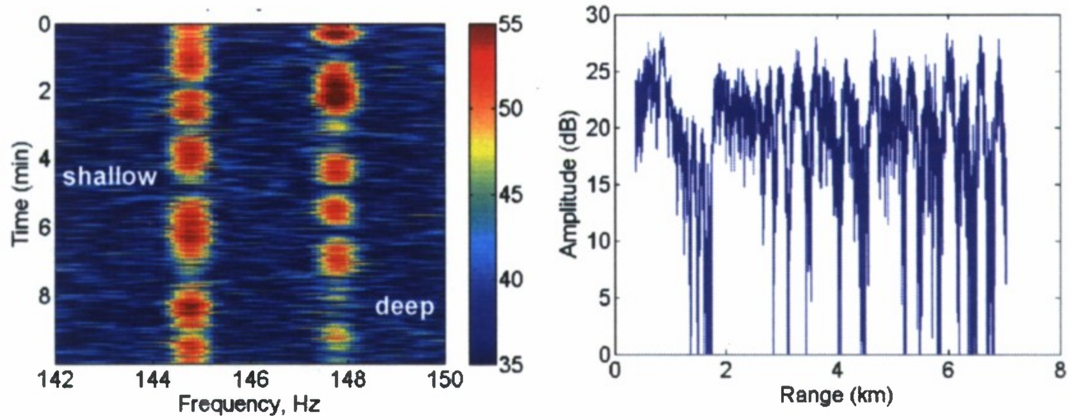

Figure 5: Received signal amplitude, dB, for Event S5, Swellex-96 data. Depth of the shallow and deep sources was 9 m and 54 m, respectively. In the right panel, the amplitude has been corrected for cylindrical spreading.

A high SNR implementation of Eqn. (8) for the deep and shallow Swellex-96 sources is shown in Fig. 6. The figure shows kernel density estimates of the signal amplitude pdf 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 for each frequency pair like that shown in the right-hand panel of Fig. 6. The left panel in Figure 7 shows the predicted processor performance calculated using synthetic data (independent and identically-distributed values drawn from the distributions derived from the Swellex-96 data). Receiver operating characteristic (ROC) curves are shown, with probability of detection P_D taken to be correct detection of a deep source, probability of false alarm P_{FA} taken to be incorrect declaration of a deep source, and N defined as the number of independent samples. Note that better performance (higher P_D for a given P_{FA}) results from processing more samples.

$$\Lambda(r) = \frac{p(r \mid shallow)}{p(r \mid deep)} =$$

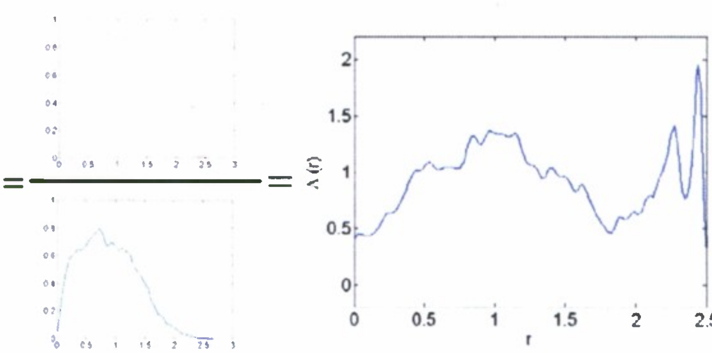

Figure 6: Likelihood ratio test constructed by point-wake dividing the kernel density estimates.

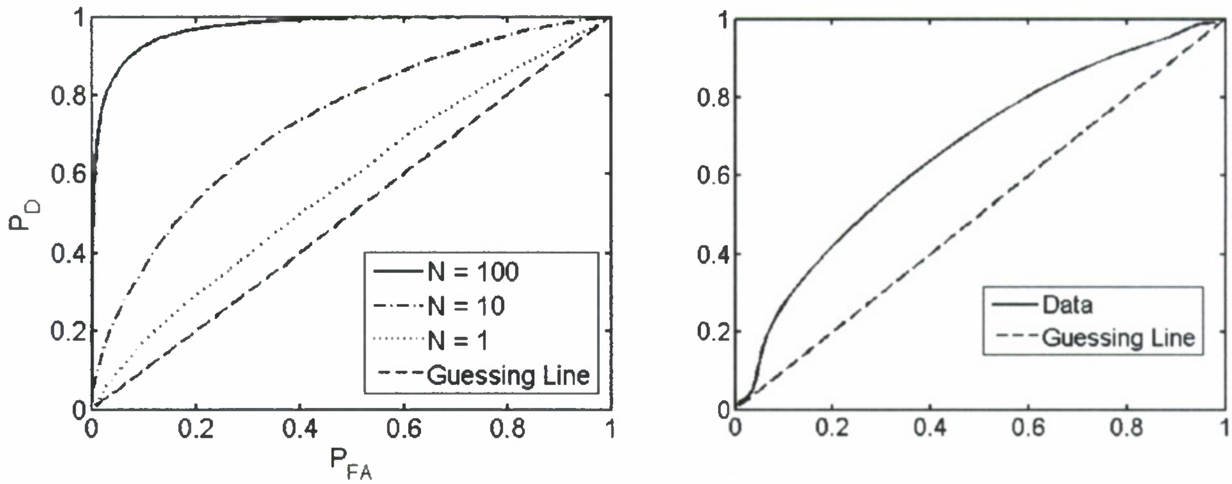

Figure 7: Receiver Operating Characteristic (ROC) curves for a detector like that shown in Fig. 6. Left panel shows predicted processor performance calculated using synthetic data (independent and identically-distributed values drawn from the distributions derived from the Swellex-96 data). The right panel shows operating on samples constructed from the two distributions.

The right panel in Fig. 7 shows a ROC obtained by processing the five minute segments of acoustic data from the SWellex data. The data are highly correlated in time, with a correlation time of about 30 sec to 1 min. This is roughly consistent with Fig. 7, which indicates there are about 10 independent samples in five minutes of data. Fig. 7 shows that the detector performed well on independent, synthetic data, as well as on the strongly correlated actual SWellEx-96 data.

Application of the LLR Receiver to 1996 Strait of Gibraltar Acoustic Monitoring Experiment (SGAME) data.

Acoustic and environmental measurements from the 1996 Strait of Gibraltar Acoustic Monitoring Experiment (SGAME) will be used in Section V to investigate use of probabilistic environment and signal parameter models in a signal processor to decide whether a received signal originated from a shallow or deep source. An overview of the measurement is presented in this section. The SGAME experiment was conducted by Scripps Institution of Oceanography, San Diego, CA and the Institut für Meereskunde, Kiel, Germany. Many details of the measurement have been reported by Tiemann et al. (2001a; 2001b). The data utilized here consist of 8 second M sequence pulses centered at 250 Hz, transmitted hourly across the Strait over a 3.5 day (84 hour) period containing just over 7 cycles of the internal tide. The measurement utilized a 100 m deep bottom-moored source and 10 bottom-moored hydrophones evenly spaced at 81 m to 387 m depth.

The 84 received signals were match filtered and the amplitudes of the first arrivals collected. The matched filter output, shown in Fig. 8 for the shallowest and deepest hydrophones, shows considerable diurnal (twice daily) variation caused by significant sound speed profile variations driven by circulation between the Atlantic and Mediterranean and moderated by a strong internal tide. The acoustic measurements were accompanied by more than 100 CTD drops spaced in range along the propagation path and in time so as to capture the sound speed profile variability.

The LLR processor was applied to the SGAME 250 Hz data to demonstrate how environment and signal parameter models are used and to illustrate dependence of processor performance upon model fidelity. The signals received hourly at the shallowest hydrophone (81 m depth) and those received at the deepest hydrophone (387 m depth) are employed. Due to reciprocity, these signals are identical to those that would be received at the source location if transmitted from the two hydrophone locations. The signal processor must utilize the received signal to decide between two hypotheses: source depth is 81 m or source depth is 387 m.

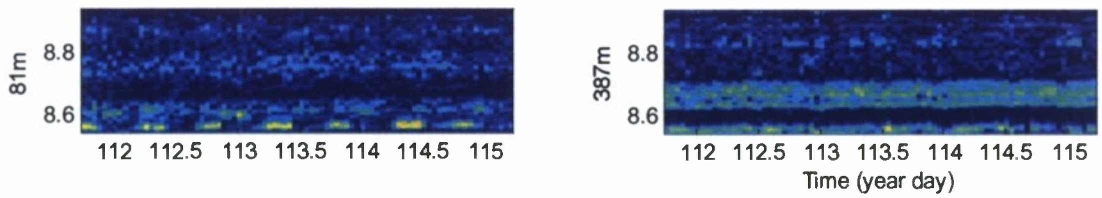

Figure 8: Matched filter output for the 84 signals received at the shallowest hydrophone (left) and deepest hydrophone (right).

Likelihood ratio receivers like that shown in Fig. 6 were constructed and used to process the peaks of the first arrivals shown in Fig. 8. The processing results are summarized in the Receiver Operating Characteristic (ROC) curve shown in Fig. 9. The data used to construct the LLR are (a) the in-water measurements, (b) predicted using the Tiemann sound speed model, (c) predicted using the mean (but time and space-varying) sound speed profiles from CTD drops, and (d) predicted using mean sound speed with uncertainty included.

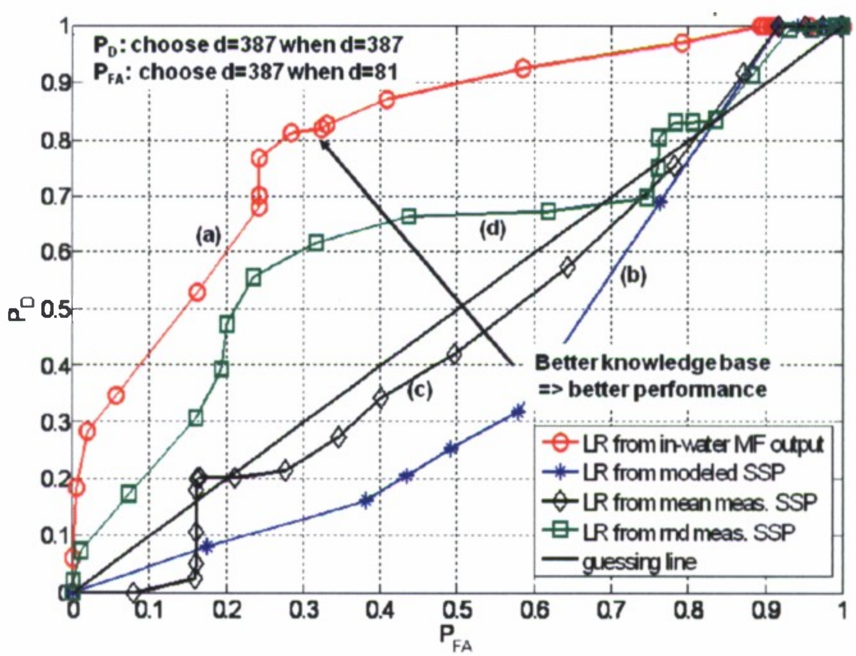

Figure 9: Receiver Operating Characteristic (ROC) curves for likelihood ratio receivers applied to 250 Hz Strait of Gibraltar acoustic data.

The ROC curves show that best performance (a) is obtained when the statistics of the received signals are known and used to construct the likelihood ratio. Poor performance was achieved using signal statistics predicted using only the mean ocean acoustic knowledge (curves (b) and (c)), but comparatively better performance was achieved when the uncertainty present in the sound speed models was included in the prediction of received signal statistics.

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 kernel density estimate 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.

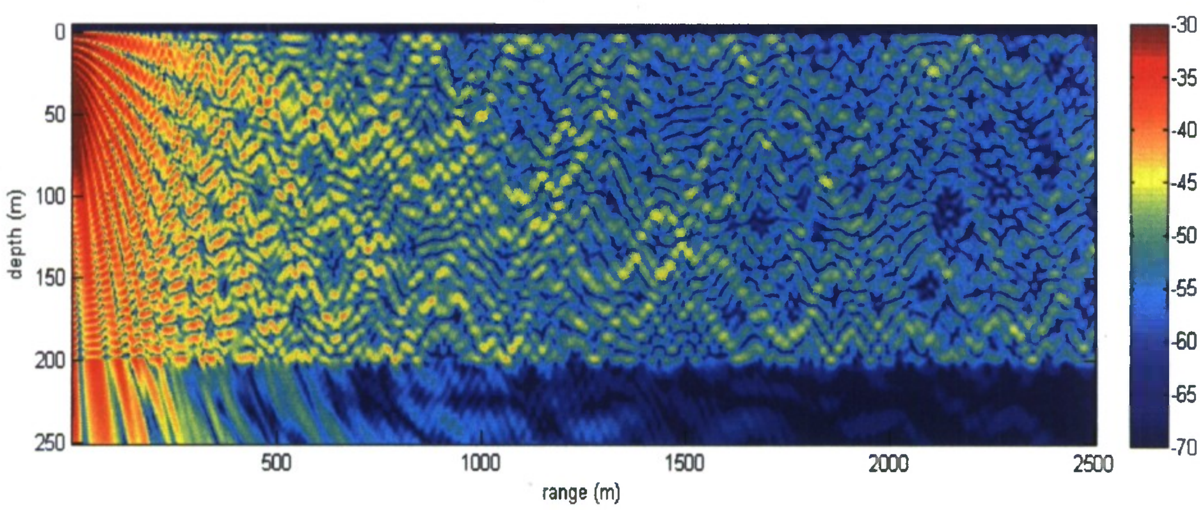

Figure 10: Transmission loss (TL) computed using rough surface PE and a wind speed of 30 kts. Structure in the TL is due to multipath and scattering by the ocean surface.

In FY07 and FY08 we investigated the capability of 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. Fig. 10 shows how transmission loss becomes variable in range and depth due to scattering by the rough surface.

The objective with the rough surface PE code is to be able to use knowledge of the ocean environment, including time- and location-dependent variation and uncertainty, to predict the statistics of the received signal. As an example, Fig. 11 shows transmission loss probability density functions for a shallow water environment and receiver variation in range and depth.

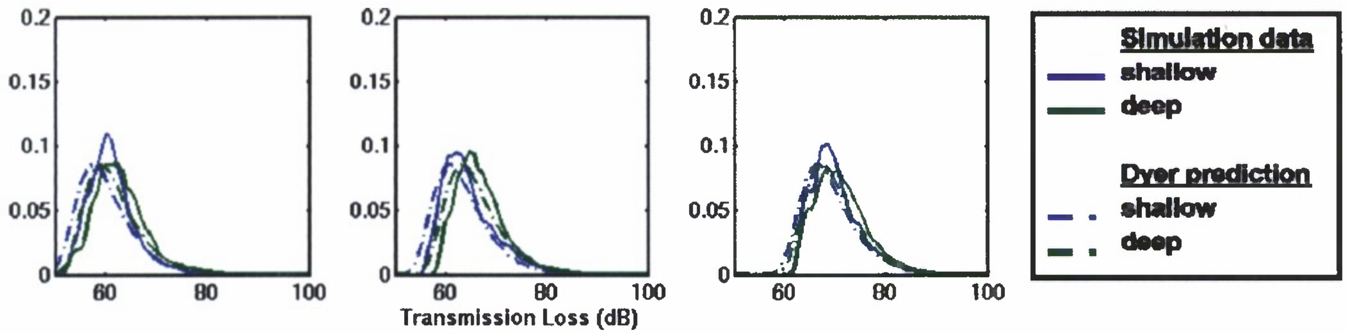

Figure 11: Predicted probability density functions of transmission loss for 50 m deep, 250 Hz source, 200 m water depth and shallow (20 m deep) and deep (150 m deep) receivers at ranges of 5 km (left), 10 km (middle) and 20 km (right). Wind speed is 4 m/s.

Higher-Order Whitening and Compressive Sampling.
As stated above, the LLR processor developed under the REVEAL program requires that the conditional likelihood function belong to the exponential class. Eqn (7) shows (and Ballard (2007) shows in greater detail) that the conditional likelihood function is in fact the pdf of the noise present at the input to the processor. The form of pdfs belonging to the exponential class was given in eqn (1). The Gaussian pdf belongs to the exponential class, but clearly the REVEAL processor admits non-Gaussian noise as well. For this reason, some work was begun in FY08 to study how best to "whiten" the processor input, or be more correctly, make the observations independent.

Whitening, in the traditional sense as originally used in filtering, prediction and smoothing of stationary random processes, orthogonalizes the data samples (or observations). In communications, such orthogonalization allows the detection algorithm to operate on each output sample independently. For example, Monk et al. (1994) show that the maximizing SNR is the main method of improving the bit error probability. A whitening filter prior to demodulation and smoothing improves the amplitude estimate. The concept of whitening is widely used in image processing and signal processing tasks of many kinds. The term whitening is used because for Gaussian-distributed noise, decorrelating the signals is equivalent to making the input spectrum. In fact, what is desired is sample-to-sample independence, or removal of redundancy between samples. For non-Gaussian noise, decorrelating the input does not in general result in removal of all redundancy. Removal of residual redundancy, sometimes referred as second-order correlation, may be desirable for subsequent processing. For example, in image processing, the increasing thrust towards higher order statistics (HOS) based signal, data, and information processing that embraces non-Gaussianity, non-stationarity and non-linear processing, the removal of redundancies by higher order whitening has been necessitated.

In FY08, some effort was devoted to investigating higher order whitening as it is done in the image processing context. A natural image or a sequence of images has considerable spatial as well as temporal (in the case of image sequences) correlation whose removal calls for whitening by linear filtering. In a non-stationary image, higher order correlations that remain require nonlinear methods for their removal based on procedures, referred to as higher order whitening, applied to statistical image models. Crucial in such modeling is the notion of scale-invariance, which refers to an image description that remains fixed with change of image-scale. Scale-invariance is a form of self-similarity, stochastically, a property manifested in a fractal, approximated by objects ubiquitous in nature, like coastlines, clouds, and snowflakes, among many other occurrences in nature.

Progress in FY08 was confined to understanding how higher order whitening is accomplished in image processing. In FY09, the ideas will be applied to an underwater acoustic problem.

RESULTS

The results of FY08 work are reported above in the context of work completed. Publications and conference talks are listed below under publications.

IMPACT/APPLICATIONS

The results of this research are expected to lead to a new passive sonar classifier that takes advantage of knowledge of medium variability and uncertainty.

RELATED PROJECTS

None.

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APPENDIX A: PUBLICATIONS

Peer Reviewed Journal Articles

N.K. Bose, U. Srinivas and R.L. Culver (**2008**). "Wavelength diversity based infrared super-resolution and condition-based maintenance," INSIGHT, British Institute for Non-Destructive Testing, Vol. 50, No. 8.

R.L. Culver and H.J. Camin (**2008**). "Sonar signal processing using probabilistic signal and ocean environmental models," accepted for publication, J. Acoust. Soc. Am. (Jan 09).

J.A. Ballard and R. L. Culver (**2008**). "The Estimated Signal Parameter Detector: Incorporating signal parameter statistics into the receiver," submitted to IEEE J. Oceanographic Engr.

Workshop and Conference Papers

Bissinger, B. E., R. L. Culver, N. K. Bose and C. W. Jemmott (**2008**). "Application of statistical methods in underwater signal classification," Acoustics '08, 155th Meeting of Acoust. Soc. Am., Paris, France.

Bissinger, B. E., R. L. Culver, and N. K. Bose (2008). "Statistical distance based signal classification," Workshop on Distributed Detection and Estimation, Virginia Tech., Blacksburg, VA. 15 July 2008.

Culver, R. L., J. A. Ballard, C. W. Jemmott, and L. H. Sibul (**2007**). "Likelihood Ratio, Maximum Entropy, and an Estimator-Correlator Structure," IEEE Underwater Acoustic Signal Processing Workshop, U. of Rhode Island, West Greenwich, RI, Oct. 17-19, 2007.

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Joseph, J. M. and R. L. Culver (**2007**). "Effect of Rough Surface on Received Signals," 154th Meeting of Acoust. Soc. Am., New Orleans, LA.

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APPENDIX B: PATENTS

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

APPENDIX C: HONORS/AWARDS/PRIZES

Colin Jemmott was awarded the 2008 National Defense Industrial Association (NDIA) Undersea Systems Division Fellowship Award, which included a check for $3,000.

Lee Culver was promoted to Senior Research Associate at the Pennsylvania State University.

DISTRIBUTION LIST

Distribution List for ARL Penn State Technical Report 09-013 titled "REVEAL: Receiver Exploiting Variability in Estimated Acoustic Levels FY08 Year End Report" by R. Lee Culver, dated 2 November 2009.

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