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14. ABSTRACT The long-term goal of the REVEAL project is to develop and demonstrate a passive sonar signal processing structure that exploits available knowledge of the environment, including uncertainty, to detect, localize and classify targets. This year, a passive sonar signal processing framework was developed that leverages acoustic propagation models to localize a moving acoustic source. The algorithm was demonstrated using data from Event S5 of SWellEx-96 experiment.					
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REVEAL:

Receiver Exploiting Variability in Estimated Acoustic Levels

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LONG-TERM GOALS

The long-term goal of the REVEAL project is to develop and demonstrate a passive sonar signal processing structure that exploits available knowledge of the environment, including uncertainty, to detect, localize and classify targets.

OBJECTIVES

The FY10 objectives were to:

- Develop and demonstrate a model-based Bayesian state estimator for passive sonar localization.
- Evaluate the capability of auto-regressive model coefficients as a source depth estimator
- Investigate passive sonar features in the time-frequency using data from the south Florida array CALOPS measurement.
- Evaluate the shallow water invariant as a classification features for passive sonar.

APPROACH

An important effort in this project is to analyze real ocean measurements to develop an understanding of the characteristics of passive sonar signals. Received signal characteristics are determined by the properties of the source and by propagation through the ocean from source to receiver. Our hypothesis is that knowledge of the environment can be used to predict propagation effects, and that they depend upon propagation path and thus the source location. Because the ocean environment is dynamic and variable in time and space, a statistical approach is necessary.

A second effort is to develop receiver structures that make use of passive sonar signal characteristics to detect, localize and classify the source. Several structures have been investigated to date, and in particular, a promising Bayesian state estimation algorithm was published in FY10. The structure is described further below. Other classification structures investigated during the past year utilized amplitude statistics, auto-regressive (AR) model coefficients, and energy striations in the time-frequency plane. The status of these developments is summarized below.

Key personnel. Acoustics graduate student Colin W. Jemmott developed the Bayesian state estimator in his PhD dissertation (Jemmott, 2010). Electrical Engineering graduate student Brett

E. Bissinger evaluated received signal amplitude and AR coefficient statistics. Acoustics graduate student Alex W. Sell evaluated the statistics of the waveguide invariant for the range-dependent bathymetry encountered in the south Florida data. Penn State Professor of Electrical Engineering David J. Miller provided advice regarding signal classification. The project Principal Investigator is R. Lee Culver, Senior Research Associate at Penn State's Applied Research Lab and Associate Professor of Acoustics.

WORK COMPLETED

The product of Colin Jemmott's research is a passive sonar signal processing framework that leverages acoustic propagation models to localize a moving acoustic source. The localization framework estimates source location using information that is unintentionally radiated, encoded by propagation effects and finally received on a single hydrophone. The framework relies on acoustic propagation models to predict received signals. The source location and other source parameters are included in a state vector. The goal of the localization framework is to estimate state vector based on the received acoustic signal.

It is well known that there is often significant uncertainty in the modeled acoustic field resulting from underlying uncertainty in the ocean environment. To properly account for this uncertainty, Bayesian signal processing is used. The Bayesian approach is a principled method which allows knowledge of environmental, target and sonar system uncertainties to be incorporated into sonar signal processing.

The primary challenges in developing the localization framework are representing the uncertain acoustic field accurately, and deriving and implementing the resulting signal processor. Figure 1 shows a flowchart of the localization framework. The resulting processor exploits prior knowledge of target, noise and environmental parameters to estimate properties of the acoustic source based on the received passive sonar signal.

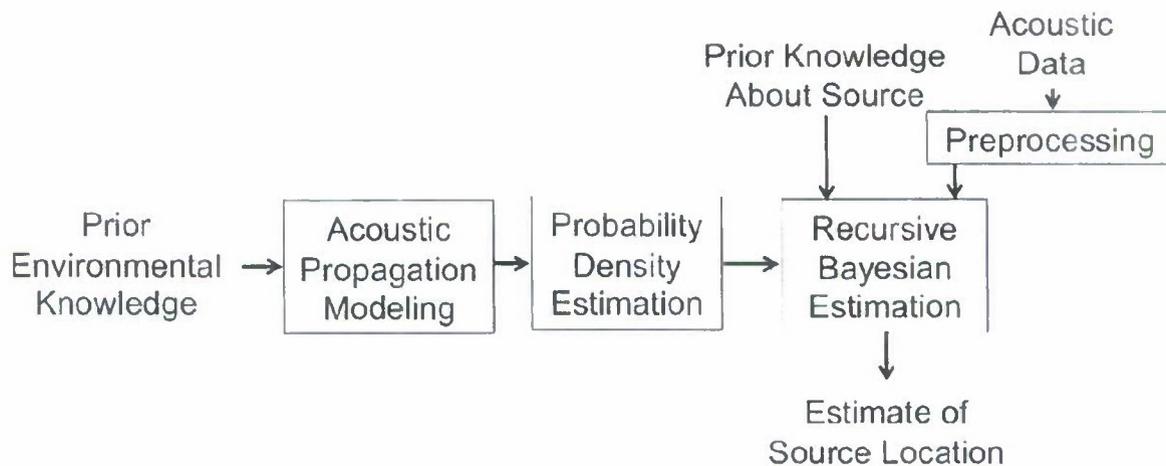


Figure 1: Bayesian state estimation flow chart.

The inputs to the localization framework are prior knowledge about the environmental state vector, prior knowledge about the source state vector, and the acoustic data itself. The output is an estimate of the location of the source. The receiver utilizes Acoustic Propagation Modeling, which is the physics-based model that describes how acoustic energy travels through the ocean. A Probability Density Estimation component transforms the results of acoustic propagation modeling into a form that permits

Bayesian signal processing. Finally, the Preprocessing and Recursive Bayesian Estimation blocks combine prior knowledge, acoustic modeling and data to make the final estimation. Results of applying the Bayesian filter to the Swellex-96 data are described below.

Three other approaches pursued during FY10 are now presented. All have the goal of passive sonar localization. The approaches are amplitude statistics, auto-regressive (AR) modeling, and time-frequency domain feature prediction using the shallow water wave guide invariant.

A binary source depth classification test has been devised whereby a received signal is classified as having originated from either a shallow or deep source. An acoustic propagation model is used to generate the class models, and a minimum divergence classifier compares the distances between the probability distribution functions of the received signal amplitude and the class models. The Hellinger distance metric provides an efficient and robust choice for making classification decisions.

An AR model was applied to the simulated signals from deep and shallow sources in the Swellex-96 environment. The signals produced by the acoustic propagation model provided the classification training set. A likelihood ratio receiver was constructed using the resultant AR coefficients for the deep and shallow sources, and the Swellex-96 signals classified according to a likelihood ratio test. Receiver operating characteristic (ROC) curves were used to demonstrate performance. The method was found to be limited by unsteady source motion, non-stationary AR coefficients (with source range) and propagation model fidelity.

Sonar systems frequently employ a time-frequency representation of beam level signals. The lofargram is an example. Time-frequency representations provide features which can be used to detect, localize and classify passive sonar sources. However, they often contain features which are not easy to understand. The shallow water wave guide invariant is a parameter that captures the effects of constructive and destructive interference on the signals transmitted by sources that are moving through the medium. Our approach is to apply the range-dependent invariant to the south Florida CALOPS data.

RESULTS

This section shows an example in which the Bayesian state estimation algorithm is applied to data from Event S5 of SWellex-96 experiment. The acoustic data can be downloaded from www.mpl.ucsd.edu/swellex96. The data presented here are from sensor 1 of the south horizontal line array (HLA South). Figure 2 is a time-frequency plot showing a pair of tones. One line corresponds to a tone broadcast from the shallow source, the other line from the deep source. The data are from minutes 30-40 of the experiment.

Without amplitude modulation due to acoustic propagation, the time-frequency plot would show two vertical solid red lines in a noisy background. However, constructive and destructive interference between sound propagating over different paths, or *multipath*, results in amplitude modulation and the signal fades in and out. Effectively, source motion maps spatial variability in the pressure field into temporal amplitude variability at the receiver. The amplitude modulation is the “signal” that the Bayesian localization framework exploits.

To implement the Bayesian filter, all of the algorithm inputs listed in Figure 1 must be specified. For this example, environmental information was obtained from the MPL website. All 51 of the sound speed measurements from the experiment were considered equally likely, and the range-independent water depth was taken to be uniformly distributed between 180 and 200 m. The acoustic field probability density functions were generated using Monte Carlo simulation and the Kraken normal mode model followed by a kernel density estimator. The source state vector consists of source range and depth, radial

velocity, and source level. A state update equation with Gaussian disturbance was utilized. The state vector prior distribution was taken to be uniform over a range of reasonable, but not restrictive, values.

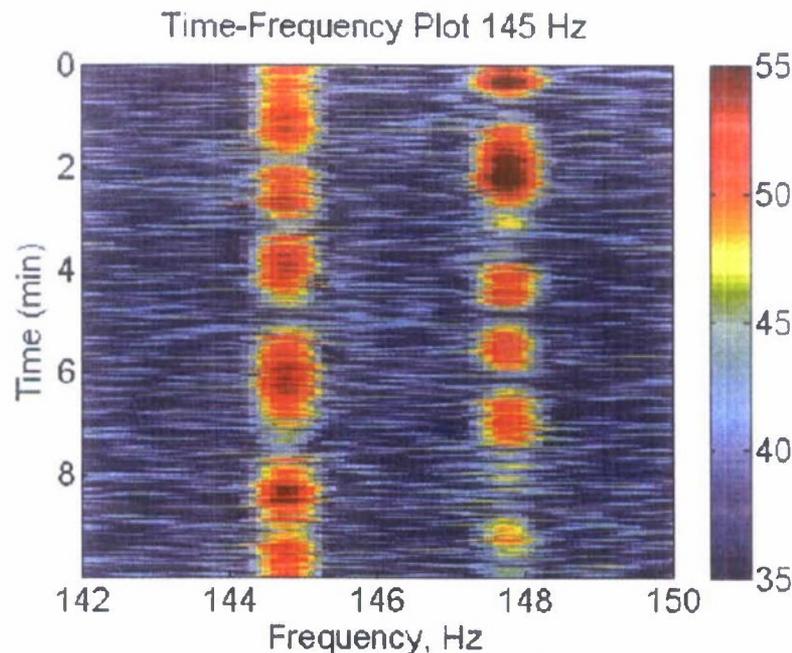


Figure 2: Time-frequency plot of signals from deep and shallow sources recording during the Event S5 of the Swellex-96 experiment. The color scale is received level, in dB (arbitrary reference). Signal amplitude modulation is caused by destructive interference between different multipaths.

The localization algorithm was run twice, once with six tones from the shallow source and again with six tones from the deep source. All of the tones were between 100 and 250 Hz. The result of the localization algorithm is a discrete posterior probability density function of the state vector at each time. Because the state vector has four components, the posterior is a unique four dimensional function at each time index. **Figure 3** shows the joint posterior probability density function of source range based on six tones radiated by the **shallow** acoustic source, while **Figure 4** shows the localization results for the **deep** source. Both figures show two dimensional slices through the four dimensional state vector posterior probability density function. The six panels correspond to different times since the start of the event. The earliest result is in the upper-left, and time increases from left to right and then from top to bottom. The grayscale is log probability density, with darker gray corresponding to higher probability density. All panels utilize the same x and y axis and color scale.

The true location of the source is indicated by the red circle. The peak of the range-depth joint posterior probability density function (the maximum a posteriori (MAP) estimate) is indicated by a red X. Perfect localization would result in the red X (the MAP estimate of source location) being in the same location as the red circle (actual source location). Distance between the estimated source location and the actual source location is localization error. In addition, with perfect localization the gray region (posterior probability density) should be compact. The prior distribution of the state vector is uniform, so a plot of the localization result at zero minutes (before data is taken) would be a solid gray background. At eight minutes in both the deep and shallow results, there is still significant ambiguity. As time passes, a subset of range-depth locations become much more likely than the others, so the posterior probability density function becomes grouped around those values.

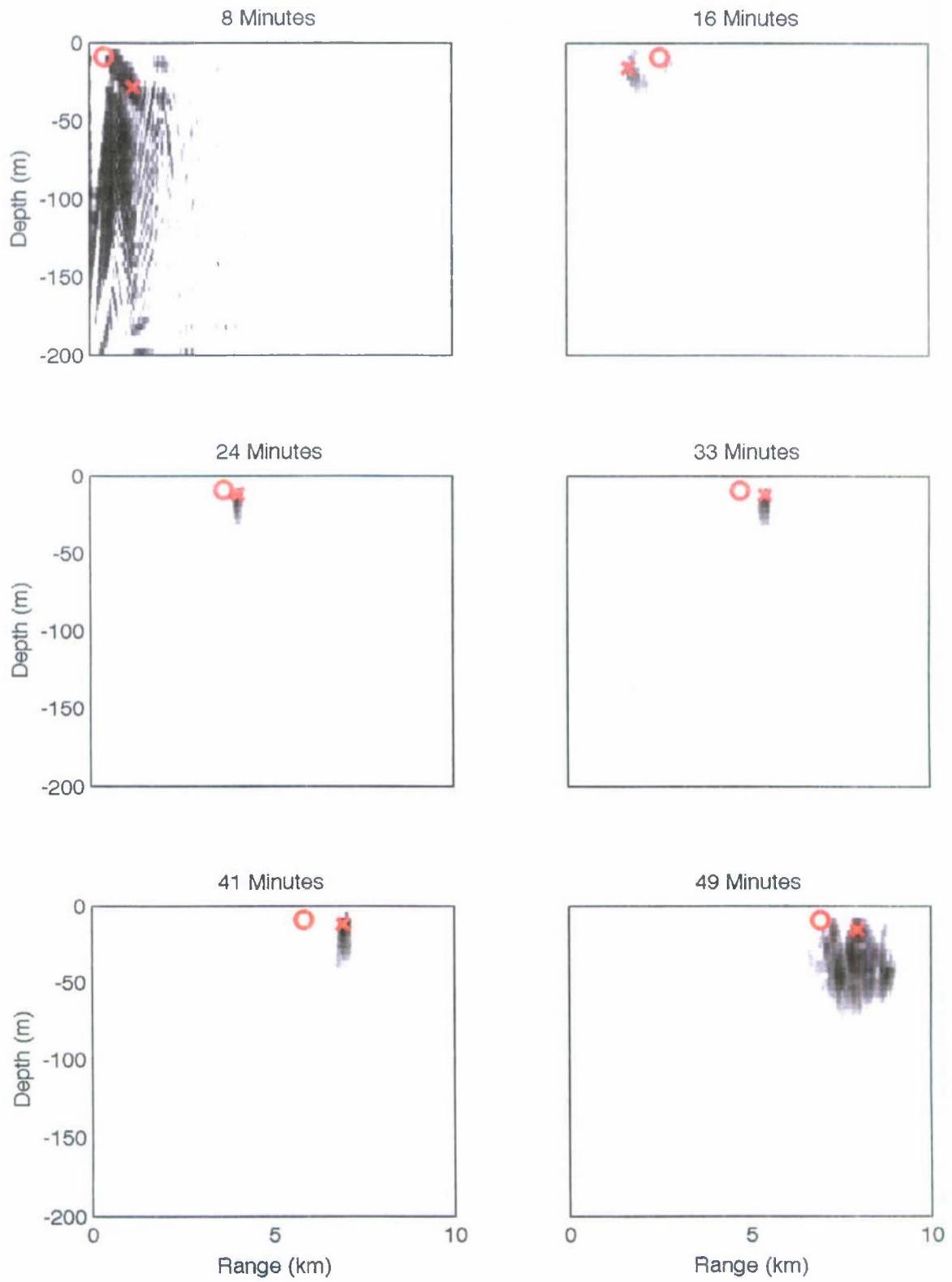


Figure 3: Joint posterior probability density function of source range and depth for 6 tones transmitted by the SHALLOW source during the Swellex-96 experiment.

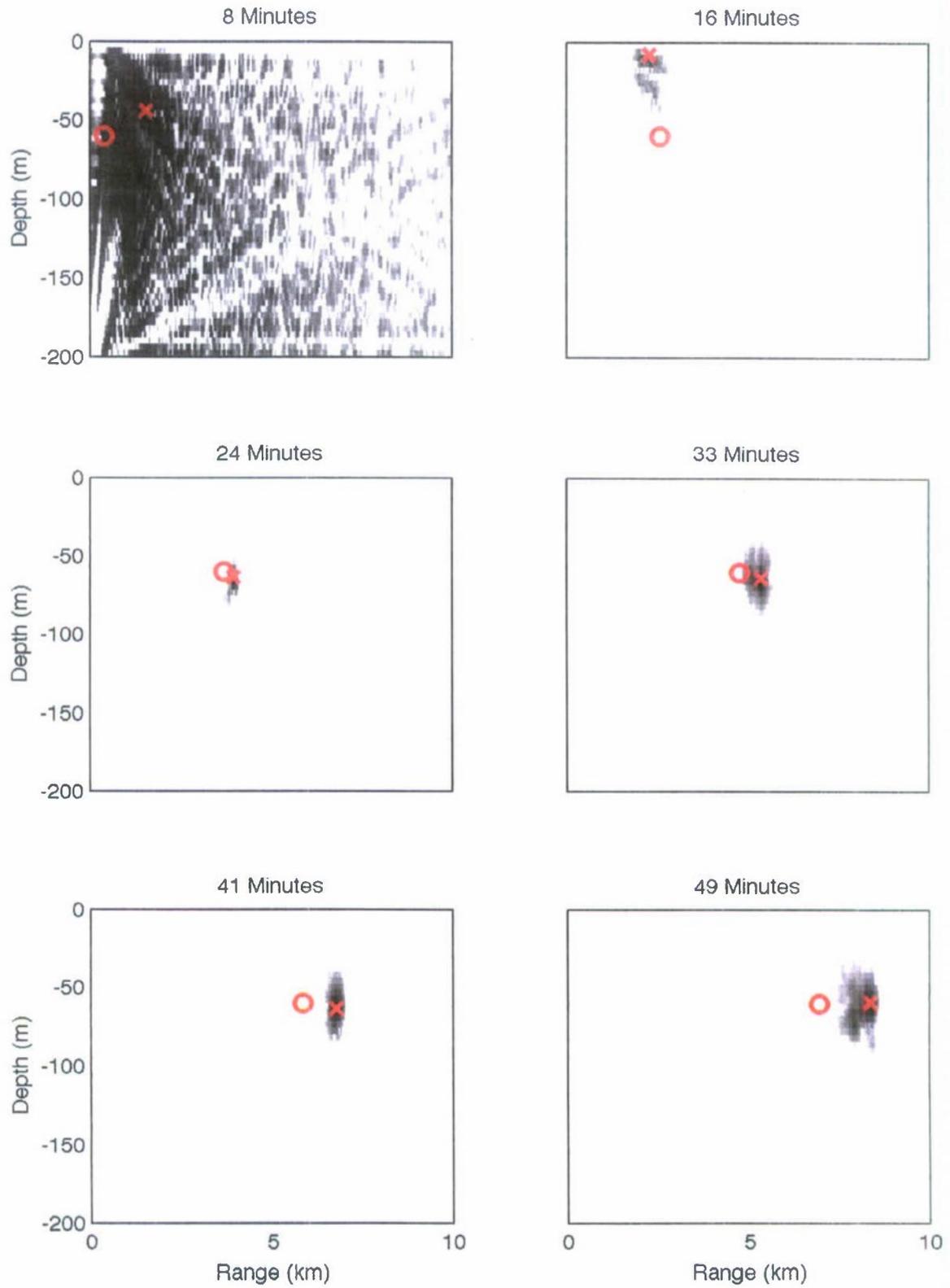


Figure 4: Joint posterior probability density function of source range and depth for 6 tones transmitted by the DEEP source during the Swellex-96 experiment.

For the results at 16, 24 and 33 minutes the range of the deep and shallow sources are well estimated, and the depth is estimated accurately in all but the 16 minute example from the deep source. For that example there is still significant uncertainty about source depth. For the 41 and 49 minute examples for the deep and shallow sources the depth estimation remains quite good, while the range estimation error increases. The reason for this is poor estimation of source velocity. This is discussed more fully by Jemmott (2010).

Localization performance can be quantified using the percentage of time that the estimated location is within a certain distance of the true source location. This information is summarized in **Error! Reference source not found.** for various distances in range and depth. Mean error can also be used to quantify the localization accuracy, and this is shown in **Error! Not a valid bookmark self-reference.** Taken together, these results indicate successful localization.

Table 1: Percentage of time that the estimated source location is within a specified distance from the true source location.

Parameter	Distance between estimated and true position	Percentage of Time: Deep Source	Percentage of Time: Shallow Source
Range	250 m	28%	13%
Range	500 m	54%	32%
Range	1000 m	94%	82%
Depth	5 m	58%	55%
Depth	10 m	63%	81%
Depth	25 m	68%	94%

Table 2: Mean localization error.

Source Location	Mean Range Error	Mean Depth Error
Shallow (9 m)	664 m	11 m
Deep (54 m)	498 m	19 m

IMPACT/APPLICATIONS

This research appears to offer promising new automation for localizing passive sonar sources. The Bayesian estimator could be applied to any undersea sensor, such as a submarine hull or towed array or a fixed sensor mounted on the ocean floor.

TRANSITIONS

We hope that the Bayesian filter will be a candidate for the FY 13 submarine Advanced Processing Build (APB 13) program.

RELATED PROJECTS

None.

REFERENCES

Jemmott, C. W. (2010). "Model-Based Recursive Bayesian State Estimation for Single Hydrophone Passive Localization," PhD dissertation, The Pennsylvania State University, State College, PA.

PUBLICATIONS

Jemmott, C. W., R. L. Culver, and J. Langelaan (2009). "Comparison of particle filter and histogram filter performance for passive sonar localization," Proceedings of Meetings on Acoustics, December 2009.

Jemmott, C. W. and R. L. Culver, "Passive sonar source depth classification using model-based amplitude statistics," submitted to the J. Ocean. Engr., Aug. 2009.

HONORS/AWARDS/PRIZES

Colin Jemmott received the Kenneth T. Simowitz Memorial Citation for publishing "An information theoretic performance bound for passive sonar localization of a moving source" in the 2010 IEEE Conference on Information Sciences and Systems, Princeton, NJ, March 2010.

Dr. Culver was elected Fellow of the Acoustical Society of America in May 2010.