Preprint
UCRL-JC-143286

Model-Based Detection in a Shallow Water Ocean Environment

J. V. Candy

This article was submitted to
Oceans 2001 Marine Technology Society/Institute of Electrical and Electronics Engineers, Honolulu, Hawaii, November 6-8, 2001

July 30, 2001

U.S. Department of Energy

Lawrence
Livermore
National
Laboratory

This work was performed under the auspices of the United States Department of Energy by the University of California, Lawrence Livermore National Laboratory under contract No. W-7405-Eng-48.

Model-Based Detection in a Shallow Water Ocean Environment

James V. Candy
University of California
Lawrence Livermore National Laboratory
P. O. Box 808, L-156
Livermore, CA 94551

***Abstract*-A model-based detector is developed to process shallow water ocean acoustic data. The function of the detector is to adaptively monitor the environment and decide whether or not a change from normal has occurred. Here we develop a processor incorporating both a normal-mode ocean acoustic model and a vertical hydrophone array. The detector is applied to data acquired from the Hudson Canyon experiments at various ranges and its performance is evaluated.**

I. INTRODUCTION

Ocean acoustic signal processing has made great strides over the past decade necessitated by the development of quiet nuclear submarines and the recent proliferation of even quieter diesel powered vessels. These improvements have been achieved by developing processors that incorporate knowledge of the surrounding ocean environment and noise into their processing schemes [1-4]. However, it is well-known that if the incorporated model is inaccurate either parametrically or an incorrect representation of the basic phenomenology, then the processor can actually perform worse in the sense that the predicted error variance is greater than that of the raw measurements [5]. In fact, one way to choose the "best" model or processor is based on comparing predicted error variances --- the processor achieving the smallest wins. In practice, the usual procedure to check for model adequacy is to analyze the statistical properties of the resulting residual or innovations sequence, that is, the difference between the measured and predicted measurements. Here again the principle of minimum (residual) variance is applied to decide on the best processor or equivalently the best embedded model [2]. Other sophisticated statistical tests have been developed for certain classes of models with high success to make this decision [5]. In any case the major problem with model-based signal processing (MBP) schemes is assuring that the model incorporated in the algorithm is adequate for the proposed application that it can faithfully represent the on-going phenomenology. Therefore, it is necessary, as part of the MBP design procedure, to estimate/update the model parameters either through separate experiments or jointly (adaptively) while performing the required processing [6]. The introduction of a recursive, on-line MBP can offer a dramatic detection improvement in a tactical passive or active sonar-type system especially when a rapid environmental assessment is required. In this paper, we discuss the development of a processor capable of adapting to the ever changing ocean environment thereby providing the required signal enhancement for detection and localization. One recent publication utilizes the processor developed in this paper as the heart of its *model-based localization* scheme [7].

With this background in mind, we investigate the development of a "model-based detector," (MBD) that is, a monitor that incorporates an initial mathematical representation of the ocean acoustic propagation model into its framework and adapts, on-line, its parameters (in this case the modal coefficients) as the ocean changes environmentally. In this paper we will use an adaptive state-space forward propagation scheme [12] and apply it to the detection and monitoring problem. This can be accomplished by constructing an "adaptive" MBP that allows continuous updating of the model parameters and is easily implemented by augmented them into the current state vector [12-14]. Currently, techniques that adjust model parameters to adapt to the changing environment are termed *environmentally adaptive*. Note that this approach mediates the so-called *mismatch problem* that plagues many processors due to their inherent non-adaptive structure [2,3].

This paper is aimed at a shallow water ocean environment; therefore, our designs are all based on the normal-mode model of ocean acoustic propagation. In order to develop the monitor, we must incorporate our knowledge about the current ocean environment and its changes as time evolves. One way to accomplish this is through models that represent the ocean acoustics coupled with other a priori information to provide initial parameters for the processor. The technique employs the *adaptive*, model-based processor (AMBP) embedded in a sequential likelihood detection scheme [4,8].

The ocean acoustic monitor passively “listens” and “learns” whether or not there is a target in the surveillance volume that is being monitored. Our approach is to develop a monitor that first “learns” about its current environment during its initialization phase and then “listens” for *changes from the normal* to declare an anomaly (possibly a target). This concept represents the basic philosophy that will be used to construct our monitors or *model-based detectors*. Once an anomaly or change from the normal is detected, the processor can then proceed to classify the target using a multiple hypothesis scheme and any other target information available.

The trade-off between modal(state)-based and innovations-based monitor designs is discussed. The underlying theory for the innovations-based design is briefly outlined and applied to an experimental data set. First, we investigate the underlying processor, conceptually to motivate the subsequent theoretical development and show that there are a number of different approaches that could be employed to solve the basic detection problem. Next, we develop one of these approaches and show how it can be implemented using the basic AMBP coupled to a detection scheme.

II. MODEL-BASED DETECTION CONCEPTS

Philosophically, the idea that we pursue in this paper is based on the fact that the typical goal of the ocean acoustic monitor will be to passively "listen" and "learn" whether or not there is a target in the surveillance volume that is being monitored. Clearly, developing models of various targets and their particular acoustic signatures is desirable, but may not be practical or for that matter even attainable. Therefore, our approach is to develop a monitor that first "learns" about its current environment during its initialization phase and the 'listens" for *changes from the normal* to declare an anomaly (possibly a target).

In order to develop a "change from normal" monitor, we must incorporate our knowledge about the current ocean environment and its changes as time evolves. One way to accomplish this is through propagation, measurement and noise models which represent the ocean acoustics coupled with other information such as sound speed, temperature, salinity etc. and any historical information available to provide initial parameters for the processor. Once initialized, the processor should then be adaptive, so it can listen and adjust its parameters (slowly) as the environment changes. Slowly is important, because as a target enters the surveillance volume the processor is not be capable of tracking rapid acoustic changes. Therefore, the monitor must decide that a change has occurred. This concept represents the basic philosophy that will be used to construct the *model-based detectors*.

The basic objective is to design a robust monitoring device capable of providing accurate estimates of the current ever changing environment and a timely detection of the target disrupting that environment. Suppose we have an L-dimensional vertical sensor array and we obtain a set of pressure-field measurements, $\{\mathbf{p}(\underline{z}_\ell)\}$ for $\ell = 1,\cdots,L$ under the narrow band assumption, where $\underline{z}_\ell$ represents the sensor spatial coordinates and $\mathbf{p}(\underline{z}_\ell)$ represents the snapshot across the array; thus, we represent the overall measurement process by the model

$$\mathbf{p}(\underline{z}_\ell) = \mathbf{c}\left[\underline{x}_\ell, \theta_\ell\right] + \mathbf{v}(\underline{z}_\ell)\,, \qquad (1.1)$$

where $\mathbf{c}\left[\underline{x}_\ell, \theta_\ell\right]$ is the nonlinear N_p-measurement vector function of the N_x-state vector $\underline{x}_\ell$ (modes, rays, etc.) and unknown N_θ-parameter vector (attenuation, wave numbers, modal coefficients, etc.) with the additive, zero-mean, white N_p-

measurement noise vector $\mathbf{v}(\underline{z}_{\ell})$ with corresponding covariance, $R_{vv}(\underline{z}_{\ell})$ representing the measurement uncertainties and the near-field ambient noise fields. Any changes in state can be used to infer an abnormal environmental condition, which must be further classified as target or not. For instance, if we assume a shallow ocean such that the states are modal functions and that the target disruption causes changes in the gains or modal coefficient parameters from the normal, then it is these changes that can be exploited to perform the detection. These states can be estimated from the noisy pressure-field snapshots using a model-based scheme, the extended Kalman filter (EKF) [4], with an ocean acoustic propagation model embedded within its structure as well as measurement and noise models as in Eq. 1.1. The output of the MBP are enhanced estimates of the states $\hat{\mathbf{x}}_{\ell}$; parameters, $\hat{\theta}_{\ell}$; pressure-field, $\hat{\mathbf{p}}(\underline{z}_{\ell})$ and the corresponding residuals or *innovations*, $\mathbf{e}(\underline{z}_{\ell})$, which is the difference between the measured and predicted pressure-fields, that is,

$$\mathbf{e}(\underline{z}_{\ell}) = \mathbf{p}(\underline{z}_{\ell}) - \hat{\mathbf{p}}(\underline{z}_{\ell}) \qquad (1.2)$$

where $\hat{\mathbf{p}}(\underline{z}_{\ell}) = \mathbf{c}\left[\hat{\underline{\mathbf{x}}}_{\ell}, \underline{\theta}_{\ell}\right]$ and the corresponding *state* is given by

$$\hat{\mathbf{x}}(\underline{z}_{\ell} \mid \underline{z}_{\ell}) = \hat{\mathbf{x}}(\underline{z}_{\ell} \mid \underline{z}_{\ell-1}) + \mathbf{K}\left[\hat{\mathbf{x}}, \hat{\theta}\right]\mathbf{e}(\underline{z}_{\ell}) \qquad (1.3)$$

with $\mathbf{K}$ a weighting (Kalman gain) matrix. Note that the notation $\hat{\mathbf{x}}(\underline{z}_{\ell} \mid \underline{z}_{\ell-1})$ implies that the state estimate at position $\underline{z}_{\ell}$ is based on $\underline{z}_{\ell-1}$ previous measurements. Equations 1.2 and 1.3 are the primary quantities of concern in the model-based detection schemes. In our modal example, the filtered (corrected) state is an estimate of the modal function at position $\underline{z}_{\ell}$, while the innovation is the error between the measurement and its prediction at $\underline{z}_{\ell}$. During normal monitoring, the processor will adaptively track changes in the ocean environment. When the model-based processor is *tuned*, the embedded models "match" the environment, the state estimates (modes, rays, parameters, etc.) are tracking and the resulting innovations are zero-mean and white [4]. Should a target enter the surveillance volume it would disrupt the environment and be reflected in the pressure-field measurement causing the innovations to become non-zero mean and/or non-white.

Various model-based monitoring schemes can be developed using this approach. We restrict them to two basic classes: (1) model the target and its environment (tracking); or (2) model the environment and investigate detectable changes due to model mismatch. Mismatch in the processor is reflected by variations in the innovation statistics, that is, they become biased and correlated. Thus, for the first class, a state-based processor is developed relying entirely on the its ability to accurately track the states of interest, while the second approach relies on detecting changes or model mismatch when an anomaly occurs causing a change. We call the tracking detection schemes, *state-based monitors* and the change detection schemes, *innovations-based monitors* (Fig. 1). There exists an inverse relationship between state-based and innovations-based monitors because the former relies on state tracking implying a "tuned" MBP while the latter relies on mismatch and therefore, an "unturned" processor for detection. We illustrate this relationship conceptually in Fig. 2 where we see the state estimate under normal conditions, the presence of a target and then the removal of the target from the surveillance volume. The ideal state-based monitor would not only know the target acoustics (or have an embedded model) but also have some a-priori knowledge of the target's track much like that of an airplane arriving at an airport where it is identified and tracked. In our case there will be a time lag when the target first enters the volume (as shown in the Fig.) because the tracker cannot instantaneously follow the target, but it eventually catches up. We show the corresponding innovations for this track and since the tracker is "tuned" the innovations are unbiased and white. For the same scenario we show the innovations-based monitor which is tuned only to the environment. With no target present, we see that the innovations are also zero mean and white, but when the target enters the volume, the innovations become biased since there is no model of the target included and therefore, we see the "jump". After the target exits, the innovations again eventually return to normal. So we see that the inverse relationship between the two distinct approaches. *State-based monitors* are based on tracking the target with the cost of a significant amount of a- priori target information required, while *innovations-based monitors* are based on not tracking and mismatch occurring and the underlying innovations statistics for the detection. Next we briefly discuss, the underlying detection theory for the innovations-based monitor design, since that approach is our primary concern with the lack of target models.

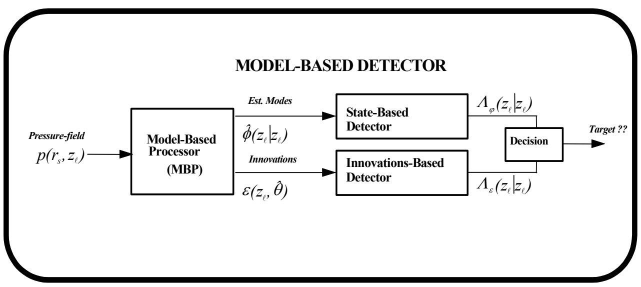

Fig. 1. Model-based detector: MBP, state-based and innovations-based detection schemes.

III. MODEL-BASED DETECTION THEORY

In this section we discuss the design of a detector to monitor the performance of the model-based processor and indicate when the model is no longer adequate or does not track the measured data. First, we briefly discuss the required theory. Once this is accomplished, we discuss the development of a practical processor and apply it to our simulated data sets.

When we employ the extended Kalman filter (EKF) algorithm as our MBP of the previous section to measured array data, we not only reconstruct the modal/range functions and pressure-field measurements, but also provide a

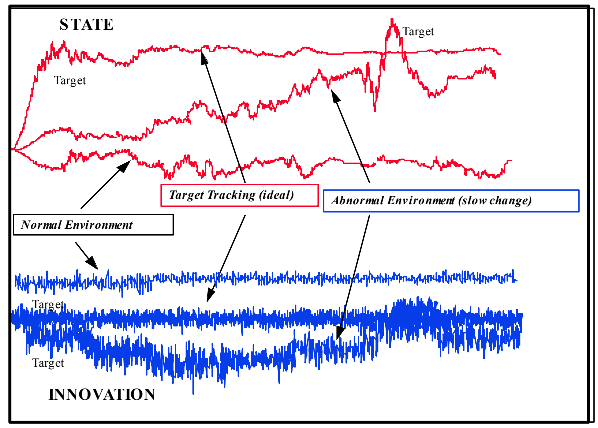

Fig. 2. Conceptual model-based detection showing state-based and innovations-based MBP outputs (monitor inputs) for normal, tracking and abnormal environments.

whitening operation transforming the correlated measurements to the uncorrelated innovations sequence, $e(\underline{z}_\ell)$. It is well known that a necessary and sufficient condition for a Kalman filter to provide optimal performance is that the innovation sequence is zero-mean and white [5]. Thus, the innovations sequence is zero-mean and white only when the propagation and measurement models reflect the true ocean acoustics and noise and the EKF is properly tuned. Statistical changes in $e(\underline{z}_\ell)$, reflect changes from the normal or expected operation; therefore, we can utilize these changes to monitor the performance of the propagation model employed in the processor. First, we develop the theoretical monitor. From the insight we gain in its development, we then investigate a more pragmatic approach and apply it to our shallow water problem.

Theoretically, it can be shown that when "model mismatch" occurs, the innovations become non-zero mean and are no longer white; therefore, we must develop a monitor that decides whether or not the innovations satisfy the required properties, that is, we test the hypothesis that

$$H_o: \quad \{\mathbf{e}(\underline{z}_\ell)\} \sim N(\mathbf{0}, \mathbf{R}_{\mathbf{ee}}(\ell)) \qquad \text{(Normal)}$$
$$H_1: \quad \{\mathbf{e}(\underline{z}_\ell)\} \sim N(\overline{\mu}_e(\underline{z}_\ell), \overline{\mathbf{R}}_{\mathbf{ee}}(\ell)) \quad \text{(Abnormal)}$$
$$(1.4)$$

which is a statistical test for the zero-mean and whiteness of the innovation sequence. Note that we assume that we *know* the model error and how to calculate $\bar{\boldsymbol{\mu}}_{\mathbf{e}}, \bar{\mathbf{R}}_{\mathbf{ee}}$ a-priori. The optimal solution to this problem is based on constructing the likelihood ratio for the *sequential innovations detector* (SID) with assumed gaussian distributions [5], that is,

$$\mathrm{L}[E(L)] \equiv \frac{\Pr[E(L) \mid H_1]}{\Pr[E(L) \mid H_o]} \underset{H_0}{\overset{H_1}{\gtrless}} \tau \tag{1.5}$$

where $E(L) \equiv \{\mathbf{e}(z_1), \mathbf{e}(z_2), \cdots, \mathbf{e}(z_L)\}$ or *recursively* we have

$$\mathrm{L}[E(\ell)] \equiv \mathrm{L}[E(\ell-1)] \frac{\Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_1]}{\Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_o]} \tag{1.6}$$

Taking logarithms gives

$$\begin{aligned} \Lambda(z_\ell) = \Lambda(z_{\ell-1}) &+ \ln \Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_1] \\ &- \ln \Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_o] \end{aligned} \tag{1.7}$$

Thus, the sequential probability ratio test (Wald test) is given by

$$\begin{array}{lll} \Lambda(z_\ell) > \tau_1 & & \text{accept } H_1 \\ \tau_o \le \Lambda(z_\ell) \le \tau_1 & & \text{continue} \\ \Lambda(z_\ell) < \tau_o & & \text{accept } H_o \end{array} \tag{1.8}$$

Under the gaussian assumptions the conditional mass functions are

$$\Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_o] = (2\pi)^{-L/2} |\mathbf{R}_{\mathbf{ee}}|^{-1/2} \times \exp\left[-\frac{1}{2}\mathbf{e}'(z_\ell)\mathbf{R}_{\mathbf{ee}}^{-1}(z_\ell)\mathbf{e}(z_\ell)\right] \tag{1.9}$$

and

$$\Pr[\mathbf{e}(z_\ell) \mid E(\ell-1), H_1] = (2\pi)^{-L/2} |\bar{\mathbf{R}}_{\mathbf{ee}}|^{-1/2} \times \exp\left[-\frac{1}{2}\left(\mathbf{e}(z_\ell) - \bar{\boldsymbol{\mu}}_{\mathbf{e}}(z_\ell)\right)' \bar{\mathbf{R}}_{\mathbf{ee}}^{-1}(z_\ell)\left(\mathbf{e}(z_\ell) - \bar{\boldsymbol{\mu}}_{\mathbf{e}}(z_\ell)\right)\right] \tag{1.10}$$

If we include the determinants in the thresholds, then we obtain the modified decision function

$$\begin{aligned} \lambda(z_{\ell+1}) = \lambda(z_\ell) &+ \frac{1}{2}\mathbf{e}'(z_\ell)\mathbf{R}_{\mathbf{ee}}^{-1}(z_\ell)\mathbf{e}(z_\ell) - \\ &\frac{1}{2}\left(\mathbf{e}(z_\ell) - \bar{\boldsymbol{\mu}}_{\mathbf{e}}(z_\ell)\right)' \bar{\mathbf{R}}_{\mathbf{ee}}^{-1}(z_\ell)\left(\mathbf{e}(z_\ell) - \bar{\boldsymbol{\mu}}_{\mathbf{e}}(z_\ell)\right) \end{aligned} \tag{1.11}$$

which is compared to a set of thresholds as in Eq. (1.8).

The implementation of this monitor presents some basic problems, but does illustrate a potential optimal solution to the model monitoring problem. As mentioned, the SID requires a-priori knowledge of the actual model "mismatch" and structurally how it enters the propagation model to obtain $[\bar{\boldsymbol{\mu}}_{\mathbf{e}}, \bar{\mathbf{R}}_{\mathbf{ee}}]$ for the monitor.

Next we consider a more practical statistical test for model mismatch, the *weighted sum squared residual* (WSSR) test [6]. The WSSR statistic essentially aggregates all of the information available in the innovation vector over some finite window of N samples. It is defined by the decision function

$$\rho(k) \equiv \sum_{k=\ell-N+1}^{\ell} \mathbf{e}'(z_\ell)\mathbf{R}_{\mathbf{ee}}^{-1}(z_\ell)\mathbf{e}(z_\ell) \qquad \ell \ge N \tag{1.12}$$

which is compared against a threshold, that is,

$$\rho(k) \underset{H_0}{\overset{H_1}{\gtrless}} \tau \text{ for } \tau = NL + 1.96\sqrt{2NL} \tag{1.13}$$

In this case H_o is the hypothesis that there is a *normal* condition with white innovations indicating no model "mismatch," while H_1 is the hypothesis that there is an *abnormal* condition or mismatch specified by non zero-mean, non-white innovations.

IV. HUDSON CANYON RESULTS

In this section we briefly discuss the results of executing the WSSR detector on Hudson Canyon shallow water data. The Hudson Canyon experiment was performed in 1988 in the Atlantic Ocean just off the coast of New Jersey. It was led by Dr. W. Carey with the primary goal of investigating acoustic propagation (transmission and attenuation). The Canyon experiment was performed at low frequencies (50-600Hz) in shallow water of 73m depth during a period of calm sea state. A calibrated acoustic source was towed radially at 36m depth to distances of 0.5-26Km. A fixed vertical hydrophone array of 24 phones spaced 2.5m apart anchored at the seafloor up to a depth of about 14.5m below the sea surface was used to make the acoustic measurements. Hudson Canyon is characterized by a flat bottom for the data sets used in this study. CTD and sound speed measurements were made at regular intervals and the data were collected under carefully controlled conditions in the ocean environment. Experimentally, the time series data collected at 50Hz is dominated by 5 modes occurring at wave numbers between 0.14 and 0.21 m^{-1} with relative amplitudes increasing with increased wave numbers (see [9] for details).

Our *normal* ocean environment is modeled by the source at 1Km synthesizing ambient noise at the array. The parameters for the run were obtained from the experimental estimates and they can be found in Refr. [9]. For the "tuned" (zero-mean, white) MBD, the results are shown in Fig. 3. where we observe the estimated (+) and raw (-) pressure-field measurements at the array in 3a with the corresponding innovations in 3b. The results of the zero-mean/whiteness test are shown in 3c along with the output of the WSSR detector in 3d. Here we see that the MBD incorporating the AMBP is tuned as demonstrated by the zero-mean/white innovations with the corresponding WSSR decision function lying beneath the threshold for the duration of the test. Thus, the *normal* condition is achieved. Next we use this tuned processor to monitor the surveillance volume. We move the source from 1.5Km and to approximately 4Km at 0.5Km increments and observe the WSSR detector performance at each different range. We show the results of the WSSR run for the "abnormal" ocean.

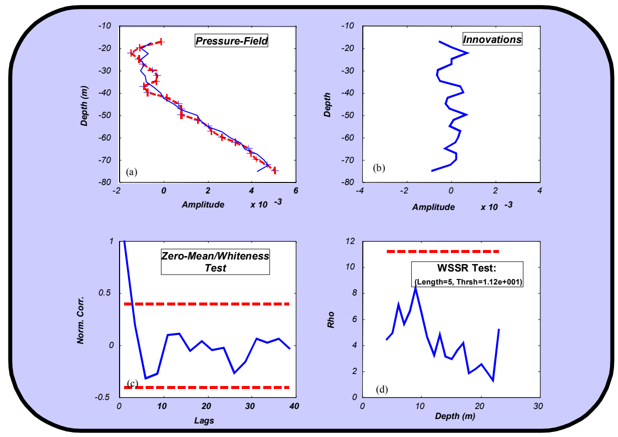

Fig. 3: Tuned Hudson Canyon Data (1Km Source): (a) Raw/Estimated Pressure-Field. (b) Innovations. (c) Normal case: Zero-Mean/White (1.5e-5<4.9e-1/0% out). (d) WSSR below threshold (White).

The results of processing the experimental Hudson Canyon data show that the WSSR monitor is capable of detecting the target (source) as it changes position within the surveillance volume. Observing the performance is Fig. 4, we see that for each range from 1.5-4.0Km under investigation, the WSSR monitor is able to detect the presence of an anomaly instantaneously using a 5-sample window length (N=5 in Eq. 1.12). Detection is rapid (< 10 samples) for the "close in" (<4Km) range differentials between array and source. It takes a longer sample period for detection at longer ranges. This can be explained by the fact that the 1Km "tuned" AMBP is close to calibration when the range of the source is reasonably close to the array. In fact, a simple zero-mean/whiteness test on each of the ranges is deemed statistically acceptable. As the range increases to a point where the "normal" model is no longer valid or the environmental adaption provided by the AMBP is slow, then source detection occurs. For instance, at 4Km the measured pressure-field is most different from the previous ranges and therefore the adaption process cannot catch up to the changes. The processor tries but fails after 15 samples (see Figs. 4 and 5) enabling the detection to occur. Note that the AMBP is not tuned for the 4Km source position as indicated by its lack of whiteness in both statistical tests (Whiteness and WSSR tests).

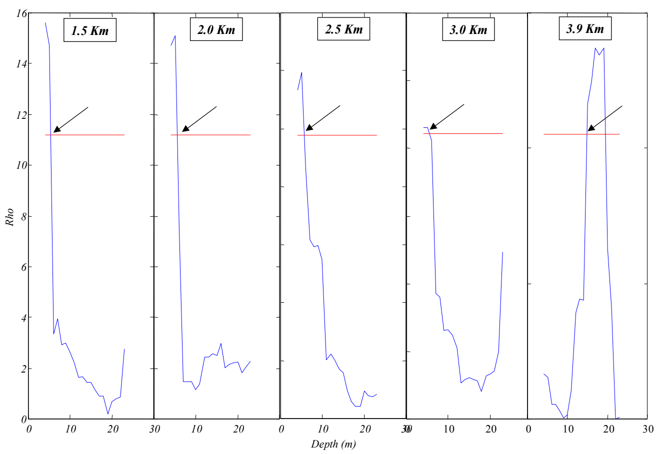

Fig. 4: Hudson Canyon Data (1.5-3.9Km Sources): WSSR detections of abnormal condition due to target (source) range position changes(arrow indicate threshold exceeded).

V. SUMMARY

In this paper we have outlined the development of a model-based detector and applied it to experimental data gathered from the Hudson Canyon [9]. We have demonstrated detection performance indicating that the use of the suboptimal WSSR scheme enables us to detect an anomaly caused by the presence of a target (source) at a range other than that used for calibration (tuning). Future effort will be aimed at developing the optimal SID scheme of Section III from historical ocean acoustic parameters characterizing the surveillance volume and using them to develop a reference model.

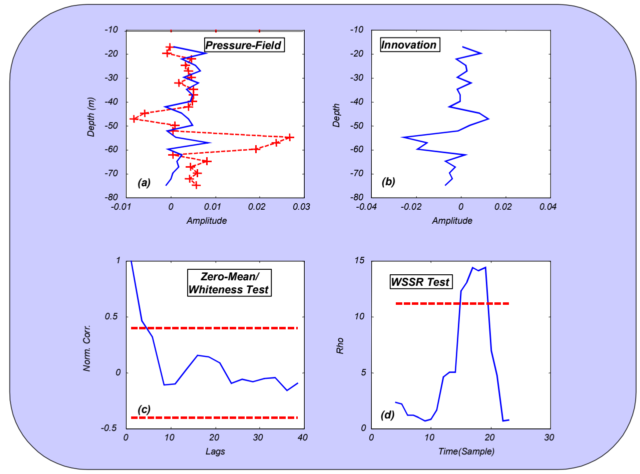

Fig. 5: UNtuned Hudson Canyon Data (4Km Source): (a) Raw/Estimated Pressure-Field. (b) Innovations. (c) Abnormal case: Zero-Mean/White Test (2.3e-3 < 4.9e-1/6.25% out). (d) WSSR Test: threshold exceeded (non-white) at 15 samples.

This work was performed under the auspices of the U.S. Department of Energy by the University of California, Lawrence Livermore National Laboratory under Contract No. W-7405-Eng-48.

REFERENCES

[1] A. Tolstoy, *Matched-Field Processing for Ocean Acoustics.* World Press: New Jersey, 1993.

[2] E. J. Sullivan and D. Middleton, "Estimation and detection issues in matched-field processing" *IEEE J. Oceanic Engr.* **18**, (3), 156-167, 1993.

[3] A. Baggeroer, W. Kuperman, and H. Schmidt, "Matched-field processing: source localization in correlated noise as an optimum parameter problem," *J. Acoust. Soc. Am.* , **83**, (2), 571-587, 1988.

[4] J. V. Candy and E. J. Sullivan, "Ocean acoustic signal processing: a model-based approach," *J. Acoust. Soc. Am.,* vol. **92**, (6), 3185-3201, 1992.

[5] J. V. Candy and E. J. Sullivan, "Model-based identification: an adaptive approach to ocean acoustic processing," *IEEE J. Oceanic Engr.* **21**, (3), 273-289 1996.

[6] J. V. Candy, *Signal Processing: The Model-Based Approach*, McGraw-Hill: New York, 1986.

[7] J. V. Candy and E. J. Sullivan, "Passive localization in ocean acoustics: a model-based approach," *J. Acoust. Soc. Am.,* vol. **98**, (3), 1455-1471, 1995.

[8] J. V. Candy and E. J. Sullivan, "Monitoring the ocean environment: a model-based detection approach," *5th European Confr. on Underwater Acoustics.,* Lyon, France, 2000.

[9] W. M. Carey, J. Doutt, R. Evans, and L. Dillman, "Shallow water transmission measurements taken on the New Jersey continental shelf," *IEEE J. Oceanic Engr.* **20**, (4), 321-336, 1995.