MODEL-BASED OCEAN ACOUSTIC SIGNAL PROCESSING

Edmund J. Sullivan
Prometheus Inc.
Newport, Rhode Island 02840

Zoi-Heleni Michalopoulou
Department of Mathematical Sciences, New Jersey Institute of Technology
University Heights, Newark, New Jersey 07102

Caglar Yardim
Marine Physical Laboratory, Scripps Institution of Oceanography
University of California San Diego, San Diego, California 92106

Background

In the ocean, acoustic information arrives at the receiver distorted by the medium and corrupted by noise. Even when the signal is deterministic, a complete description must minimally be a statistical one. If information regarding the medium or the form of the signal is available, it too can and should be included, leading to what is known as Model-Based signal processing. In other words, any processing carried out on the received signal should contain the best characterization of the distortion by the medium and corruption by the measurement noise that is available.

> *"…any processing carried out on the received signal should contain the best characterization of the signal, the distortion by the medium and the corruption by the measurement noise that is available."*

Signal processing is conventionally divided into three tasks; detection, estimation, and classification. Detection is defined as the determination of the existence or non-existence of a postulated signal at the receiver, and in its simplest form, is a simple binary (yes/no) decision. Detection *per se* is not discussed in detail in this article. Estimation is the determination of the values of certain parameters of the signal, the source, or the medium. A simple example is the determination of the bearing (angle) of an acoustic source at a receiving array of hydrophones. At its most complex, estimation leads to a class of problems called Inverse Problems, an example of which could be the extraction of the value of some property of the ocean (sound speed), the ocean bottom (density, sound speed, etc.) from the signal, or the characterization of a source or scatterer, commonly called Identification.

The quantification of detection and estimation is where statistics plays its major role. In the case of detection, the performance is measured in terms of the probability of detection for a given probability of false alarm. This is embodied by the so-called Neyman-Pearson detector,[1] which seeks the maximum probability of detection for a fixed probability of false alarm. There are more sophisticated approaches to detection based on formal hypothesis testing, and information on these approaches is can be found in Ref. 2 and references therein.[2]

In estimation, which is the main focus of this article, the quality of the estimate is usually measured by its variance, which is a measure of the statistical spread of the estimate about its true value. Both of these criteria require the specification of a probability density function. In these cases, it is convenient to divide the processing task into two classes; parametric and non-parametric. What is meant by non-parametric is that the processing does not concern itself with other than the detection decision or the value of the estimate. Parametric, on the other hand, attempts to assign values to certain parameters of the signal, as in time series analysis, or parameters describing the source and the medium. These parameters may or may not be easily identified as directly representing actual physical parameters. When they are, it is convenient to call this type of parametric processing Model-Based Processing (MBP),[3,4] which is the main subject of this article.

In Fig. 1, we show a sketch of an inverse problem approached with MBP. In ocean acoustics, a mathematical model (denoted in the figure as the forward model) is selected (the wave or Helmholtz equation, for example), expressing the physics of the medium. In the forward problem, equations are then solved under the assumption of a known set of parameters; sound speed and source location is a potential set of such parameters. The solution provides the acoustic field under the assumed conditions. Data collected in the ocean consist of measurements of the actual field. In the inverse problem, we now treat the parameters (previously assumed as known), as unknown or uncertain quantities and move backwards from the measured data for the estimation of the optimal set of parameters generating the field best resembling the measurements. It is the estimation performance that we wish to improve using MBP, connecting a physical/mathematical model and signal processing.

Fig. 1. An inverse problem.

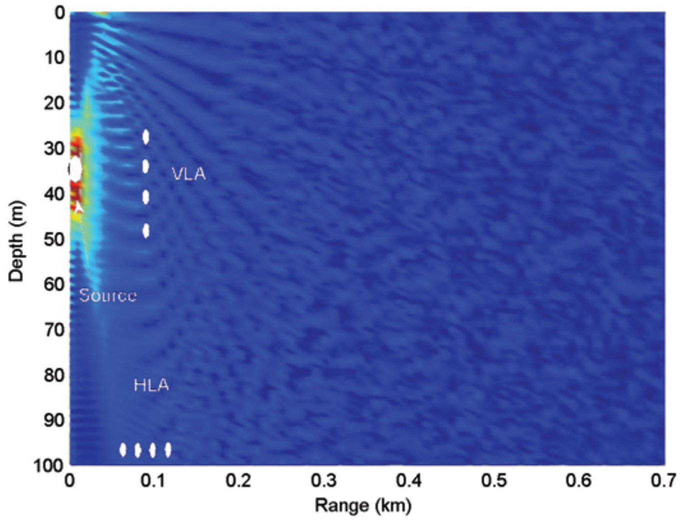

Fig. 2. Measuring the acoustic field in the ocean.

Figure 2 illustrates the ocean acoustics estimation problem. A source emits sound, which is sensed at an array of phones. The array could be a vertical line array (VLA), a horizontal line array (HLA), or a more complex configuration of a sensor geometry. We wish to "invert" the measured data for estimation purposes. Parameters to be estimated may include source location, array tilt and shift, sound speed in the ocean and seafloor sediments, sediment thickness, attenuation, and density.

Model-Based signal processing

The concept of MBP is not a new one, because the specification of a model is required for any inverse problem. However, its use as a means of improving the performance of an ocean acoustic processor is a relatively novel idea. Historically, its use in ocean acoustics probably began with the work of Hinich,[5] who showed that by including the propagation model in the algorithm, the depth of an acoustic source in an acoustic waveguide could be readily estimated. Bucker[6] later showed that both the range and depth of the source could be estimated and introduced the term "Matched-Field processing," or MFP. A more detailed description of the history and methods of MFP can be found[7] in a special dedicated issue of the Institute of Electrical and Electronic Engineers (IEEE) *Journal of Oceanic Engineering*.

Originally, MFP was applied solely to source localization problems, under the assumption that the parameters describing the medium are known. Although a great deal was done in the field of MFP for source localization, still a rather useful approach to many ocean acoustic problems, there remains a fundamental problem which plagues it, sometimes referred to as the "Mismatch Problem." This problem arises from the fact that the solution can be highly sensitive to errors in the model parameters. This is not surprising, because it is the complexity of the model itself that leads to the observability of the desired parameters. Thus, if the model is not correct, it will lead to degradation. Sometimes this degradation can be catastrophic.

Although there have been many approaches to try to remedy this, the first major step forward was the work of Richardson and Nolte,[8] who, working within a Bayesian framework, included *a priori* probabilities in the MFP algorithm to account for uncertainties in the troublesome parameters. As a result, they obtained posterior probability density functions (PDFs) for source location, which described the uncertainty in the estimation process resulting from the lack of precise knowledge on the propagation medium characteristics.

MFP was soon after extended to inversion for environmental parameters. The first such application of MFP was presented by Livingston and Diachok,[9] who estimated the under-ice reflection coefficient applying MFP to data and sound propagation models in the Arctic. Inversion for the characteristics of the propagation medium subsequently expanded with estimation of geoacoustic parameters in highly complex environments.[10-16]

Within a Bayesian framework, but with dynamic models in mind—namely Bayesian filtering, Candy and Sullivan[17] sought to remedy the mismatch problem by embedding the propagation model into a Kalman filter (KF). This has the advantage of allowing the troublesome parameters to be included as part of the state vector of unknowns, a procedure known as "augmentation." A further advantage is that the Kalman formalism provides a natural and self-consistent framework for the inclusion of essentially any model. Most subsequent work has improved on this approach, especially by use of the so-called Extended and Unscented Kalman filters[18,19] (EKFs and UKFs, respectively) and several variants, and the particle filter (PF),[20] the latter pioneered in ocean acoustics by Candy[21,22] and subsequently extended.[23-26] PFs provide a powerful framework for performing signal processing in nonstationary dynamic systems involving nonlinear equations and non-Gaussian PDFs as well as a stream of incoming data. A summary of applications of the family of Kalman and particle filters to problems in ocean acoustics[27] is available. These methods are often referred to as sequential Bayesian filtering and rely on a two-stage process. During the first stage, unknown state variables x_k at step k are predicted using estimates from step k–1. The second stage entails an update stemming from physical and statistical models that relate acoustic measurements y_k to state variables x_k. Figure 3 illustrates the two steps of sequential Bayesian filtering. In addition to providing point estimates for the state variables, sequential Bayesian filtering also provides posterior PDFs at every step, as will be shown.

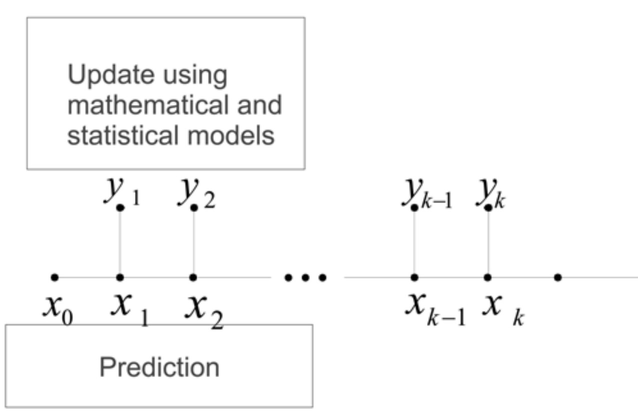

Fig. 3. Sequential Bayesian filtering.

Sequential Bayesian filtering has been frequently applied

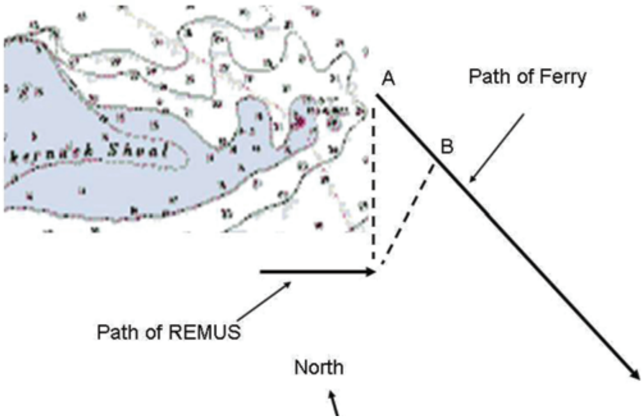

Fig. 4. Ferry and Remus tracks.

to source localization and tracking. It has also been successfully employed in geoacoustic inversion,[24,28,29] tracking of internal wave fields,[30] tracking of frequencies in time-frequency representations,[23] and spatial arrival tracking across an array.[26] Some applications of MBP in ocean acoustics with sequential Bayesian filtering (with Kalman or particle filters) are discussed next.

Applications

Towed array processing

One novel application of MBP in ocean acoustics is its use as a processor for a short towed array. Because a towed array is a moving sensor, it naturally incurs Doppler in the received signal. Here, MBP is a means of exploiting the bearing information in the Doppler.

A simple example of this can be seen from the following. Suppose a narrow-band plane wave signal of radian frequency ω_0 is arriving at a receiver moving with speed v, where the direction of propagation of the signal is at angle θ with respect to the normal to the direction of motion of the receiver, sometimes referred to as *broadside*. The frequency of the received signal will be Doppler-shifted to frequency ω, and the sign of the product $v\sin\theta$ determines the sign of the Doppler, i.e., positive implying up-Doppler. The relation between ω and ω_0 is given by the following well known expression:

$$\omega = \omega_0(1 \pm (v/c)\sin\theta) \qquad (1)$$

Here, c is the speed of sound in the water. It is clear then, that if one has knowledge of the source frequency, the bearing can be estimated. Passive synthetic aperture bearing estimation exploits this idea by casting the problem as joint estimation of the source frequency and the bearing angle.

Although the signal in this example is narrowband, the same approach can be used in the broadband case. More information on passive synthetic aperture and its history is available.[31,32] (The term "synthetic aperture" refers to the fact that this processor outperforms the conventional processor, and therefore is equivalent to a conventional processor with a significantly longer aperture.) In the following example, the problem is solved by the use of a Kalman Filter.

During an experiment carried out jointly by Boston University and Woods Hole Oceanographic Institution, using the autonomous undersea vehicle REMUS, a short (six-element) array was towed. During the experiment, a ferry from the mainland of Cape Cod on its way to the island of Nantucket passed through the area. The resulting data provide the basis for this example.[33,34]

The six-element array, which had an element spacing of 0.75 m, was towed at a speed of 1.5 m/s. The ferry first appeared at an angle very close to broadside (0^0) to the towed array. The array was moving in a straight line toward the course of the ferry, which was moving at approximately 20 kts, on a straight course from left to right with respect to forward endfire of the array. This configuration is depicted in Fig. 4. The points A and B are the ferry positions for the respective onset and closest point of approach (CPA) of the ferry source used in this work. The distance between these two points is approximately 2 km. Although the radiated sound from the ferry was quite broadband, extending over a band from about 100 to 1000 Hz, there was a particularly strong band of energy occurring between 890 and 920 Hz. This energy band was

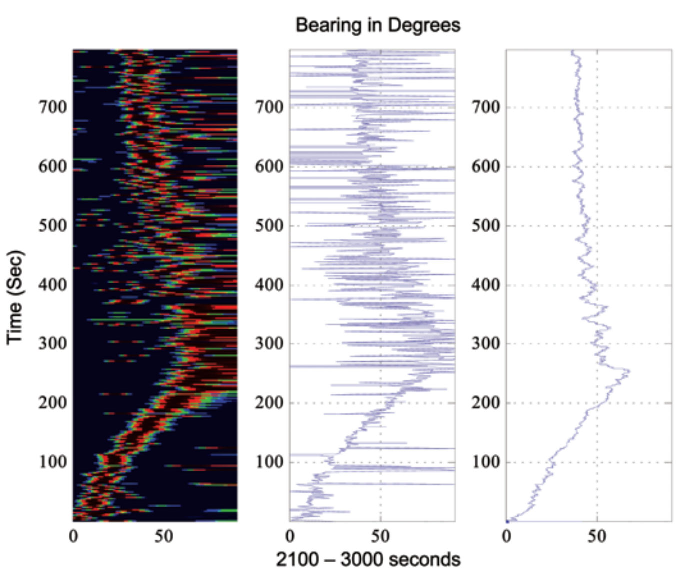

Fig. 5. Results for the random walk case.

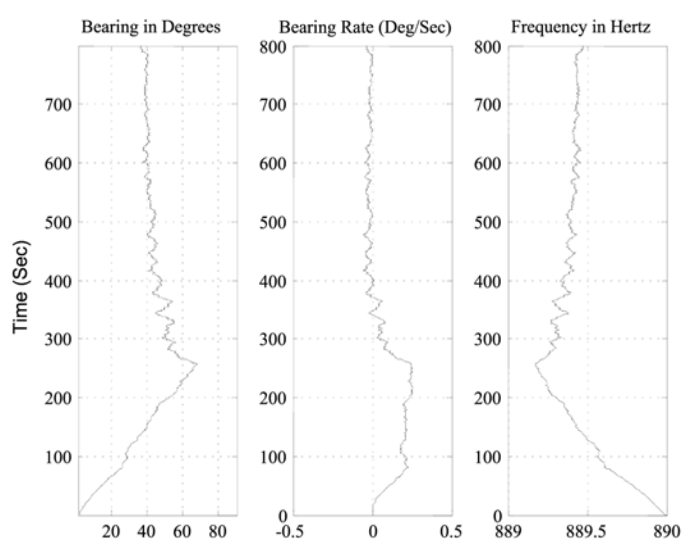

Fig. 6. Results for the bearing-rate augmented case.

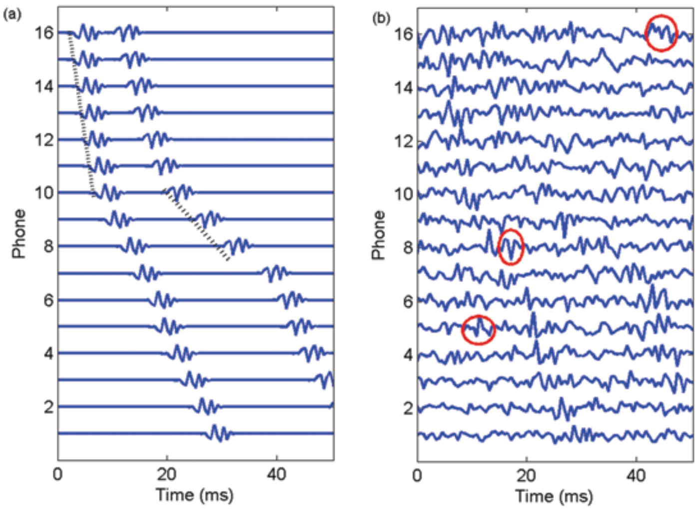

Fig. 7. (a) Synthetic, noise-free time series received at an array of vertically and horizontally separated hydrophones; (b) time series after noise has been added.

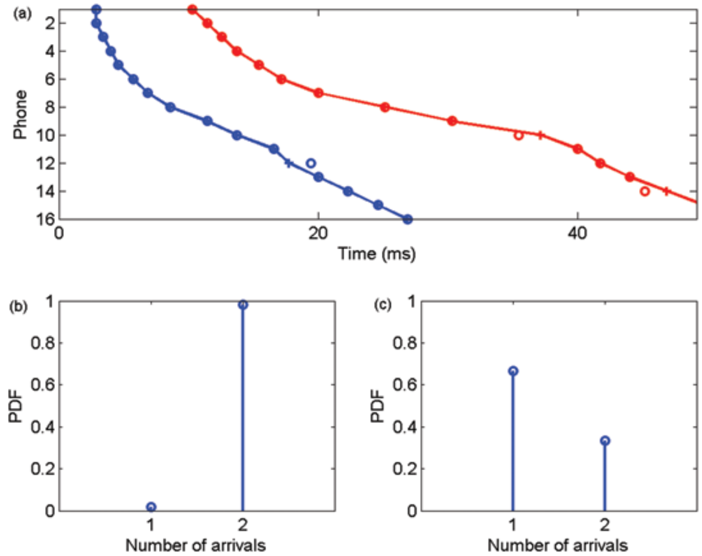

Fig. 8. (a) True arrival times (+) and particle filter (PF) estimates (o). Posterior probability density functions (PDFs) for the number of arrivals at phone (b) 14, and (c) 15.

selected for the data in this paper. At this band of frequencies, the array has an acoustic length of approximately 2.3 λ.

A KF was then used to process the data. The state vector consisted of the target bearing and the source frequency, which in this broadband case, was the lowest frequency of a sequence of short fast Fourier transforms (FFTs) of the time series data from each hydrophone. The measurement equation was made up of the six hydrophone time series and the observed frequency mentioned above. The results are shown in Figs. 5 and 6. In both figures the vertical axis is time in seconds. The left panel of Figure 5 is the result of beamforming the data with a conventional frequency-domain beamformer.

The center panel shows the maxima of the plot in the left panel, and the right panel shows the synthetic aperture result. As expected, both estimators fail to resolve the bearing in the neighborhood of endfire. After endfire, beginning at about 400 seconds, the synthetic aperture clearly shows the cumulative effect expected of such a processor.

Figure 6 depicts the results for the case where the bearing rate is augmented into the processor, which adds another element to the state vector. The left panel shows the bearing estimate, the center panel shows the estimate of the bearing rate, and the right-hand panel shows the estimate of the source fundamental frequency. Note that this frequency is not constant, because the source itself is undergoing non-zero accelerations. Thus, before endfire it has an up Doppler and, after endfire, a down Doppler and the apparent fundamental frequency of the source must adapt to these speed changes.

The fact that the bearing estimate in Fig. 6 shows some improvement over that of Fig. 5 bears some explanation. The KF requires that the user specify a trial value for the state error covariance. The value chosen constitutes a lower bound on the eventual state error covariance. This provides a means for the user to control the convergence rate of the process. That is, the larger this covariance is chosen to be, the faster the convergence of the processor, but at the price of a noisier estimate. The estimate in Fig. 6 allowed a smaller value for this covariance to be used, because the convergence requirements for the case of a non-zero bearing rate are eased by the inclusion of the bearing rate directly into the dynamics. Thus, the limiting state estimation error is smaller in Fig. 6 (left panel), than that in Fig. 5 (right panel). This adjustment of the covariance input to the KF is referred to as *tuning*, and is discussed in Refs. 35 and 36.

The performance of the synthetic aperture processor presented here is a consequence of proper modeling. There are three elements to the model structure. First, the proper inclusion of the Doppler provides additional bearing angle information; second, the modeling of the state as a Gauss-Markov process exploits the memory implicit in such a recursive model; and third, explicitly including the bearing rate in the model further decreases the bearing error.

Spatial time delay tracking

Estimating difference in arrival times of signals at a set of receiving phones provides critical information on the propagation medium and geometry. It is commonly referred to as time-delay or arrival time estimation[37] and has a vast number of applications in sonar, communications, speech processing, architectural acoustics, and medical diagnostics among other fields. In ocean acoustics, in particular, it has been shown in the past how arrival time estimation can lead to accurate bathymetry estimation, source localization, and geoacoustic inversion.[37-40] As expected, the accuracy of arrival time estimates determines source localization and environmental parameter inversion quality.

Typically, arrival time estimation pertains to identifying arrival times of distinct signals at a specific phone or finding the time difference between arrivals of the same signal at different receivers. The idea that is explored here is to combine both aspects. We are interested in not only estimating times at which distinct paths arrive at a given phone, but also employing information on arrival times from one receiver to the next, in order to improve arrival time estimation at each phone. Using information from one hydrophone for the estimation process at another hydrophone leads to the concept

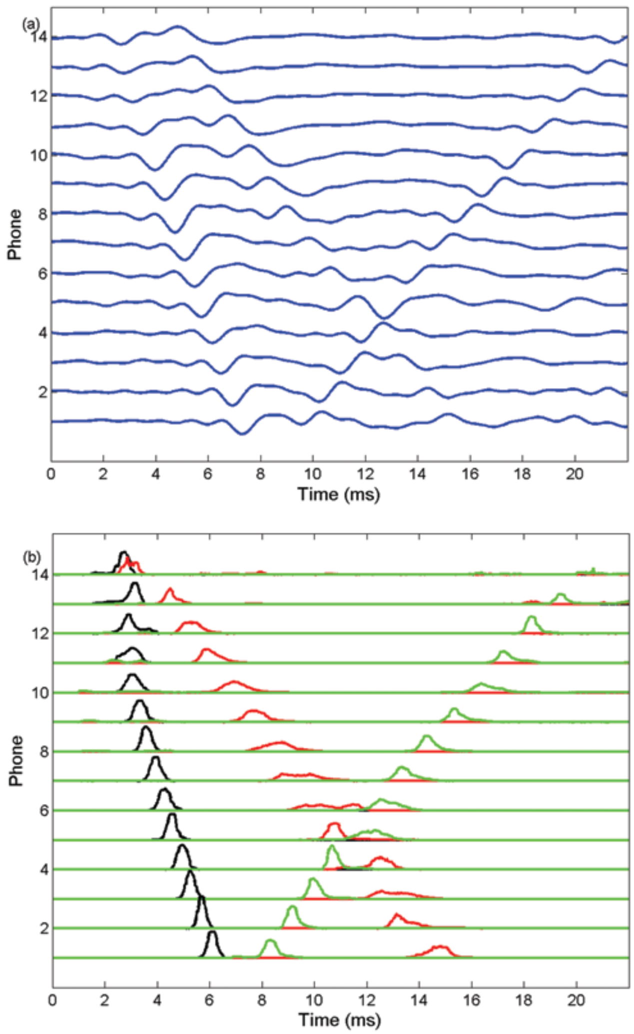

Fig. 9. (a) SW06 time-series at 14 phones, (b) PDFs for D (black), SR (red) and BR (green) paths at the 14 phones.

of sequential Bayesian filtering in space, that is, across phones. Because Bayesian filters have the power to exploit the correlation of motion of a target from one space/time point to another, it is possible to estimate parameters such as arrival times more tightly when we exploit spatial information rather than by only employing data at a single phone. Specifically, our signal arrives at a set of receivers via multiple paths and the *movement* of each arrival up and down the array of receivers can be compared to the motion of a target.

Figure 7(a) shows synthetic, noise-free time series at a tilted very large array (VLA) of 16 hydrophones in an isovelocity shallow water waveguide, similar to that of the Haro Strait Primer experiment.[39] The hydrophones have varying, nonuniform vertical and horizontal separations, causing nonlinearities in the arrival time patterns. The direct (D) and surface reflection (SR) paths that sound follows can be identified in the time series, although the SR is not present at the last two phones. Black dotted lines in the figure indicate the evolution of arrival times in space for each path. If we have a reliable arrival time estimate for one path at hydrophone $k-1$, we should be able to get an estimate for the same path at phone k, that is superior to an estimate obtained without taking into account arrival times at neighboring receivers. Figure 7(b) shows the same signals after noise has been added. The Signal-to-Noise Ratio (SNR) was 14 dB. Red ellipses show spurious peaks introduced by noise that could be potentially identified by an arrival time estimator as true sound arrivals.

Treating each path in space as a moving target, Bayesian MBP exploits the spatial evolution described above and shown in Fig. 7(a). The state vector consists of the arrival times for the D and SR paths. An observation model relates the received time series to those state variables. A prediction model is also selected, that predicts arrival times at receiver k using arrival time knowledge at receiver $k-1$. Because of the non-linearity of the observation model, KFs are not suitable for this problem. Instead, MBP is implemented with particle filtering.[26] We consider here, as an additional state variable, the number of arrivals that are present in the time series.

Figure 8(a) illustrates the true arrival times (+) and the corresponding estimates (o) for the 16 phones obtained via PF. Estimates are very close to the true arrivals with small deviations because of the added noise. Although two arrivals are detected for $K=1,\ldots,14$, the filter correctly switches to a single arrival at phones 15 and 16. Figure 8(b) shows the PDF for the estimated number of arrivals at phone 14, where the PF clearly identifies two arrivals with probability of one. At phone 15, the PDF in Fig. 8(c) demonstrates that the filter has estimated the presence of a single arrival. Because of the transition between phones 14 and 15, there is still significant probability (0.4) corresponding to the presence of two arrivals.

Similarly,[27] we applied the PF arrival time estimation approach to data from the Shallow Water 06 (SW06) experiment.[41] The data were collected in August 2006 at the 16-element MPL-VLA1 array. The source signal was a linear frequency modulated pulse with frequencies between 100 and 900 Hz; the sampling rate was 50 kHz. Received data were match-filtered to produce the time series of Fig. 9(a). Because of low SNR at the 15th and 16th phones, data at only the 14 lower phones were used.

We consider three paths: D, SR, and Bottom Reflection (BR). As discussed,[42] estimating accurately those arrivals can reduce uncertainty in source localization and subsequently, in inversion for other parameters. The state variables for the PF are the arrival times for the three paths.

Figure 9(b) demonstrates the PDFs of arrival times as calculated by the PF. Notable uncertainty is present at the 16th phone, as the PDF spread demonstrates. This is expected, because no prior information from previous states (phones) is available; the 14th phone is where the PF begins. However, although the D and SR arrivals are very close at that phone, the PDFs show that the paths are clearly identified. The uncertainty is reduced at lower phones, where estimates are improved because of the incorporation of prior information. As also discussed,[41] uncertainty, manifested by an increase in the spread of the PDFs, becomes more pronounced when the SR and BR paths cross at receivers six through three.

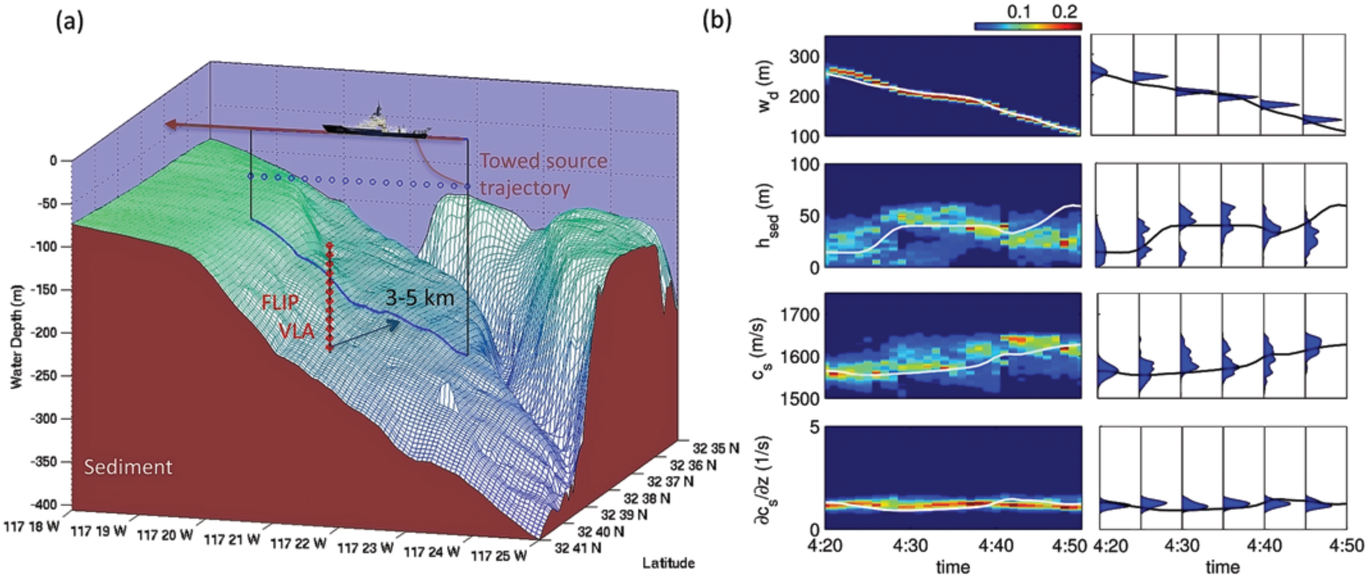

Fig. 10. Geoacoustic and source tracking example from SWellEx-96 experiment. (a) Towed source trajectory and a vertical line array (VLA) in a range dependent environment with varying geoacoustic parameters and (b) posterior probability density functions (PDFs) of water depth and sediment properties [25] obtained using a particle filter with five minute snapshots provided on the right. Solid curves are the true values calculated from the Bachman database.

Using the same approach, amplitudes of distinct paths can be readily estimated as well, in addition to their arrival times,[26] and can be subsequently used for estimation of attenuation.

Source and geoacoustic tracking

Another application of Model-Based ocean acoustic signal processing is the tracking of source and ocean environmental properties using sequential Bayesian techniques. These techniques provide a suitable framework for sequentially estimating in time and space the unknown ocean environment and source parameters as data become available. KFs deal with systems where the acoustic measurements are related to unknown parameters via linear equations and all the underlying uncertainty can be represented with Gaussian PDFs. Geoacoustic tracking involves nonlinear interactions between the environmental parameters and the measured acoustic field with non-Gaussian PDFs. Hence, EKFs, UKFs, and PFs were used to handle the nonlinear/non-Gaussian geoacoustic tracking problem.[24] The performances of the EKF, UKF, and PF were analyzed and compared to the Bayesian Cramér-Rao lower bound, that provides a lower bound for achievable performance in tracking geoacoustic parameters.[24] The results showed that, for slowly varying environments, all filters performed similarly. However, when abrupt changes such as a rapid transition to a different sedimentary rock formation occurred, the PF outperformed the KF variants. The trade-off for better track quality is the increased computational cost of the PF compared to the KF variants.

Sequential geoacoustic tracking was demonstrated on SWellEx-96 data.[25] Because the source parameters were also unknown, the state vector included the unknown source parameters (source depth, range, and speed) together with the geoacoustic parameters, effectively tracking the source in an unknown and changing environment. A constant velocity model was adopted in that problem. The algorithm was tested in a region with bathymetry ranging from 100 to 250 m and a range-dependent sedimentary layer given by the Bachman profile[43] as shown in Fig. 10(a). It was conducted in May 1996, off the coast of San Diego, CA, near Point Loma. A 118 m long, 21-element VLA was deployed from *R/P Flip* at 216.5 m deep water north of Loma Canyon. The source was towed at 2.6 m/s at a depth of 55 m. The source was a comb signal composed of 13 frequencies from 49 to 388 Hz. A PF with 200 particles was able to track the moving source array and the environmental parameters that included array tilt, water depth, sediment thickness, sediment top and bottom sound speed values. The posterior PDFs for four of these parameters, shown in Fig. 10(b), are in agreement with the true values obtained from the Bachman database. Note that the PF allows the PDFs to be non-Gaussian as is the case for the sediment thickness and upper sound speed.

The ocean shelfbreak region is characterized by rapid change in bathymetry and large variations in geoacoustic parameters. The ocean sound speed can be evolving rapidly both temporally and spatially due to the interplay between deep and shallow water. The capabilities of sequential Bayesian geoacoustic and source tracking were also tested in the shelfbreak regions with strong spatial and temporal variability[44] using the data from the SW06 experiment. The PF was able to track the source and bottom parameters as well as the sound speed profile in terms of empirical orthogonal functions. **AT**

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Edmund J. Sullivan received bachelors and masters degrees in Electrical Engineering in 1965 and 1967, respectively, and a Ph.D. in Nuclear Physics in 1970, all from the University of Rhode Island. Dr Sullivan served on the research and technology staff of the Naval Underwater Systems Center until February 1985 when he was appointed head of the Signal Processing Group at the SACLANT Undersea Research Centre in La Spezia, Italy. There he performed both theoretical and experimental research in matched-field processing, bispectral analysis of radiated noise, and passive synthetic aperture processing. He held this post until July 1988. He served as the Signal Processing editor for the *Journal of the Acoustical Society of America* from 1983-85 and as associate editor for the IEEE Journal of Oceanic Engineering for nine years ending in 1999. He was reappointed as Signal Processing editor for the *Journal of the Acoustical Society of America* in 2003. Previous to his retirement he was a staff scientist for the Physics and Technology Division at the Naval Undersea Warfare Center (NUWC). Dr. Sullivan has published numerous journal articles, two encyclopedia articles, six book chapters, and several NATO and Government reports covering the subjects of Underwater Acoustics, Signal Processing, Nuclear Physics, and Electromagnetics. Among the awards he has received are the IEEE OCEANS 94/OSATES Distinguished Technical Achievement Award, the Acoustical Society of America Silver Medal in Signal Processing, and the NUWC Excellence in Science Award, both in 1978 and 1991. He is the holder of several patents in the areas of underwater acoustics and array processing. His present interests are in polyspectra, model-based signal processing, and synthetic-aperture array processing. He is a fellow of both the Acoustical Society of America and the IEEE, is listed in "Who's Who in American Science and Engineering" and "American Men and Women of Science." He is also a member of Tau Beta Pi and Sigma Pi Sigma.

Zoi-Heleni Michalopoulou received the Diploma in Electrical Engineering from the National Technical University of Athens, Athens, Greece, in 1988 and M.S. and Ph.D. degrees in Electrical Engineering from Duke University, Durham, NC, in 1990 and 1993, respectively. Currently, she is a Professor of Mathematical Sciences at the New Jersey Institute of Technology, Newark, NJ. Her research interests include ocean acoustics, signal processing, Bayesian modeling, inverse problems, and spectroscopy. Dr. Michalopoulou is a Fellow of the Acoustical Society of America.

Caglar Yardim received B.S. and M.S. degrees in electrical engineering from the Middle East Technical University, Ankara, Turkey in 1998 and 2001, respectively, and a Ph.D. in electrical engineering from the University of California, San Diego (UCSD) in 2007. Since 2010 he has been a Scientist at the Marine Physical Laboratory, UCSD. His research interests include signal processing, propagation, optimization, modeling, and inversion of electromagnetic and acoustic signals. Dr. Yardim was the recipient of the Best Student Paper Award at the 2007 IEEE Radar Conference and the Union Radio-Scientifique Internationale (URSI) Young Scientist Award in 2008. He is a member of the IEEE and the Acoustical Society of America.