

A BAYESIAN FRAMEWORK FOR GEOACOUSTIC INVERSION OF WIND-DRIVEN AMBIENT NOISE IN SHALLOW WATER

Jorge E. Quijano, Stan E. Dosso, and Jan Dettmer

School of Earth and Ocean Sciences, University of Victoria, 3800 Finnerty Road, Victoria, B.C., Canada, V8P 5C2
 jorgeq@uvic.ca

1. INTRODUCTION

Knowledge of seabed geoacoustic parameters in shallow water is of great importance for the operation of active-sonar systems, to properly identify and classify acoustic returns, and to predict levels of reverberation. Estimation of parameters such as sediment sound speed, density, attenuation, and layering structure remains a challenging task due to constraints on hardware, data collection and analysis, and cost of maritime surveys. This work presents a Bayesian framework for estimating seabed parameters based on inversion of wind-driven ambient-noise data collected at a vertical linear array (VLA) of hydrophones¹.

Remote sensing for acoustic characterization of large areas of the seabed has relied on active-source methods, in which broadband pulses are transmitted in the water column and echoes reflected from the seabed are analyzed to determine geoacoustic parameters. Although the reflection data obtained this way is rich in information on the seabed structure, there are concerns due to increasing levels of man-made noise in the oceans, which are likely to have a negative impact on marine mammals. In addition, the high power demand of active-source systems makes them unsuitable for implementation in autonomous underwater vehicles (for which battery life is limited).

The use of the ambient-noise field produced by wind-driven breaking waves to probe the seabed has been suggested¹ as an alternative (passive) method of remote sensing. This field is modelled as an extended source consisting of surface acoustic monopoles arranged in a thin layer near the air-water interface (Fig. 1).

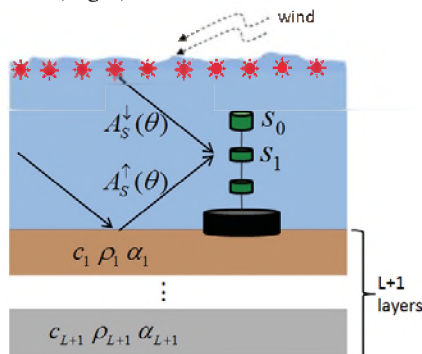


Figure 1. Estimation of the bottom loss by measurement and beamforming of the wind-driven ambient-noise field.

The resulting field is recorded at an N -element VLA and separated into angle-dependent power flux components. The

input data \mathbf{d} to the inversion algorithm in this work consist of the angle- and frequency-dependent bottom loss (BL), computed as $10 \log_{10}(A_S^{\uparrow}(\theta)/A_S^{\downarrow}(\theta))$ since the upward power flux differs from the downward component by a single interaction with the sediment.

In this work, Bayesian inversion is applied to estimate the joint posterior probability density (PPD) of geoacoustic parameters¹⁻². Properties of the PPD such as the maximum *a posteriori* model, mean model, parameter marginal probability distributions, and inter-parameter correlations can be estimated from sampling the PPD. A fundamental step in the inversion is the selection of a model parametrization (e.g., number of seabed layers) consistent with the data information content. To this end, a trans-dimensional (trans-D) inversion approach² is applied.

2. METHOD

The estimated BL data carry information of the seabed geoacoustic parameters¹. Geoacoustic inversion of these data poses a high-dimensional non-linear problem that can be efficiently handled by the Bayesian framework, which requires a model to represent the physical system (i.e. the seabed) that gives rise to the data. With the trans-D method², models I_k from a set of K candidates are included in the estimation of the joint PPD

$$P(\mathbf{m}_k, I_k | \mathbf{d}) = \frac{P(\mathbf{d} | \mathbf{m}_k, I_k)P(\mathbf{m}_k | I_k)P(I_k)}{P(\mathbf{d})}, \quad (1)$$

where $P(\mathbf{d} | \mathbf{m}_k, I_k)$ is the likelihood function (defined here based on the assumption of Gaussian-distributed residuals¹), and $P(I_k)$ is the prior distribution for the parametrization, assumed here as a discrete uniform distribution. The distribution $P(\mathbf{m}_k | I_k)$ is the prior for the geoacoustic parameters \mathbf{m}_k corresponding to a layered seabed with k interfaces. The vector \mathbf{m}_k is defined as

$$\mathbf{m}_k = [c_1 \ \rho_1 \ \alpha_1 \ h_1 \ \dots \ c_{k+1} \ \rho_{k+1} \ \alpha_{k+1} \ SNR_1 \ \dots \ SNR_F]^T \quad (2)$$

where c_b , ρ_b , α_b and h_i are the sound speed, density, attenuation and thickness of the i^{th} layer, respectively, and the SNRs account for the unknown strength of the wind-driven ambient-noise data (i.e. the useful signal) versus other unwanted sources of noise. Details on the interpretation of the SNR parameters and the computation of \mathbf{d} from the ambient-noise field are given elsewhere¹.

The PPD is sampled by a reversible-jump Markov chain Monte Carlo (rjMCMC) algorithm², which uses an extended Metropolis-Hasting (MH) criterion that allows trans-D jumps between parameterizations I_k , quantifying the uncertainty due to the lack of knowledge of the model parameterization.

For data collected with a drifting array, the PPD evolves with time as the array moves over sediments in which the number of layers, the depth of interfaces of high acoustic contrast, or the geoacoustic parameters change as a function of range. Sequential datasets can then be obtained by discretizing continuous-time recordings of ambient noise. For this application, a particle filter³ is used to update the estimated geoacoustic parameters from one array position to the next as new data become available.

3. RESULTS

Geoacoustic inversion of experimental ambient-noise data from moored VLAs has been shown to produce results in agreement with active-source methods¹. Results with simulated sequential data are shown in this summary. To generate the sequential data, the environment shown in Fig.2 (a) was input to the numerical propagation model OASES⁴ for computation of the range-dependent ambient-noise field in a 32-element VLA with 0.18 m inter-element spacing. Conventional beamforming was used to estimate the BL at 8 frequencies in the range 550 Hz to 1400 Hz.

The BL data at 20 uniformly-spaced grazing angles from 14° to 90° was provided to the sequential Bayesian trans-D Monte Carlo algorithm for estimation of the PPD (details found in ref. 3). Figure 2 (b) shows the mean value of the sediment sound speed and density. Note that the estimated geoacoustic parameters and the depth (and number) of acoustic interfaces closely resemble the true profiles.

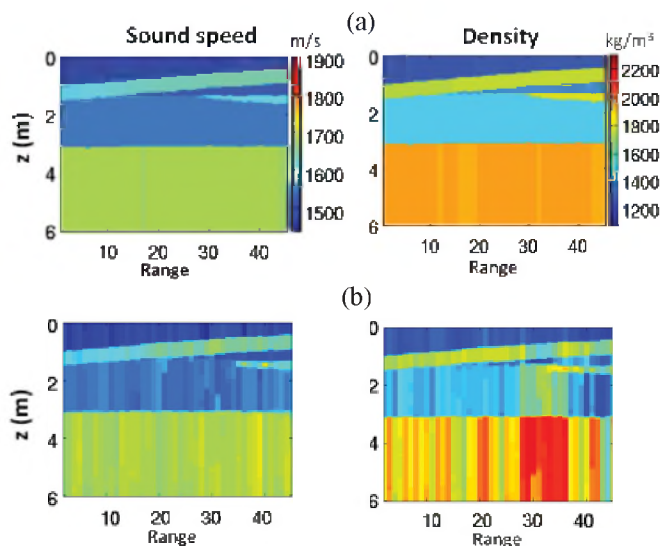


Figure 2. (a) True seabed environment input to OASES to generate simulated data. (b) Mean sediment sound speed and density from the estimated PPD via inversion.

Figure 3 shows the marginal PPDs for sound speed and density at range=25 (arbitrary units) in Fig.2 (b), from which parameter uncertainties can be quantified as the spread of the PPD support around the true values (shown as dashed lines).

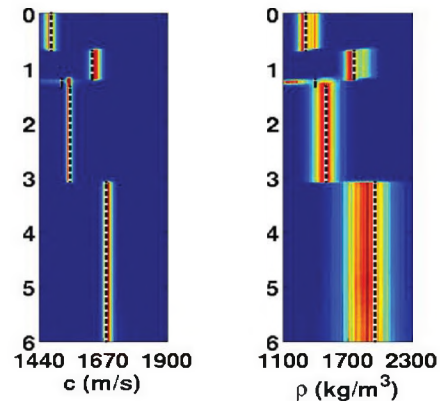


Figure 3. Marginal probability profiles for the sediment sound speed and density at range=25 in Fig. 2. True profiles are indicated by dashed lines.

4. CONCLUSION

Geoacoustic inversion of ambient-noise data has great potential as a remote sensing technique. It has advantages over traditional active-source methods in terms of reduced power and ship time requirements, simplified and unobtrusive surveys, and zero environmental impact. Ongoing research with sequential datasets suggests the possibility of obtaining true-depth (rather than travel-time based) images of the seabed layering structure, along with estimates of parameter uncertainties, required for a meaningful interpretation of range-dependent variability of geoacoustic parameters.

REFERENCES

1. J. E. Quijano, S. E. Dosso, J. Dettmer, L. M. Zurk, M. Siderius, and C. H. Harrison, "Bayesian geoacoustic inversion using wind-driven ambient noise", *J. Acoust. Soc. Am.* 131, 2658-2667 (2012).
2. J. Dettmer, S. E. Dosso, and C. W. Holland, "Trans-dimensional geoacoustic inversion", *J. Acoust. Soc. Am.* 128, 3393-3405 (2010).
3. J. Dettmer, S. E. Dosso, and C. W. Holland, "Sequential trans-dimensional Monte carlo for range-dependent geoacoustic inversion", *J. Acoust. Soc. Am.* 129, 1794-1806 (2011).
4. H. Schmidt, OASES version 3.1 User guide and reference manual; <http://acoustics.mit.edu/faculty/henrik/oases.html>. Last accessed 07/30/2012.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Office of Naval Research postdoctoral fellowship and the Ocean Acoustics Program (ONR-OA Code 3211).