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Inversion of acoustical data from the SW06 experiment, using a statistical method for signal characterization

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Abstract

This paper presents an application of an acoustic signal characterization scheme for ocean acoustic tomography and geoacoustic inversions proposed by Taroudakis et al. [1], using real data. The work is the first attempt to validate the proposed scheme with data taken from sea experiments. The data have been collected during the SW06 experiment held in the New Jersey Continental Shelf and the inversion results (sea-bed geoacoustic parameters and source range) are compared with those reported by Bonnel and Chapman [2]. The comparison and the signal reconstruction using estimated values of the model parameters is satisfactory being an indication that the new signal characterization method can be used in practical applications of acoustical oceanography.

I Introduction

In 2006 a multipurpose experiment (SW06) was carried out off the coast of New Jersey. For geoacoustic inversion purposes, light bulb were dropped in water and the sound of their implosion, which occurred at a depth of approximately 22 m were recorded at a distance about 7 km away from the source location. The geoacoustic model of the environment where the experiment was held is illustrated in Fig. 1. It is a shallow water waveguide with range-independent characteristics. The water depth (79.1 m) and the sound speed profile in the water (Table 1) were known. The sea-bed is described as a two layer medium with a sand layer of approximately 20 m thickness overlying a harder substrate. For the purposes of our study, both layers will be considered as fluid. The recordings were made at an array of hydrophones but in the present work a single recording of a hydrophone placed at the depth of 67.1 m was used. One of the tasks of the experiment was the validation of geoacoustic inversion schemes. To this end, the sound speeds and densities of the sediment layer and the substrate as well as the thickness of the layer and the actual range of the source were the unknowns to be recovered. Bonnel and Chapman [2] presented inversion results based on dispersion curves estimation using warping operators to improve mode separability. It was our purpose to use same data from the experiment under consideration to test the applicability of the new method of signal characterization based on the statistical distributions of the wavelet sub-band coefficients already presented in [1] and validated with simulated data as in [3, 4, 5], in real world applications. The scheme will thereafter be cited as "SCS". An important issue in this respect is the modeling of the source excitation function which will be briefly presented in the next section. Section III presents the inversion results to be discussed in Section IV.

II Simulation of the Source Excitation Function

For inversion purposes, the SCS is associated with an optimization process based on repeated simulations of the received signal for a class of candidate environments. The simulations are

Depth z (m)	Sound Speed Profile c_w (m/s)
0.0	1525.0
10.0	1525.0
27.0	1483.0
79.1	1490.0

Table 1: The sound speed profile in the water column.

made by calculating the system transfer function $H(\mathbf{x}_s, \mathbf{x}_r; \omega)$, where \mathbf{x}_s and \mathbf{x}_r are the source and receiver position vector respectively, at a specific frequency ω multiplying it with the source excitation function $S(\omega)$,

$$p(\mathbf{x}_s, \mathbf{x}_r; \omega) = H(\mathbf{x}_s, \mathbf{x}_r; \omega)S(\omega), \quad (1)$$

repeating this process for all frequencies in the effective signal bandwidth and taking the signal in the time domain by inverse Fourier transform. Here, the system transfer function is calculated using a forward propagation model, which in our case is the MODE1 program based on normal-mode representation of the acoustic field). Therefore, the source excitation function must be given or calculated prior to the application of the inversion algorithm. Raw data of the light bulb implosions implied that the effective bandwidth of the acoustic signals was from 30 to 200 Hz ([2]). Thus, we passed the raw data from a band-pass filter allowing frequencies in this spectrum. By further inspection of the signal spectrum we decided to model the source signal using a Gaussian excitation function with central frequency $f_0 = 150$ Hz and bandwidth $\Delta f = 100$ Hz :

$$S(\omega) = \frac{1}{2\pi \cdot \Delta f \sqrt{2\pi}} \exp\left(-\frac{(\omega - 2\pi \cdot f_0)^2}{2(2\pi \cdot \Delta f)^2}\right). \quad (2)$$

At this point, we needed a validation test for the eligibility of the Gaussian as a model of the light-bulb excitation function. This was in particular important as the Gaussian function is not an obvious simulation of the light bulb signal function. To this end, we used the estimated values of the bottom geoacoustic parameters by Bonnel and Chapman

to simulate the received signal using the hypothesis of a Gaussian excitation function. The values estimated by Bonnel and Chapman appear in Table 2.

For consistency reasons we have used in our study the same recording as in the case of Bonnel and Chapman's inversions. Figure 2 presents a comparison of the energy significant part of the actual signal (recording) after the band-pass filter has been applied (dashed line) with respect to the simulated signal, using the inversion results of Bonnel and Chapman (continuous line), the Gaussian source excitation function as described above and the Normal Mode program MODE1 for the calculation of the system transfer function. The comparison can be considered satisfactory although not perfect. Changing the parameters of the Gaussian function no improvement was observed. Eventually we decided to use this specific excitation function for inversion purposes.

III The Inversion Procedure and Results

Following the work by Taroudakis et al. [1] an acoustic signal is characterized by the statistical parameters of the wavelet sub-band coefficients. In particular, for typical signals used in applications of Acoustical Oceanography, it has been shown that the wavelet coefficients obey a symmetric alpha stable distribution (SaS) characterized by two parameters (α, γ) . For a L -level wavelet analysis, the signal can be characterized by L detailed and 1 approximation coefficient vectors Φ , each one of which consisting of only two elements. Hence the signal feature is represented by a vector \mathbf{d} as following:

$$S \leftrightarrow \{\Phi^0, \dots, \Phi^L\} \leftrightarrow \mathbf{d} = [(\alpha^0, \gamma^0, \alpha^1, \gamma^1, \dots, \alpha^L, \gamma^L)]^T, \quad (3)$$

where T denotes the transpose.

It has been shown in previous works [3, 4, 5] that $L = 3$ is an adequate limit of the multilevel analysis of typical underwater acoustic signals. Therefore in our work we have

used a feature vector in \mathbb{R}^8

$$\mathbf{d} = [\alpha^0, \gamma^0, \alpha^1, \gamma^1, \alpha^2, \gamma^2, \alpha^3, \gamma^3]^T \quad (4)$$

for signal characterization.

For the geoacoustic inversion experiment under consideration, the six unknown parameters can be described by a vector in \mathbb{R}^6 as

$$\mathbf{m} = [r, c_p, \rho_p, h, c_b, \rho_b]^T \quad (5)$$

Using the concepts described above, the following non-linear inverse problem is formulated :

- Given a single acoustic signal characterized by the vector \mathbf{d} , estimate the model parameters \mathbf{m} given a certain propagation model and the specific signal characterization scheme (SCS), jointly described by means of the vector function \mathbf{T} through an equation of the form :

$$\mathbf{T}(\mathbf{d}, \mathbf{m}) = 0 \quad (6)$$

The problem being non-linear and ill-posed is amenable to a solution based on an optimization process, where the cost function is chosen so that the statistical character of the feature vector is exploited. It has been shown that the Kullback-Leibler Divergence (KLD) written analytically for the case of SaS distributions by the following closed form relation :

$$D_s(S_1, S_2) = \sum_{k=0}^L \left\{ \ln \left(\frac{c_2^k}{c_1^k} \right) - \frac{1}{\alpha_1^k} + \left(\frac{\gamma_2^k}{\gamma_1^k} \right)^{\alpha_2^k} \frac{\Gamma \left(\frac{\alpha_2^k + 1}{\alpha_1^k} \right)}{\Gamma \left(\frac{1}{\alpha_1^k} \right)} \right\}, \quad (7)$$

where $\Gamma(x)$ is the Gamma function and

$$c_i^k = \frac{2\Gamma(\frac{1}{\alpha_i^k})}{\alpha_i^k \gamma_i^k}, i = 1, 2, \dots, L, k = 0, \dots, L. \quad (8)$$

is an appropriate cost function [4] expressing the difference between signals S_1 and S_2 .

The optimization process in our work is controlled by a Genetic Algorithm (GA) (see [4, 5]). Here, the GA was applied for 50 generations of 80 individuals each, with probabilities of crossover 0.8 and mutation 0.02. The search space was chosen to be exactly the same as in the work by Bonnel and Chapman [2]. Figure 3 presents the a-posteriori probability distribution of the individual members of the final population indicating by cross symbol the best individual of the GA algorithm and by "x" the inversion results obtained by Bonnel and Chapman.

Both inversion results are presented in Table 2. The results by Bonnel and Chapman are denoted as "B-C" and the results by the SCS are denoted as "SCS".

The comparison of the results obtained by the two totally different inversion schemes can be summarized as following :

The source range estimated by both methods is practically the same. The sound speed in the sediment layer is estimated by the two methods with a difference of approximately 15 m/sec. The difference for most applications of acoustical oceanography is not considered important. The sound speed in the substrate is estimated by the two methods with a difference of 75 m/sec. Although this difference in absolute terms seems considerable, given the fact that the substrate is very hard this difference again can be considered as non-important. The densities of the sediment layer and the substrate are estimated by the two methods with values exhibiting larger differences. It is however well known that the density is among the parameters that are hardly estimated by acoustical means with high accuracy. Finally the sediment thickness estimated by the two methods gave different values. It is interesting to note that the results by Bonnel and Chapman indicate value at the upper limit of the search

space, whereas in the SCS results the best individual lies in the middle of the search space. Moreover the inversion results by the SCS method indicate a thickness much closer to its a-priori estimation being approximately 20 m.

By comparing the energy significant part of the signal simulated using the inversion results of the two methods and the MODE1 program for the calculation of the system transfer function (Fig. 4), it can be seen that the differences are not important. The two sets of model parameters lead to signals with very similar shape. This is an interesting result, suggesting that the inversion scheme based on the statistical characterization of the recorded signal can give estimations of the model parameters that reproduce the signal in similar quality with respect to other inversion schemes.

Unknown Parameters		B-C estimations	SCS estimations
Range	$r(m)$	6951.0	6958.8
Sediment sound speed	$c_p(m/s)$	1603.0	1586.1
Sediment density	$\rho_p(g/m^3)$	1890.0	2022.2
Sediment thickness	$h(m)$	26.9	21.0
Basement sound speed	$c_b(m/s)$	2199.0	2121.3
Basement density	$\rho_b(g/m^3)$	2280.0	2657.1

Table 2: Inversion results

IV Conclusions

The paper presented a first attempt to apply a new method of acoustic signal characterization for geoaoustic inversions with real data. A Genetic Algorithm was used in the optimization process associated with the characterization scheme and the source excitation function was modelled by a Gaussian function. The inversion results were compared with those reported by Bonnel and Chapman [2] and it was shown that, they lead to a similar reconstruction of the acoustic signal. The obvious differences between the actually recorded signal and the simulated ones can be attributed to the modeling of the source and the presence of noise which was not taken into account in the simulated signals. The important conclusion from

the work presented here, is that the acoustic signal characterization scheme based on the statistics of the sub-band wavelet coefficients validated so far by simulations only, can indeed be used for geoacoustic inversions in real world experiments.

V Acknowledgments

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References

- [1] M. Taroudakis, G. Tzagkarakis, and P. Tsakalides, "Classification of shallow water acoustic signals via alpha stable modeling of the one dimensional wavelet coefficients", *J. Acoust. Soc. Am.* **119**, 1396–1405 (2006).
- [2] J. Bonnel and N.R. Chapman, "Geoacoustic inversion in a dispersive waveguide using warping operators", *J. Acoust. Soc. Am.* **130(2)**, EL101-EL107 (2011).
- [3] G. Tzagkarakis, M.I. Taroudakis, and P. Tsakalides, "A statistical geoacoustic inversion scheme based on a modified radial basis functions neural network", *J. Acoust. Soc. Am.* **122**, 1959-1968 (2007).
- [4] M.I Taroudakis, C. Smaragdakis, "On the use of Genetic Algorithms and a statistical characterization of the acoustic signal for tomographic and bottom geoacoustic inversions", *Acta Acust. united with Acust.* **95**, 814-822 (2009).

- [5] M. Taroudakis, C. Smaragdakis, “Inversions of statistical parameters of an acoustic signal in range-dependent environments with applications in ocean acoustic tomography”, *J. Acoust. Soc. Am.* **134**, 2814–2823 (2013).

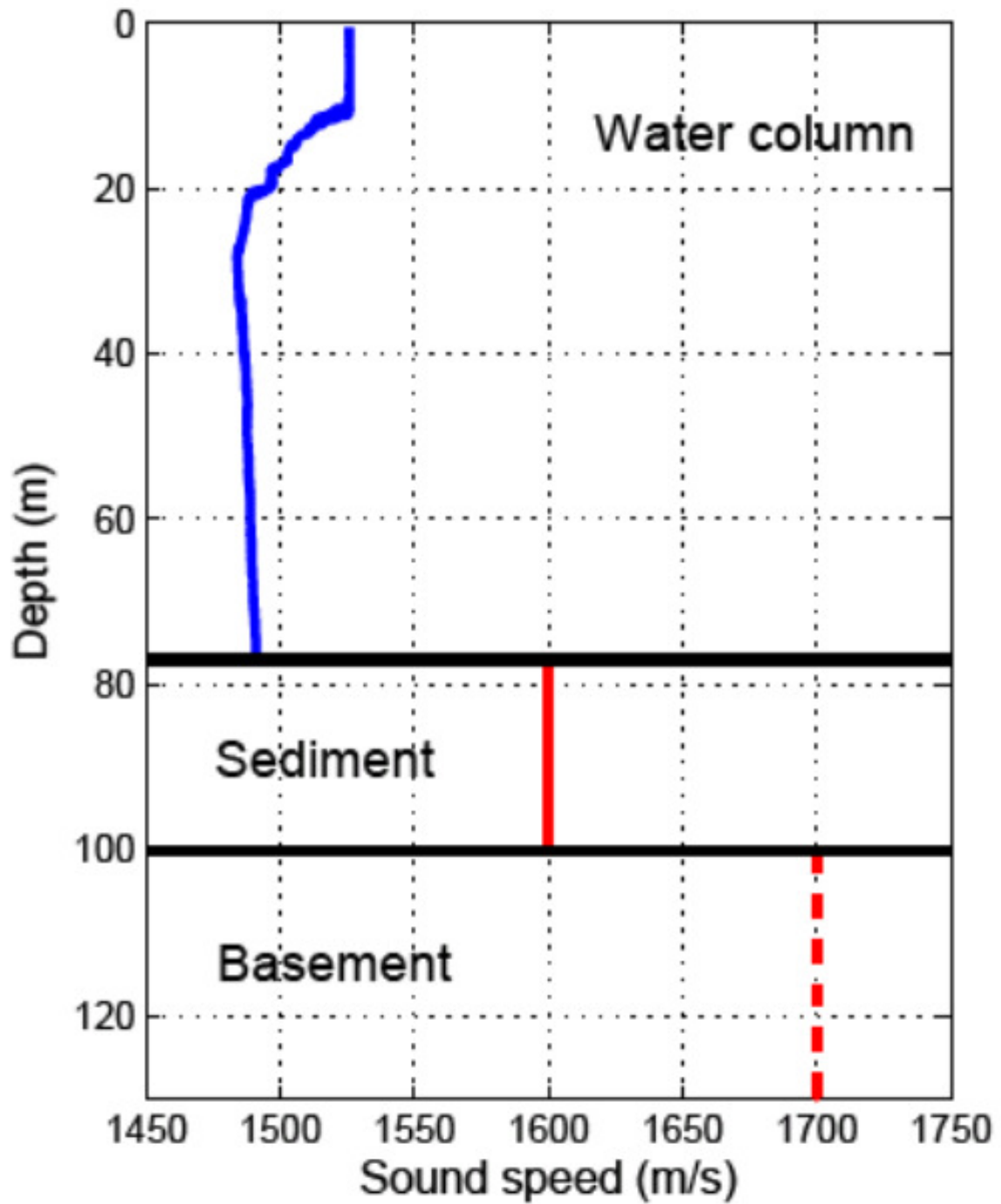


Figure 1: A geoaoustic model of the environment.

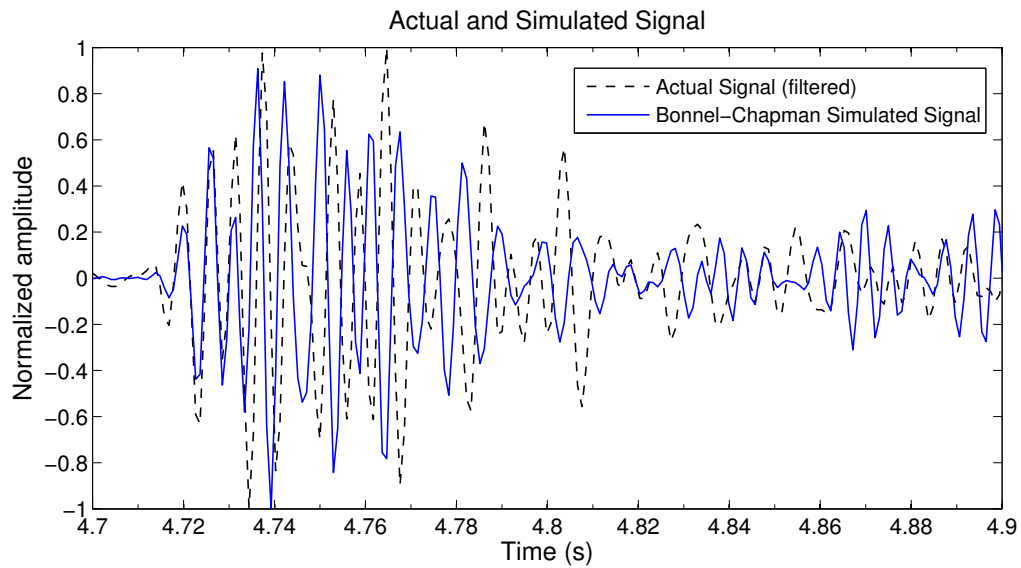


Figure 2: Actual and simulated signals. The simulated signal are based on the inversion results by Bonnel and Chapman.

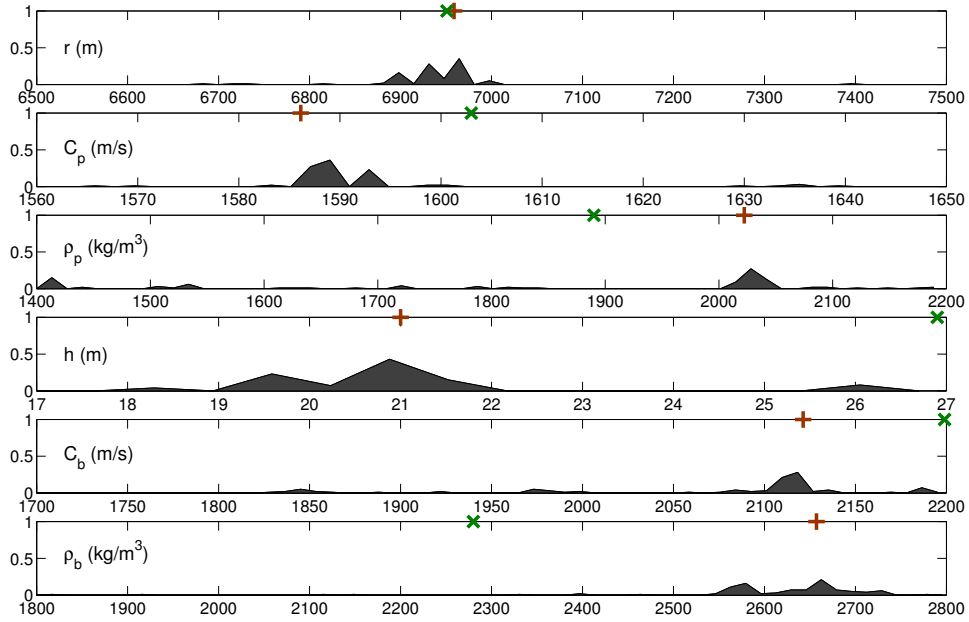


Figure 3: A-posteriori statistical distributions of the final population of the GA. A cross denotes the value of the model parameter corresponding to the best individual of the final population according to SCS and X denotes the value of the parameter estimated by Bonnel and Chapman

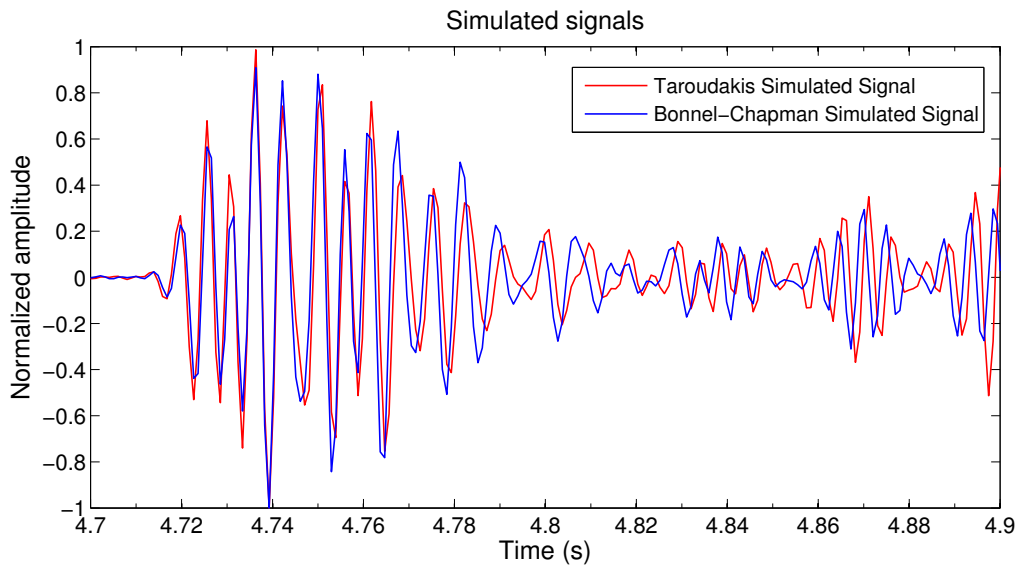


Figure 4: Simulated signals using model parameters estimated by the two inversion methods.