Blind separation of underwater sources in shallow water

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Abstract

In underwater acoustics, the signals received by sensors are mixtures of different elementary sources, filtered by the environment. Using blind separation of sources, we can isolate individual sources from their mixtures without any *a priori* information, except for the assumption of statistical independence. Two French researchers, J. Herault and C. Jutten had earlier proposed a neuromimetic solution to the problem. We obtain promising results by applying this method to separating linear mixtures of simulated underwater signals. We next extend the work to separating convolutive mixtures in a shallow water environment. The initial results will be presented. Blind separation of sources can also be applied to reducing self-noise and as a pre-processing technique for signal classification.

1 Introduction

The blind separation of sources problem arises in many fields such as astronomy, astrophysics, communications and underwater acoustics. In underwater acoustics, the signals received by hydrophones are mixtures of different elementary sources, each filtered by the environment. The sources could be ship signatures, sounds of marine organisms, ambient noise or self-noise. The environment is assumed to be isotropically deterministic, stationary and linear. The propagation of the source signals through the environment is modelled by passing the signals through linear time-invariant (LTI) filters. Thus, the signals received at the hydrophones are *convolutive mixtures* of the source signals. The goal of blind separation of sources techniques is to retrieve the individual source signals from their convolutive mixtures.

2 Generation of Convolutive Mixtures

Convolutive mixtures of underwater sources in shallow water can be produced by a synthetic signal generator. These signals could be used to test various signal processing algorithms, including blind source separation. We have implemented a signal generator, called ANGUS (Artificial Noise Generator for Underwater Sounds), that could be used as a tool for simulating realistic underwater signals received by a hydrophone array placed in shallow water [1].

ANGUS allows the simulation of scenarios involving multiple sources with different source and receiver locations. With multiple sources, the signals received at the hydrophones are convolutive mixtures of the source signals. If the channel is treated as a linear time-invariant (LTI) system, there will be a propagation loss filter, with impulse response $h_{ij}(t)$, between each source-receiver pair. An example of a propagation impulse response and transfer function is shown in Fig 1. These impulse responses are generated from GAMARAY, a ray-based model developed by E. K. Westwood [2, 3].

A typical shallow water environment is shown in Fig 2. This environment consists of a shallow water channel with a depth of 100m overlaying a fluid half-space. The compressional sound velocity is 1500 ms^{-1} in the water and 1600 ms^{-1} in the bottom. A vertical line array with 9 hydrophones is placed 2km away from the source.

The received signal $r_j(t)$, j = [1, 2...N] is the sum of the contributions from each the M source signals, $s_i(t)$, after they have propagated through the environment. The equation for $r_j(t)$ is given by

$$r_j(t) = \sum_{i=1}^{M} h_{ij}(t) \otimes s_i(t) , \qquad (1)$$

where ⊗ stands for time-domain convolution. The signal at the receivers can thus be considered as *convolutive mixtures* of the source signals. In the frequency domain, the received signal is

$$R_j(f) = \sum_{i=1}^{M} H_{ij}(f) \cdot S_i(f) , \qquad (2)$$

where $H_{ij}(f)$ is the frequency response of the propagation filter between source S_i and receiver R_j. Hence, in the frequency domain, the Fourier Transform (FT) of the receiver signals Rj(f) can be seen as *linear mixtures* of the FT of the source signals, $S_i(f)$, scaled by the corresponding $H_{ij}(f)$. The block diagram representation for $M = 2$ and $N = 2$ is shown in Fig 3. Although blind source separation can be applied to more complex systems, our discussions will be limited to this setup for simplicity.

3 Case Study using Synthetic Signals

The following case study presents a two dimensional situation. The source signals are synthetic signals corresponding to submarine noise (signal 1) and broadband noise containing a pure tone at about 500 Hz (signal 2). Both signals are mixed using the scheme presented in Fig 3, where the filters H_{11} and H_{22} are assumed to be all-pass, i.e.

$$H_{11}(f) = H_{22}(f) = 1. \qquad (3)$$

As shown in Fig 4, the filters H_{12} and H_{21} consist of sparse echoes corresponding to the arrivals of the eigenrays. These filters contain information that characterises the propagation of the source signals through the environment.

The signals at the receivers, $r_1(t)$ and $r_2(t)$, are convoluted mixtures of the source signals, $s_1(t)$ and $s_2(t)$. Treating the environment as a LTI system, $r_1(t)$ and $r_2(t)$ are given by

$$r_1(t) = s_1(t) + s_2(t) \otimes h_{21}(t), \quad (4)$$

$$r_2(t) = s_2(t) + s_1(t) \otimes h_{12}(t). \quad (5)$$

Starting from the received signals, $r_1(t)$ and $r_2(t)$, a neuromimetic source separation algorithm is used [4]. Fig 5 shows the block diagram representation of this method. The expressions for the output signals are given by

$$\hat{s}_1(t) = r_1(t) - C_{12} \otimes \hat{s}_2(t), \quad (6)$$

$$\hat{s}_2(t) = r_2(t) - C_{21} \otimes \hat{s}_1(t), \quad (7)$$

where $C12$ and $C21$ are the unknown separating filter coefficients to be estimated.

The source signals, $s_1(t)$ and $s_2(t)$, are independent. This implies that the outputs of a successful source separation algorithm, $\hat{s}_1(t)$ and $\hat{s}_2(t)$, should also be independent. The goal of the blind source separation algorithm is to derive a set of output signals that are *as independent as possible*. In our implementation, the independence criteria (INDEP) is chosen as the cross fourth order moment. Both the independent criteria and the separating filter coefficients, C_{12} and C_{21}, are estimated adaptively using a Robbins-Monro type algorithm. The independence criteria is used as the cost function for updating the output signals at each step of the algorithm. The algorithm can be summarised with the following lines of pseudocode.

```
For all samples
Begin
    Estimate the independence criteria (INDEP).
    Update all the coefficients using:
    C_ij(t + 1) = C_ij(t) + μ · INDEP.
    Estimate the output signals.
End
```

The resulting output signals are independent and related to the true sources through a linear filter. In this example, this filter is equal to 1 for better visual interpretation of the results.

Fig 6 shows the power spectrum density (PSD) of both sources, $S_1(f)$ and $S_2(f)$, the received signals, $R_1(f)$ and $R_2(f)$ and the results obtained using separating filters with 30 taps. The bandwidth of the signals is 1 kHz and the signal duration is 5 seconds. As shown in the figure, the main characteristics of the source PSDs have been recovered at the outputs. The PSD is estimated using 2000 data points and taken as a 512-point Welch periodogram with 50% overlap.

Fig 7 shows the cross-coherence function between the received signals, $r_1(t)$ and $r_2(t)$, and the cross-coherence function between the output signals, $\hat{s}_1(t)$ and $\hat{s}_2(t)$. By definition, the cross-coherence between two independent signals is zero. The estimated outputs show this characteristic up to 500 Hz. This frequency range contains the main portion of the source signal power. The cross-coherence functions are estimated using 2000 data points and taken with a 64-point FFT with 50% overlap.

Although the preliminary results obtained are promising, some issues have to be addressed before the algorithm could be applied to real underwater signals. As illustrated in Fig 1, the main problem encountered concerns the large number of filter coefficients to be estimated. To include all the eigenray arrivals, the filter impulse response has to be sufficiently long. Otherwise, eigenrays that arrive at a later time may be excluded and the propagation channel would not be properly characterised. For a problem involving more than two dimensions, this factor may become critical to the convergence of the algorithm.

4. Future Work

The setup of the blind source separation model, shown in Fig 3, consists of two sources S_1 and S_2 and two receivers, R_1 and R_2. In general, there should be four propagation loss filters, $H_{11}(f)$, $H_{12}(f)$, $H_{21}(f)$ and $H_{22}(f)$. However, this only allows the separation of the sources up to a filter term. To simplify the model, we assumed that $H_{11}(f) = H_{22}(f) = 1$. This assumption is valid if S_1 is very close to R_1 and S_2 is very close to R_2. However, for a hydrophone array placed in shallow water, the sources are typically far away from the receivers. A better assumption is to let $H_{11}(f) = H_{12}(f)$ and $H_{21}(f) = H_{22}(f)$. This is reasonable provided that the path taken by the signal from S_1 to R_1 is similar to the path taken by S_2 to R_1. The same argument holds for R_2. Applying to a shallow water receiver array, this means that the hydrophones, R_1 and R_2, must not be physically too far apart.

As stated in the previous section, the length of the propagation impulse responses also poses a problem to the implementation of the blind source separation algorithm. Blind source separation could still work with long impulse responses but the algorithm may take too long to converge. However, it is possible to obtain an efficient representation of the impulse response. As shown in Fig 1, the impulse response is zero most of the time. Non-zero values only exist at or near the points corresponding to the arrival of the eigenrays. It may be adequate to represent the propagation impulse response with only the positions and magnitudes of the peaks in the graph. This encodes sufficient information about the channel for an accurate simulation and at the same time, enables the algorithm to converge more efficiently.

5 Conclusions

We describe a study on the application of blind source separation techniques to underwater signals in shallow water. The algorithm assumes no *a priori* knowledge about the signals except that they are statistically independent. From simulated mixtures of underwater signals, the algorithm is able to retrieve the original source signals. Constraints imposed by the shallow water environment are highlighted. The initial results are promising and future work will address some of the current problems encountered. Blind source separation can be used as a preprocessing step for signal classification as well as a technique for self-noise reduction.

References

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[3] E.K. Westwood and C.T. Tindle. Shallow water time series simulation using ray theory. *J. Acoust. Soc. Am.*, 81:1752-1761, 1987.

[4] T. Nguyen and C. Jutten. Blind source separation for convolutive mixtures. *Signal Processing*, 45:209-229, 1995.

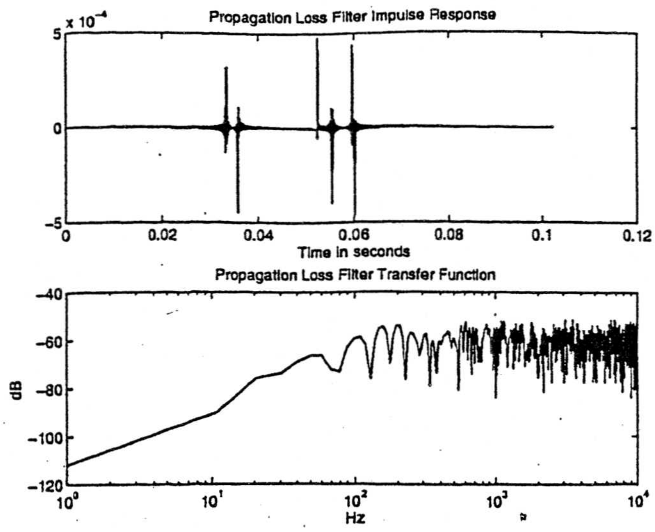

Figure 1: Impulse response and transfer function of a shallow water propagation loss filter .

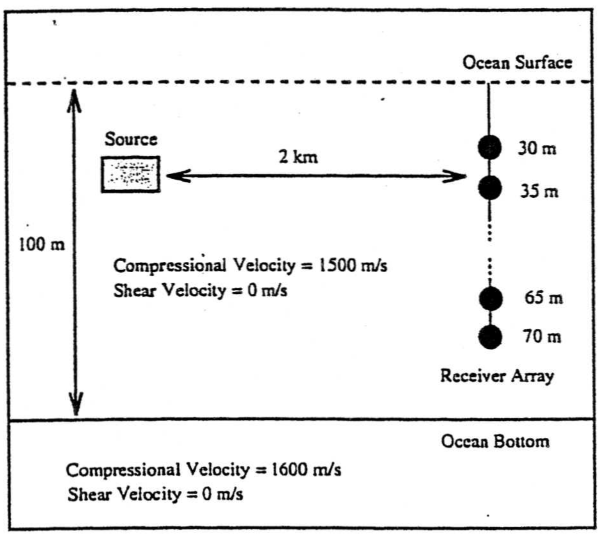

Figure 2: Example of a shallow water environment

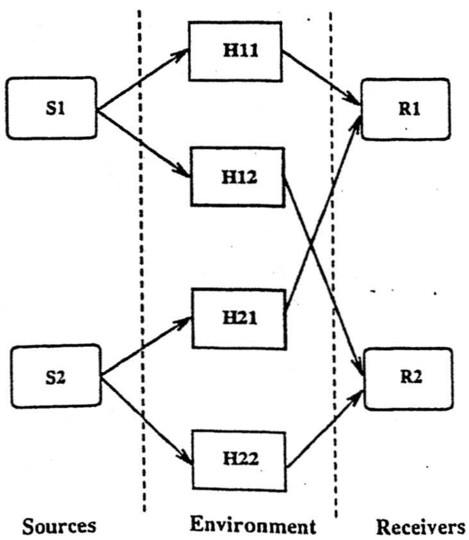

Figure 3: Modelling of shallow water transmission as a linear time-invariant system

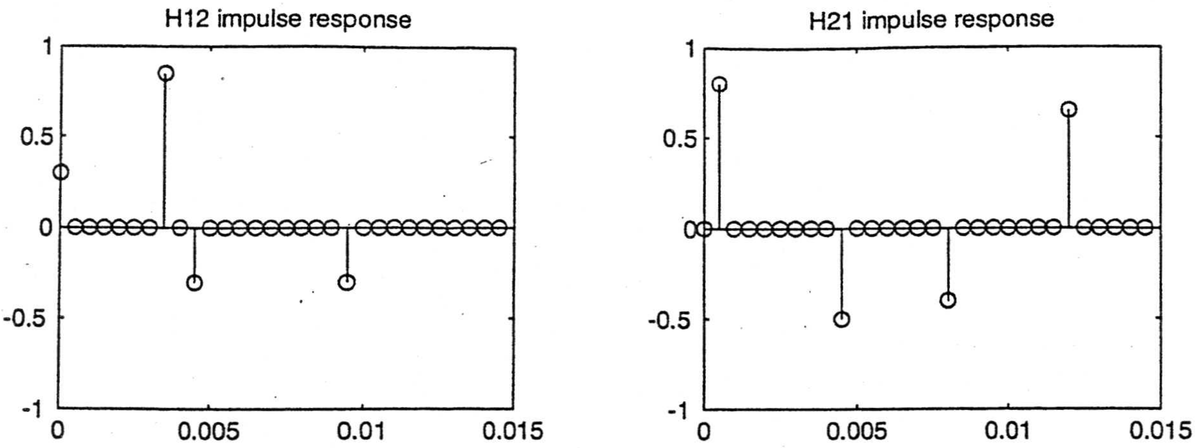

Figure 4: Propagation loss impulse responses used in case study of synthetic signals

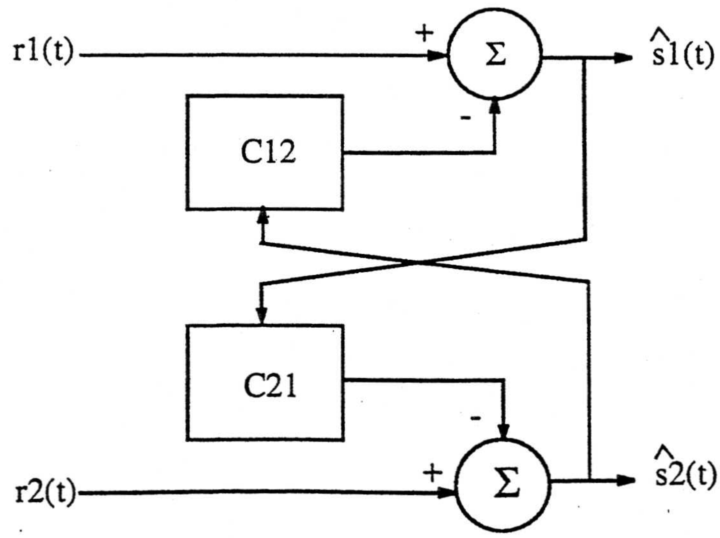

Figure 5: Block diagram representation of the blind source separation algorithm

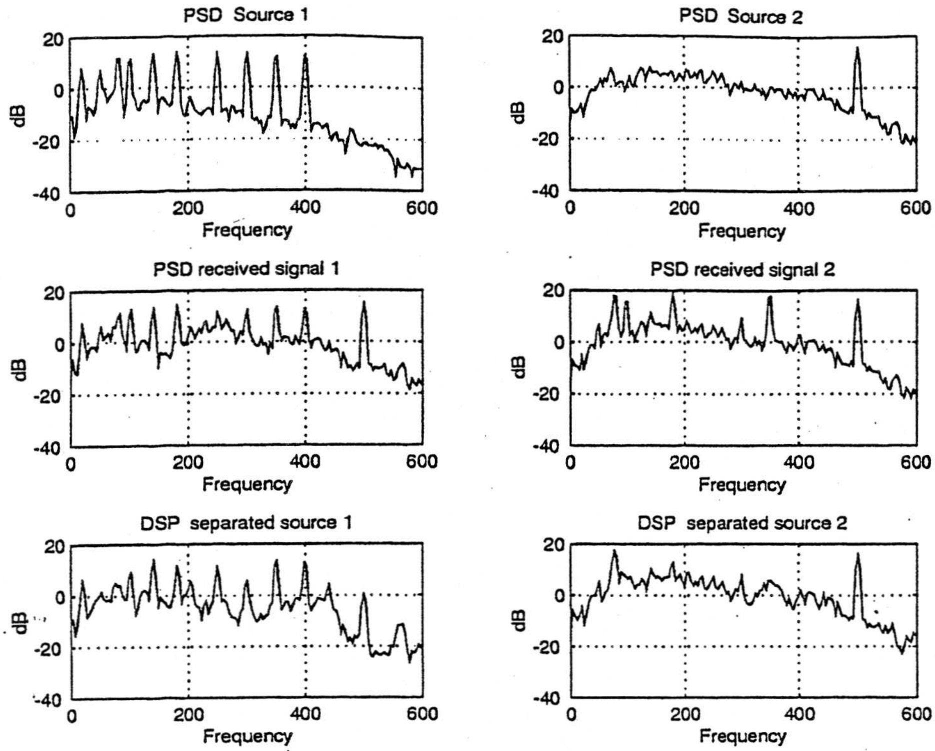

Figure 6: Spectra of source signals, receiver mixtures and output signals

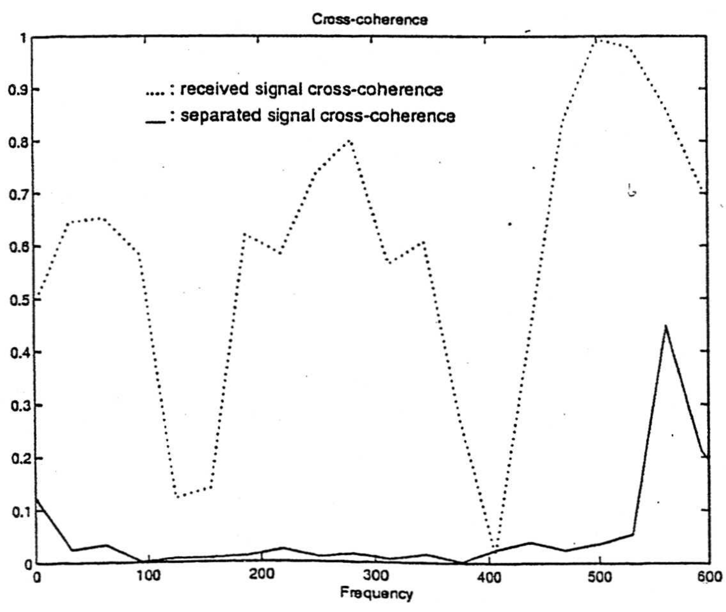

Figure 7: Cross-coherence functions of receiver signals and output signals