Noise cancellation and source localization

Michael D. Collins, Nicholas C. Makris, and Laurie T. Fialkowski
Naval Research Laboratory, Washington, DC 20375

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A noise-canceling processor is developed for matched-field processing problems involving a signal buried in noise. This processor is based on modeling both signal and noise and searching the space of unknown parameters to achieve the best agreement between covariances. The noise-canceling processor reduces to the Bartlett processor in the limit of high signal-to-noise ratio. The examples illustrate the localization of a source obscured by interference from ambient noise or a second source. The noise-canceling processor is also applied to localize a silent object using scattered ambient noise.

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INTRODUCTION

Matched-field processing (MFP) is an approach for determining the location of an acoustic source.[1] This topic has been an active area of research for more than a decade.[2] MFP methods are based on comparing acoustic data from an array of hydrophones with solutions of the wave equation that correspond to test source locations. The unknown parameters of MFP usually consist of the coordinates of the source. The MFP search space has recently been expanded to include environmental parameters,[3] source path parameters,[4] and the coordinates of additional sources.[5] In this paper, we expand the MFP search space to include noise parameters.

The noise-canceling processor, which is described in Sec. I, is based on modeling both signal and noise and searching the space of unknown parameters to achieve the best agreement between covariances. This processor can localize sources buried in interference due to loud sources or ambient noise and reduces to the Bartlett processor in the noise-free case. Since the Bartlett processor is tolerant of the deviations from ideal conditions that are prevalent in applications, the noise-canceling processor should perform well for applications. The development of the noise-canceling processor was motivated by the success of a noise-canceling beamformer (which is based on similar techniques) for data from a towed array.[6]

Examples are presented in Sec. II to illustrate the localization of a source obscured by interference from ambient noise or a second source. The noise-canceling processor is also applied to localize a silent object using scattered ambient noise. There has recently been a great deal of interest in problems of this type.[7–11]

I. A NOISE-CANCELING PROCESSOR

In this section, we derive a noise-canceling processor that is a generalization of the Bartlett processor and should therefore be robust for applications. Since it is difficult to model time series snapshots of noise, we work with covariances.

The $m\times m$ covariance matrix for the acoustic data from an array of m receivers is defined by

$$K=\langle \mathbf{p}\mathbf{p}^*\rangle, \tag{1}$$

where the vector $\mathbf{p}$ contains a snapshot[2] of the complex pressure (obtained by taking a Fourier transform over a relatively short time interval), the superscript asterisk denotes the complex conjugate transpose, and the brackets denote an average of the outer product over a sequence of snapshots. We assume the data are dominated by n temporally uncorrelated processes to obtain

$$K=\sum_{j=1}^{n} K_j, \tag{2}$$

where K_j is the covariance matrix for the jth process.

Some or all of the covariance matrices depend on unknown parameters, such as source coordinates, source levels, noise parameters, and environmental parameters. To estimate these parameters, the least-squares difference between the measured and modeled covariance matrices is minimized over the parameter space. We place the entries of the covariance matrices appearing in Eq. (2) into vectors that contain m^2 entries, normalize these vectors, and define the cost function,

$$E\equiv\left|\hat{\mathbf{u}}-\sum_{j=1}^{n} e_j\hat{\mathbf{v}}_j\right|^2, \tag{3}$$

where the unit vector $\hat{\mathbf{u}}$ corresponds to K, the unit vector $\hat{\mathbf{v}}_j$ corresponds to K_j, and the energy levels e_j are assumed to be unknown. To evaluate the right side of Eq. (3), the $\hat{\mathbf{v}}_j$ are either modeled or estimated from data. We define A to be the $m^2\times n$ matrix whose jth column is $\hat{\mathbf{v}}_j$, and Eq. (3) becomes

$$E=|\hat{\mathbf{u}}-A\mathbf{e}|^2, \tag{4}$$

where $\mathbf{e}$ contains the entries e_j.

To eliminate the energy levels from the parameter space, we minimize E over $\mathbf{e}$ while holding the other parameters constant. The least-squares minimum over the energy levels occurs for

$$\mathbf{e}=(A^*A)^{-1}A^*\hat{\mathbf{u}}. \tag{5}$$

Substituting this solution into Eq. (4), we obtain

$$\min_{\mathbf{e}} E=1-B^2, \tag{6}$$

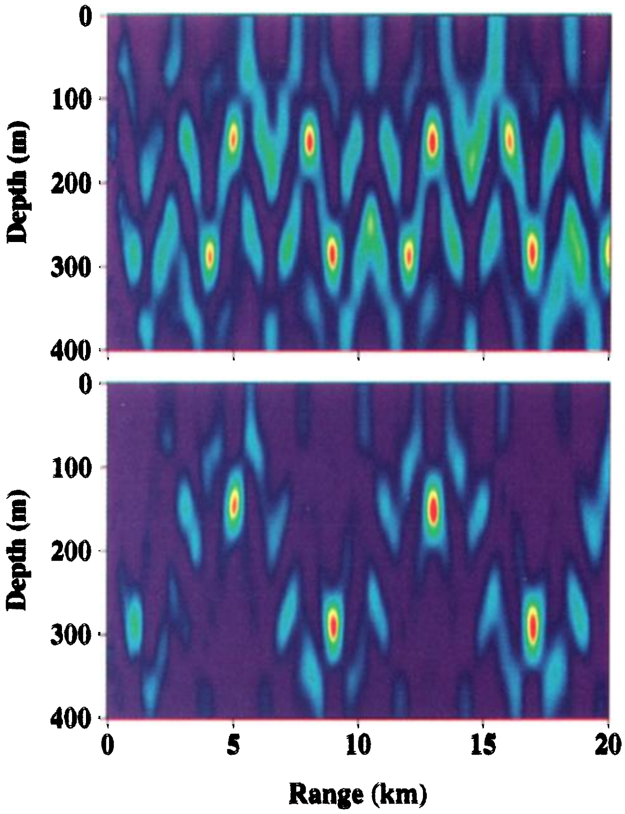

FIG. 1. The Bartlett processor (top) and the noise-canceling processor (bottom) for example A, which involves sources at $(r,z)=(13$ km, 150 m) and $(r,z)=(8$ km, 150 m). Red corresponds to the most likely source locations. Purple corresponds to the least likely source locations.

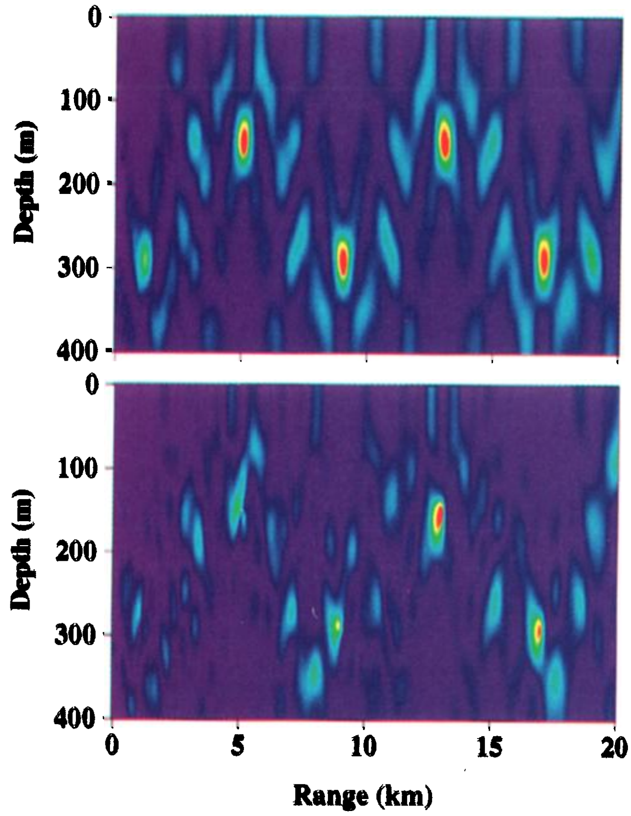

FIG. 2. The Bartlett processor (top) and the noise-canceling processor (bottom) for example B, which involves sources at $(r,z)=(13$ km, 150 m) and $(r,z)=(5.12$ km, 150 m). Red corresponds to the most likely source locations. Purple corresponds to the least likely source locations.

$$B^2 \equiv \hat{\mathbf{u}}^* A (A^* A)^{-1} A^* \hat{\mathbf{u}}. \tag{7}$$

The $n \times n$ matrix A^*A reduces to the identity matrix if the $\hat{\mathbf{v}}_j$ are mutually orthogonal. In this case, B^2 is in the form of a Bartlett processor. For the case $n=1$, the noise-canceling processor B reduces to the Bartlett processor. Although A^*A is not invertible if the columns of A are linearly dependent at a point in the search space (this occurs for some of the examples in Sec. II), the singularity in the bounded function B^2 is removable.

An estimate for the unknown parameters is obtained by maximizing B. If this ambiguity function depends on a large number of parameters (such as source, environmental, and noise parameters), this task may call for an optimization method such as simulated annealing,[12,13] which was used in Refs. 3 and 6. For a low-dimensional parameter space, it is often practical to evaluate the ambiguity function on a dense subset of the space. This approach is commonly used for MFP problems (including the examples in Sec. II) in which the range and depth of a source are the unknowns.

II. EXAMPLES

In this section, we illustrate the performance of the noise-canceling processor. Each of the examples involves a range-independent ocean environment consisting of a homogeneous water column in which the sound speed is 1500 m/s and a homogeneous sediment. The approach of Ref. 14 is used to model ambient noise.

Examples A, B, and C involve a 25-Hz source at the unknown location $(r,z)=(13$ km, 150 m), a 400-m deep ocean, and an array of 13 hydrophones with the jth hydrophone placed at $z=(-15+30j)$m. For these examples, the sediment sound speed is 1700 m/s, the sediment density is 1.5 g/cm^3, and the sediment attenuation is 0.5 dB/λ. An interfering source is placed at $(r,z)=(8$ km, 150 m) for example A. The location of this source, which radiates at the same level as the other source, is assumed to be known *a priori*. For these source locations, the signals due to the two sources are uncorrelated on the array.

Results for example A generated with the Bartlett and noise-canceling processors appear in Fig. 1. The Bartlett processor provides an ambiguous estimate of the location of the unknown source. The main peak in the noise-canceling processor, which closely resembles the Bartlett processor for a single source, occurs at the location of the unknown source. We also tested the sensitivity of the noise-canceling processor to mismatch[2] for this problem by computing the replica fields using an assumed sediment sound speed of 1725 m/s. We found that this amount of mismatch causes the performance of the noise-canceling processor to be only slightly degraded (the main peak is slightly reduced relative to the main sidelobes).

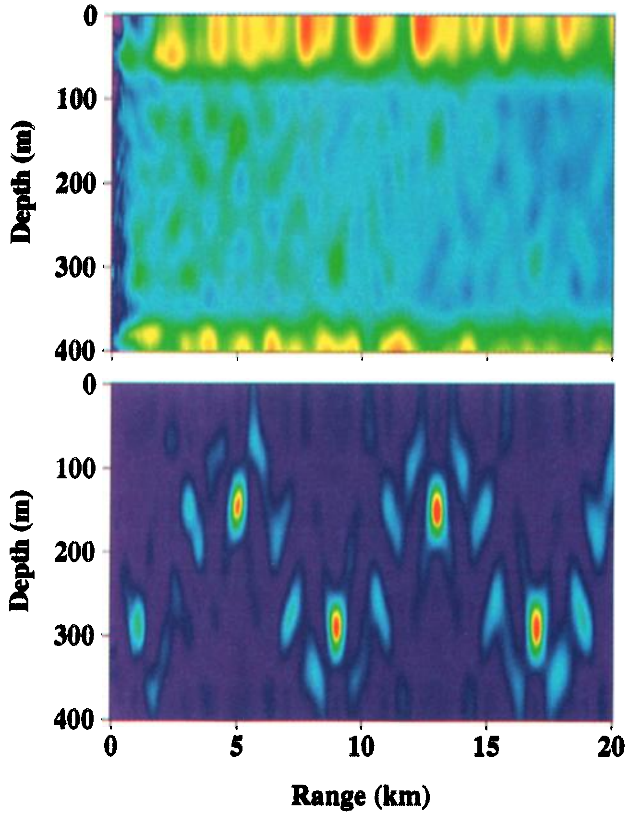

FIG. 3. The Bartlett processor (top) and the noise-canceling processor (bottom) for example C, which involves a source at $(r,z)=(13$ km, 150 m) buried in ambient noise. Red corresponds to the most likely source locations. Purple corresponds to the least likely source locations.

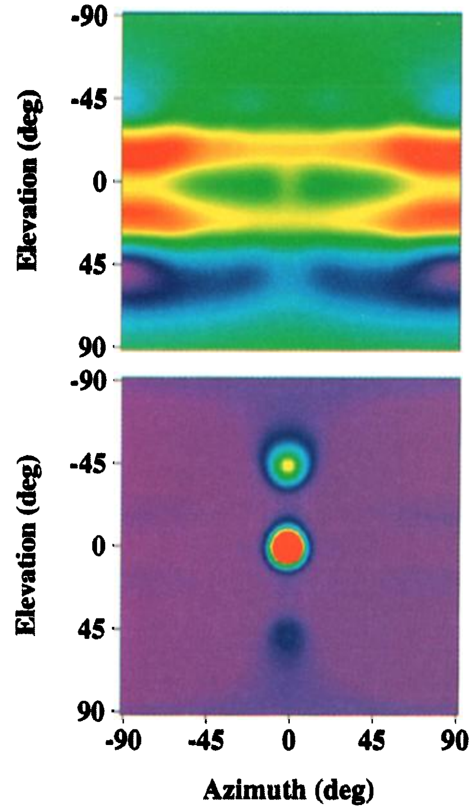

FIG. 4. The Bartlett processor (top) and the noise-canceling processor (bottom) for example D, which involves a 10-m sphere that scatters ambient noise. Red corresponds to the most likely source locations. Purple corresponds to the least likely source locations.

Example B is identical to example A with the exception that the interfering source is moved to $(r,z)=(5.12$ km, 150 m). For this location, the signals due to the two sources are correlated on the array. Results for example B generated with the Bartlett and noise-canceling processors appear in Fig. 2. For the Bartlett processor, the sidelobe near $r=9$ km is comparable to the peak at the location of the unknown source. The noise-canceling processor has a large peak at the location of the unknown source. The sidelobes in the noise-canceling processor are less prominent than for example A.

Example C involves ambient noise that is 14 dB above the signal due to the unknown source on the array. Results for example C generated with the Bartlett and noise-canceling processors appear in Fig. 3. For the Bartlett processor, there are large peaks near the ocean surface (where the noise is generated) and near the ocean bottom (which resembles the ocean surface in the acoustic sense). The source peak and the sidelobes show up faintly in this ambiguity surface. However, the peak corresponding to the source location is dominated by one of the sidelobes. The main peak in the noise-canceling processor corresponds to the source location.

Example D involves 300-Hz processing to localize a pressure-release sphere that scatters ambient noise. The approach of Ref. 11 is used to solve the scattering problem. The sphere is of radius 10 m and is centered at $z=50$ m in a 100-m-deep ocean. A 7×7 billboard array of hydrophones, which are placed in a square grid with a spacing of 2.5 m, is placed in the middle of the water column 100 m away from the sphere and oriented facing the sphere. In the sediment, the sound speed is 1700 m/s, the density is 1.9 g/cm^3, and the attenuation is 0.4 dB/λ.

The signal-to-noise ratio is -20 dB. The sphere was imaged using plane-wave replica fields. Results for example D generated with the Bartlett and noise-canceling processors appear in Fig. 4. Little or no evidence of the scatterer appears in the Bartlett processor. The scatterer and its reflection from the ocean surface show up clearly in the noise-canceling processor. The reflection from the ocean bottom also shows up faintly.

III. CONCLUSION

The noise-canceling processor localizes sources buried in noise by matching the covariance of the data with a combination of signal and noise covariances. This processor reduces to the Bartlett processor in the limit of high signal-to-noise ratio and is related to a noise-cancellation technique for plane-wave beamforming that has been applied successfully to data. The noise-canceling processor has been tested for problems involving interference from an additional source and ambient noise. The noise-canceling processor was also applied to localize a silent object using scattered ambient noise.

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