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A comparison of the sparseness (simplicity) norm criterion blind deconvolution methods of Cabrelli and Wiggins is made in order to ascertain relative performance for underwater acoustic transient source signal estimation, especially in the presence of noise. Both methods perform well at high signal-to-noise ratios, producing source estimates that are significant improvements over the original received signal for classification purposes. At moderate and lower SNRs, the Cabrelli method tends to generate results that are superior to the Wiggins method. This is especially true for a damped sinusoid transient source, for which the Wiggins method fails completely at lower SNRs, while the Cabrelli method can still produce good source estimates. [S0001-4966(00)06601-7]

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INTRODUCTION

An area of interest in several fields of underwater acoustics signal processing involves accounting for environmental acoustic distortion introduced into a propagating pulse (Broadhead et al., 1993). One useful mathematical model representing this process is that of convolution, which in turn leads to the consideration of the deconvolution problem. When only the received signal is available, along with statistical information about the system transfer function or input, then the problem under consideration is called a “blind” deconvolution problem (Haykin, 1994). Such problems, with specific emphasis on underwater acoustics applications, are the subject of this paper.

In previous work we have discussed the blind deconvolution technique introduced by Wiggins (1978), and its application to underwater acoustics problems (Broadhead, 1995; Broadhead et al., 1996). Wiggins’ idea, based on intuition, was to use the varimax norm (or $V$-norm) as a measure of sparseness, which was a statistical property his signal model exploited. He termed this method “minimum entropy” (not to be confused with maximum entropy or minimum cross-entropy techniques), which, in hindsight, was not the most appropriate choice of terminology. However, the idea was fundamentally new—to develop a filter that would drive the received signal to a sparser representation in order to recover the underlying Green’s function. This stimulated research on a wide range of related deconvolution methods (e.g., exponential transformation, parsimonious deconvolution, zero-memory, variable norm, etc.; see Walden, 1985).

This first period of research activity ended in the mid 1980’s, and the higher order statistics community then took up the problem by considering the blind system identification problem with non-Gaussian input (refer to bibliography in Hatzinakos and Nikias, 1994). Modern terminology would cast Wiggins’ method as a cumulant maximization technique (see, for example, Cadzow, 1996), although it seems that he has not as yet been universally recognized by that research community as the founder of such methods. By the time Walden’s review paper was written, it was understood that Wiggins’ method had less to do with entropy than with non-Gaussianity. The $V$-norm could be viewed, essentially, as kurtosis, which Wiggins’ algorithm seeks to maximize. This is appropriate, since positive kurtosis is a measure of the degree of departure from a Gaussian distribution to one with a longer tail. This is consistent with sparseness (or simplicity) in the structure of the input random process to the blind deconvolution problem. This point of view allows one to view Wiggins’ method as a higher order statistics method (Walden, 1985).

Another important paper on “minimum entropy” methods, that by Cabrelli (1984), appeared toward the end of the first period of research activity. As far as we can ascertain, his method is relatively unknown by the modern blind deconvolution community. Cabrelli developed a measure of simplicity (or sparseness) that he referred to as the $D$-norm. Otherwise, he proceeded much the same as Wiggins, and the resulting system of equations gave similar solutions for his test cases. Cabrelli noted that his algorithm should be more robust in the presence of noise. However, only two simulation examples are given in his paper to illustrate the successful application of his method in noise. The examples show successful estimation of two- and three-spike impulse response functions with levels of additive noise which are, for the underwater acoustics problem, considered to be very low.

In the present work, we study the relative performance of the Wiggins and Cabrelli methods with significantly varying levels of Gaussian noise in a realistic underwater acoustics propagation environment, and verify, at least to some degree, Cabrelli’s conjecture. We also propose and test some variations of his algorithm.

I. PROBLEM MOTIVATION AND SIGNAL MODEL

When a sound pulse travels through the ocean, especially in shallow water, it reflects back and forth between the sea surface and the ocean bottom. Further interaction with geologic strata in the ocean bottom may also occur, producing attenuation, scattering, and other distortions. Thus the pulse at the receiver, some distance from the source location,
can look quite different from the original pulse. Furthermore, the addition of noise will create even more distortion. An automatic pattern classifier may then fail to recognize a signal after these propagation distortions have been introduced.

In order to account for the effects of environmental distortion in signal processing schemes, a signal model is needed. In this paper, we do not explicitly include noise in the signal model, but rather seek algorithms that are stable in the presence of noise (considering also possible hybridization with noise reduction methods). We concentrate, then, on accounting for wave propagation effects (primarily multipath) in the signal model, by using the wave equation

\[ D_2 \psi(\mathbf{r},t) = \tilde{F}(\mathbf{r},t), \quad (1) \]

where

\[ D_2 = \rho \nabla \left( \frac{1}{\rho} \right) - \frac{1}{c^2(\mathbf{r})} \partial_{tt}. \quad (2) \]

Here, \( c(\mathbf{r}) \) is the sound speed, \( \rho \) is density, \( \psi(\mathbf{r},t) \) is acoustic pressure, and \( \tilde{F}(\mathbf{r},t) \) is the sound source. Let us define the Green’s function \( \tilde{G}(\cdot) \), such that

\[ D_2 \tilde{G}(\mathbf{r},t|\mathbf{r}',t') = \delta(\mathbf{r}-\mathbf{r}') \delta(t-t'), \quad (3) \]

and assume a separable source

\[ \tilde{F}(\mathbf{r},t) = F(\mathbf{r})S(t). \quad (4) \]

Now,

\[ F(\mathbf{r}')S(t')D_2 \tilde{G}(\mathbf{r},t|\mathbf{r}',t') = D_2 \tilde{G}(\mathbf{r},t|\mathbf{r}',t')F(\mathbf{r}')S(t'), \quad (5) \]

because \( D_2 \) operates on unprimed coordinates. Hence,

\[ D_2 \tilde{G}(\mathbf{r},t|\mathbf{r}',t')F(\mathbf{r}')S(t') = F(\mathbf{r}') \delta(\mathbf{r}-\mathbf{r}')S(t') \delta(t-t'). \quad (6) \]

Furthermore,

\[ D_2 \int_v^{\infty} \int_v^{\infty} \tilde{G}(\mathbf{r},t|\mathbf{r}',t')F(\mathbf{r}')S(t')dV'dt' \]
\[ = \int_v^{\infty} F(\mathbf{r}') \delta(\mathbf{r}-\mathbf{r}')dV' \int_{-\infty}^{\infty} S(t') \delta(t-t')dt' \]
\[ = F(\mathbf{r})S(t) = \tilde{F}(\mathbf{r},t). \quad (7) \]

This implies that

\[ \psi(\mathbf{r},t) = \int_v^{\infty} \int_v^{\infty} \tilde{G}(\mathbf{r},t|\mathbf{r}',t')F(\mathbf{r}')S(t')dV'dt'. \quad (8) \]

If we define

\[ G(\mathbf{r},t;\mathbf{r}',t') = \int_v^{\infty} \tilde{G}(\mathbf{r},t|\mathbf{r}',t')F(\mathbf{r}')dV', \quad (9) \]

then

\[ \psi(\mathbf{r},t) = \int_{-\infty}^{\infty} G(\mathbf{r},t;\mathbf{r}',t')S(t')dt'. \quad (10) \]

Note that, for a spatial point source, \( G=\tilde{G} \). Since we assume that the environment changes on a time scale significantly greater than the acoustic propagation time scale, \( G(\cdot) \) can be considered independent of the time origin. This property is called time invariance, and implies that

\[ G(\mathbf{r},t;\mathbf{r}',t') = G(\mathbf{r},t+\tau;\mathbf{r}',t+\tau), \quad (11) \]

where \( \tau \) is a (sufficiently small) time shift. This condition would be satisfied if \( G(\cdot) \) only depended on \(|t-t'|\), or

\[ G(\mathbf{r},t;\mathbf{r}',t') = G(\mathbf{r},|t-t'|). \quad (12) \]

No contribution from \( G(\cdot) \) occurs until the first arrival time \( t_0 \) (due to causality). Let us assume that the pulse length \( (t_L) \) is less than \( (t_0) \), so that \( t_\geq t' \), for \( t' \leq t_L \). Then,

\[ G(\mathbf{r},t;\mathbf{r}',t') = G(\mathbf{r},t-t'), \quad (13) \]

giving

\[ \psi(\mathbf{r},t) = \int_{-\infty}^{\infty} G(\mathbf{r},t-t')S(t')dt', \quad (14) \]

which is the convolution equation.

Note that this development always holds for point sources, and also holds for extended sources when the separability condition is (at least approximately) appropriate. Henceforth, we will adopt the convolution equation as the basis for our signal model, where \( S(t) \) is the source signature that is propagated, \( G(\mathbf{r},t;\mathbf{r}') \) encodes the multipath environmental distortion effects, and \( \psi(\mathbf{r},t) \) is the received signal at range \( r \) and depth \( z \). The source is placed at the origin at depth \( z' \), and \( \mathbf{r}=(r,z) \) (we use cylindrical coordinates, and assume azimuthal symmetry). In a briefer form we could write

\[ \psi(\mathbf{r},t) = S(t) \ast G(t), \quad (15) \]

where it is understood that \( G(t) \) is associated with some fixed, specified source–receiver geometry.

II. THE DECONVOLUTION PROBLEM

To exploit the convolutional signal model to remove the environmental distortion introduced by \( G(t) \) into measurements of a propagating \( S(t) \), it is necessary to solve the following inverse problem: given \( \psi(t) \) and \( \tilde{G}(t) \), solve for \( S(t) \). This is called the deconvolution problem, and has received much study. For some discussion of this problem and its literature in the area of ocean acoustics, see Broadhead et al. (1993).

In general, the classical single channel deconvolution problem is mathematically ill-posed. This implies that it may be difficult, even under the best conditions, to achieve stable and meaningful results. In the presence of uncertainties in \( G(t) \), and with additive noise, the problem is exacerbated. Two potential remedies are the use of multichannel methods and regularization methods [see Broadhead et al. (1993) for further discussion]. In this paper, however, we set aside the deterministic approach and focus our attention on implementing a statistical interpretation of the signal model. This avoids the need for accurate knowledge of the source location, and complete environmental information, in order to calculate \( G(t) \).
A. Reduced problem

We will, in general, assume knowledge of two things: (1) the received signal, and (2) some appropriate, exploitable statistical characterization of \( G(t) \) [but, not \( G(t) \) itself]. Under these "blind" conditions, and some appropriate parameterization associated with the signal model, we should be able to produce a class of candidate solutions. Our goal is to produce schemes such that (1) the candidate solution class contains one or more elements that are "sufficiently close" to \( S(t) \), and (2) the class size is sufficiently small.

This reduced goal may not be achievable in general problems; but for classification the solution class can be presented to the classifier to see if there is any recognition. Then, in a sense, the classifier and its training signature set become part of the information exploited in the statistical approach. Of course, additional information or assumptions about the signal model invoked will help reduce ambiguity in the solution class. Also, when multiple received signals over significantly different transmission paths are available, significant ambiguity reduction can probably be accomplished. The results of that study will be published elsewhere.

B. Statistical signal model

Wiggins (1978) gives the key idea that we employ here in a slightly generalized form. We consider \( G(t) \) to be a realization of a non-Gaussian random process, input to a linear system whose impulse response is \( S(t) \). From previous calculations (Broadhead et al., 1996), we know that non-Gaussianity is appropriate because of the high, positive kurtosis of \( G(t) \). This is due to its sparseness (or simple structure, or lower entropy) relative to a Gaussian random signal.

How, then, do we accomplish the estimation of \( S(t) \)? The following approach is a generalization, and in some sense, an extension of Wiggins’ approach. We wish to design a filter \( f(t) \) that increases the sparseness measure of the received signal. The goal is to "drive" the received signal toward \( G(t) \). The rationale is that the convolution process is a smearing process that moves the signal to less sparseness (i.e., it makes it more Gaussian). The main assumption is that increasing the non-Gaussianity will drive it towards \( G(t) \).

After deconvolution is used to estimate the filter, an estimate of \( S(t) \) is readily provided by the inverse filter \( f^{-1}(t) \). Let \( sp\{\cdot\} \) represent some sparseness measure. We seek \( f(t) \) such that

\[
sp\{f*\psi\} > sp\{\psi\}. \tag{16}
\]

To do this, we can use a gradient operator (Cadzow, 1996). If \( f*\psi = G \),

\[
f*\psi = G, \tag{17}
\]

then we have

\[
f^{-1}*f*\psi = f^{-1}*G, \tag{18}
\]

\[
\psi = f^{-1}*G. \tag{19}
\]

Comparing to the initial assumption \( \psi = S*G \),

we conclude that

\[
S = f^{-1}. \tag{20}
\]

III. DECONVOLUTION METHODS

A. Wiggins’ method

Wiggins (1978) used a measure of "simplicity" (or "sparseness") borrowed from factor analysis, i.e., the V-norm:

\[
V(y) = \sum_j y_j^4 / \left( \sum_j y_j^2 \right)^2. \tag{21}
\]

Here we give Cabrelli’s (1984) statement of Wiggins’ algorithm (also see Walden, 1985). Consider \( N \) observed signals \( x_1...x_N \), for each \( i (i = 1,...,N) \), and let \( x_i \) be represented by

\[
x_i = s*g_i. \tag{22}
\]

where \( s \) is the source signal, and \( g_i \) represents the propagation distortion. Suppose that each signal \( x_i \) is convolved with the same filter \( f \) in order to obtain an output

\[
y_i = f*x_i = (f*s)*g_i. \tag{23}
\]

To determine the filter, the varimax criterion is then applied to the outputs \( y_i \) in order to maximize \( V(y) \) over all filters \( f=(f_1,...,f_l) \) of fixed length \( l \). Differentiating \( V(y) \) with respect to the filter coefficients \( f_l \), and equating to zero, a nonlinear system of equations is obtained which can be rewritten in matrix form as

\[
R(f) \cdot f = h(f), \tag{24}
\]

where \( R=R(f) \) is a Toeplitz matrix, and \( h=h(f) \) is a column vector whose coefficients depend upon \( f \). Choosing an initial filter \( f^0=(0,...,0,1,0,...,0) \), an iterative algorithm can be generated by taking

\[
f^{l+1} = \{R(f^l)\}^{-1} h(f^l), \tag{25}
\]

which leads to a satisfactory solution.

B. The D-norm and Cabrelli’s method

Cabrelli used certain geometrical considerations to suggest another criterion for simplicity, which he called the D-norm, defined by

\[
D(y) = \max_{1 \leq i, j \leq m} |y_{ij}|/\|y\|, \tag{26}
\]

where \( \|y\| = (\sum_j y_j^2)^{1/2} \) is the Euclidean norm. The D-norm leads to a noniterative algorithm for the multichannel blind deconvolution problem. The \( N \times m \) matrix \( Y=(y_{ij}) \) is defined by

\[
y_{ij} = \sum_l f_l x_{i,j-l+1}, \tag{27}
\]

where \( f \) is a filter to be determined, and the \( x_j \) are input channels of data. Let us rewrite the matrix \( Y \) as a \( Nm \)-dimensional vector, \( Y=(y_{11}, y_{1m}, y_{21}, ..., y_{2m}, ..., y_{N1}, ..., y_{Nm}) \). The D-norm applied to this vector yields

\[
D(Y) = \max_{i,j} (|y_{ij}|/\|Y\|), \tag{28}
\]
where \( \| \mathbf{Y} \| = \left( \sum_{i,j} Y_{ij}^2 \right)^{1/2} \). The formation of the vector \( \mathbf{Y} \) is based on the multichannel kurtosis norm introduced by Ooe and Ulrych (1979). With respect to Cabrelli’s method, \( \mathbf{Y} \) defines the sparseness measure over the set of all the filter outputs instead of summing the sparseness measure over the individual filter outputs. Use of this idea makes extension of the \( D \)-norm to multichannel straightforward. The next step is to compute

\[
\max_{i,j} \left\{ \sup_{f \in \mathcal{F}} \left( |y_{ij}| / \| \mathbf{Y} \| \right) \right\},
\]

(29)

which can be found by considering \( \partial \| \mathbf{Y} \| / \partial f_i \). The algorithm obtained requires the computation of

\[
\mathbf{R} = \sum_i \mathbf{R}_i,
\]

(30)

where \( \mathbf{R}_i \) is the matrix of autocorrelations of the \( i \)th sample input, and \( x_{i,j} \) is the transpose of \([x_{i,j}, x_{i,j-1}, \ldots, x_{i,j-(l-1)}]\), with \( x_k = 0 \) if \( k \notin \{1, \ldots, m\} \). A set of filters is then generated by calculating

\[
f_{ij} = \mathbf{R}_i^{-1} x_{ij}.
\]

(31)

The filters are applied to the input to generate \( \mathbf{Y}_{(ij)}^{(ij)} \), and the algorithm terminates by computing \( \max_{i,j} \left( |y_{ij}^{(ij)}| / \| \mathbf{Y}^{(ij)} \| \right) \). The filter is then the \( i \)th filter associated with the \( D \)-norm.

### IV. DECONVOLUTION RESULTS

Two test transient signals are used to compare the performance of the Wiggins and Cabrelli deconvolution methods. The first transient is a short duration pulse shown with its amplitude spectrum in Fig. 1. The second is a longer duration exponentially damped sinusoid, shown with its amplitude spectrum in Fig. 2.

Multipath propagation-distorted versions of the signals are generated by convolution of the two source transients with three model Green’s functions. The Green’s functions were created using a time-domain parabolic equation model and realistic geoaoustic parameters for an experimental site in the Atlantic Ocean at the southern end of the Blake Plateau (Field and Leclere, 1993). The receiver depth is 250 m in a 915-m water column, and the Green’s functions are calculated at 600 m, 4300 m, and 7900 m upslope from the receiver. Thus the Green’s functions, shown at the three source-to-receiver ranges in Fig. 3, are realistic representations of those that occur in the ocean. Note that the closeness of the multipath interactions in the Green’s functions occur over much shorter time durations than either of the test signals, indicating that the multipath arrivals in the propagated signals will not be visually separable.

The two blind deconvolution methods evaluated in this paper require sparse Green’s functions, or high kurtosis, to work successfully. Each of the three Green’s functions has a significantly large value of kurtosis, at 124.63, 37.98, and 27.33 for the 600-m, 4300-m, and 7900-m ranges, respectively.

To evaluate the performance of the deconvolution algorithms, the source estimate generated by the algorithm is compared to the known source signal using the peak absolute value of the correlation coefficient, given by

\[
\gamma = \max \left| \frac{u \otimes v}{\sigma_u \sigma_v} \right|
\]

(32)

for two functions \( u \) and \( v \). Higher values of \( \gamma \) indicate more similarity between \( u \) and \( v \), and \( \gamma = 1 \) indicates that the two signals are equal (within a scale factor). Although the classifiers used in practice will generally be much more sophis-
ticated and involve many signal features, the correlation coefficient is a convenient numerical measure of performance that lends itself to straightforward comparison between the deconvolution methods.

In this paper, determining whether a method is “successful” depends on three factors. If a classifier is designed to sort through each source estimate produced by a set of filter lengths, searching for a match to a known signal type, then a method is successful if it produces only one source estimate with a high correlation coefficient. However, if several source estimates with high correlation coefficients are produced, a classifier can identify a signal with more confidence. Thus the number of good source estimates for a given set of filter lengths is a second measure of a method’s success. Finally, a method is conditionally successful if it produces source estimates that are superior to the unprocessed or original source estimate, which is the original received signal, corrupted by propagation. The term “conditional” encompasses the uncertainty of how much improvement will ultimately be enough to significantly improve classification capability.

A. Simulations without noise

The Wiggins and Cabrelli methods are initially compared using the two test signals with no additive noise. The Wiggins method requires that a convergence criterion be chosen for determining the stopping point for the iterations. It was found that a useful stopping criterion was when the current and previous source estimates have a correlation coefficient between them of 0.9999. The Wiggins and Cabrelli methods both occasionally require a small degree of prewhitening during the autocorrelation inversion. A value of 0.01% is found to be sufficient for stabilization in the cases where prewhitening is required, and is thus used for all test cases to preserve consistency, and reflect a realistic application scenario where instabilities cannot be predicted efficiently. Filter length in each method ranges from 1 to 50 points.

We also assume that it is reasonable to expect that an estimate of the signal passband would be available for use in the deconvolution routines. As such, the source estimates produced by the two deconvolution methods are subjected to a bandpass filter before processing as well as again preceding classification, i.e., before the correlation coefficient of the source estimate is calculated. For the pulse, the passband filter is defined over 25–150 Hz, and for the damped sinusoid, over 0–100 Hz. The primary effect of this step will be to improve SNR when we add noise.

The results from the two methods are shown in Figs. 4 and 5 for the pulse and damped sinusoid signals, respectively. These figures show the correlation coefficients for the source estimates versus filter length for the three test ranges of 600 m, 4300 m, and 7900 m. For completeness, the correlation coefficient for the original received signal, i.e., the source estimate that is available with no processing, is depicted by the dashed horizontal lines for the three ranges. Note that use of the original received signal for classification includes the initial application of the bandpass filter. The maximum correlation coefficients over filter length for the two methods are also provided in the legend boxes.

For both test signals, the Wiggins and Cabrelli methods produce several to many source estimates that are superior to the original received signal (the solid curves exceed the dashed lines). This indicates that, although filter length is an important parameter, the methods often produce good results for several filter lengths. Except for the pulse signal at the 4300-m range, the Wiggins method produces as many or more source estimates with correlation coefficients of 0.90 or higher for the tested filter lengths than the Cabrelli method, as indicated by the results in Table I. Also, as indicated by the maximum correlation coefficients in Figs. 4 and 5, the best source estimate over filter length is generated by the Wiggins method, rather than the Cabrelli method, in all but one case.

B. Simulations with noise

To assess the performance of the Wiggins and Cabrelli methods in noise, simulated independent Gaussian noise is generated and added to each received signal before application of the deconvolution algorithms. The SNR is defined as the ratio of signal and noise standard deviations, and converted to decibels (dB) for display. Again, in these simula-

![FIG. 3. Modeled Green’s functions at 250 m depth and ranges of (a) 600 m, (b) 4300 m, and (c) 7900 m.](image-url)
tions, the bandpass filter is applied twice: first, it is applied to the received signal before input to the deconvolution algorithm; and second, it is applied to the source estimate generated by the algorithm.

Results depicting the maximum correlation coefficients produced by the two methods for a series of SNRs from $-10$ dB to $30$ dB are shown in Figs. 6 and 7 for the pulse and damped sinusoid signals, respectively. The correlation coefficients for the original received signal (no processing) are also included (solid curves).

At all three ranges, both the Wiggins and Cabrelli methods produce source estimates that are superior to the original received for the pulse signal (Fig. 6). At the 600-m range, the Wiggins method produces slightly better results than the Cabrelli method at SNRs above $22$ dB, but the Cabrelli method produces better results at all the lower SNRs. In the 4300-m
range case, the Wiggins and Cabrelli methods produce comparable results at SNRs above 14 dB, but the Cabrelli method is superior at lower SNRs. In the 7900-m case, the Wiggins method performs better at SNRs between 14 dB and 20 dB, but the Cabrelli method performs better at all other SNRs. Below about 8 dB, at all three ranges, the best Wiggins methods source estimate occurs at a filter length of 1

\[ \text{correlation coefficient} \approx 0.67 \]

While this result seems better than the unprocessed signal, it is only because the particular source signal is a pulse-type signal, similar in form to the approximate delta function source estimate generated by the filter length of 1. Thus this moderately high correlation coefficient of 0.67 is strictly signal dependent, and cannot generally be expected to occur. In fact, it does not occur for the second test signal used in this paper.

Figure 7 depicts the deconvolution results for the damped sinusoid signal. In this case, the Wiggins method completely fails at SNRs below 10–14 dB while the Cabrelli method performs better at SNRs between 14 dB and 20 dB, but the Cabrelli method performs better at all other SNRs. Below about 8 dB, at all three ranges, the best Wiggins methods source estimate occurs at a filter length of 1 (correlation coefficient = 0.67). While this result seems better than the unprocessed signal, it is only because the particular source signal is a pulse-type signal, similar in form to the approximate delta function source estimate generated by the filter length of 1. Thus this moderately high correlation coefficient of 0.67 is strictly signal dependent, and cannot generally be expected to occur. In fact, it does not occur for the second test signal used in this paper.

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V. CABRELLI METHOD WITH ALTERNATIVE NORMS

The Cabrelli method uses maximization of the D-norm to extract a source signature from received data. Alternative
norms can also be used in the Cabrelli method. As an example, we implement the Cabrelli algorithm with the $D$-norm at the final stage in the algorithm replaced by the $r$th order normalized cumulant

$$C_r = \sum_k y_k^r / \|y_r\|^r,$$

for cumulant orders $r = 3, 4, 5,$ and $6$. For the damped sinusoid signal at range $= 7900$ m, the fourth and sixth order cumulant norms give results comparable to the $D$-norm, as shown in Fig. 10 (no prewhitening is used in this example). In contrast, the third and fifth order cumulant norms do not produce good source estimates at most SNRs. This example is representative of the $r$th order results for the damped si-
VI. CONCLUSIONS

The Green’s function in this example is close to symmetrically distributed (i.e., a skewness of −0.93), the poor performance with the odd order cumulants is not surprising. Odd order cumulants may work well, however, for other applications. Examples of successful odd order alternate norms in the Wiggins method can be found in Nandi (1997), and a comparison of alternate norms in the Wiggins and Cabrelli methods can be found in Pflug and Broadhead (1998).

![Graph showing correlation coefficients for the Cabrelli method using the D-norm and rth order cumulant norms for the damped sinusoid signal at range = 7900 m. No prewhitening is used in this example.](image)

FIG. 10. Correlation coefficients for the Cabrelli method using the D-norm and rth order cumulant norms for the damped sinusoid signal at range = 7900 m. No prewhitening is used in this example.

In this paper, we presented a general scheme for applying blind deconvolution as a preprocessor to improve classifier performance for passive acoustic transients. We also presented two particular algorithms from the literature and showed that they can perform well in an ocean acoustics setting (albeit, they were both developed for oil-exploration related problems in reflection seismology). Furthermore, we have given a relative performance comparison in the presence of significant levels of additive noise. The evaluation included using the correlation coefficient between the source estimate and true source to quantify similarity, and compared the level and frequency of occurrence of correlation coefficients produced for a predefined set of filter lengths. The two methods gave good results for both the pulse and damped sinusoid test signals when noise was absent or the SNR was high. At moderate and lower SNRs, the Cabrelli method tended to generate results that were superior to the Wiggins method. For the damped sinusoid signal, the Wiggins method failed completely below SNR = 10 dB, producing source estimates that were more distorted than the original received signal. In contrast, the Cabrelli method at this and lower SNRs still produced some good source estimates. We also implemented a variation of the Cabrelli algorithm to accommodate third through sixth order cumulants and presented simulation results from the modified method that showed comparable results for the D-norm, fourth, and sixth order cumulant norms.

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