CONDITIONING OF SONAR DATA

Mika Levonen and Leif Persson
Swedish Defence Research Agency, SE-17290 Stockholm, Sweden.
e-mail: {leifp, mika}@foi.se

Abstract – **Spectral source characterization is crucial in passive sonar surveillance. The appearance and pattern of spectral lines in the time-frequency domain are important indicators for source identification. The ability of the estimated spectrum to resolve the components of the source is dependent on the quality of the recorded data. The sonar data may be a composition of both narrowband components and broadband transients. Here, we use a stepwise outlier rejection algorithm for removal of non-stationarities. We compare several methods for imputation of the reduced data set. The methods are all based on finding alternative values to the rejected outliers in the bispectral domain. We demonstrate the performance of these methods by means of real sonar data.**

I. INTRODUCTION

Identification of underwater sources is important in sonar surveillance. The recorded sonar data is processed in many different ways for improved signal enhancement. The analysis of source separation is often performed in the time-frequency domain, e.g. Lofargram. Narrowband components appear as long-time duration lines and transients as broadband short-time duration pulses. The transients may be generated by the same source as the lines, from another near distance source or be a part of the additional ambient noise. If the transients are considered as disturbances they are preferable suppressed in the Lofargram. Also, conventional spectral estimation methods are based on the assumption of stationarity. If transients and narrowband components are mixed in the estimation window distortion and masking of the lines may occur especially in the low signal-to-noise ratio regimes. If suppression or removal of transients is possible, the source signal identification of spectral lines may be improved. Here, we use the stepwise outlier rejection method to reveal and remove the data containing the disturbances. This method of rejection of outliers has been used earlier for sonar data conditioning, see [9] and [10]. One disadvantage with the outlier rejection method is the requirement of relatively long data sets for significant estimates due to the properties in the bicoherence domain, see [8]. Also, in the identification procedure the quadratic phase couplings (QPC) are used for testing of independence of sources. Therefore, the length of the data estimation window should be intact and not reduced. Instead of a reducing the data set by the removal of the rejection method we replace the data points by imputation. Four different methods for replacement of rejected data is used.

The most common approach to replace rejected values is by using zeros. We use a method based on the nearest neighbor (NN) of the rejected value in the bispectral domain in three different ways. Two methods are based on taking the mean or the median of the eight NN bispectral values. We also use a slice in the bispectral domain. This leads to improvement of the spectral lines. For the analysis we use experimental sonar data recorded in a shallow bay of the Baltic Sea. The source is a small boat running from long distances, approaching the hydrophones and passing with a constant speed during each run. The main objective is to improve conventional Lofargram analysis by the proposed sonar conditioning method based on rejection of outliers and imputation.

II. PRELIMINARIES

In this section we present some definitions and a brief discussion of the bispectrum, the stepwise outlier rejection algorithm and the different approaches for imputation of rejected values.

The recorded time series $x(t)$ (t=1,…, K) is assumed to be a real periodic discrete data vector divided into L blocks each with N samples. The Fourier spectrum $X^n(f)$ of the time series $x(t)$ for block n is,

$$X^n(f) = \sum_{t=1}^{N} x(t) e^{-j2\pi ft/N} . \qquad (2.1)$$

The power spectrum is formed as an average over all blocks L as

$$P(f) = \frac{1}{L}\sum_{n=1}^{L} X^n(f) X^{n*}(f) , \qquad (2.2)$$

where * denotes complex conjugate. We only estimate the positive part of the power spectrum due to symmetry, i.e. $P(f) = P(-f)$.

The bispectrum is a complex function and has an equivalent definition via the Fourier spectrum in (2.1),

$$B(f_1, f_2) = \frac{1}{L}\sum_{n=1}^{L} X^n(f_1) X^n(f_2) X^{n*}(f_1 + f_2) . \qquad (2.3)$$

The bispectral estimations require larger data sets compared to power spectra to yield consistent estimates, e.g. [1]. The variance of the estimate from a record of N samples is $N/2$ times larger for the bispectrum compared to the power spectrum, [6]. To reduce the variance the data is segmented into L records and the average is calculated. The normalized bispectrum called the bicoherence $b(f_1, f_2)$ is a useful function for estimating both quadratic frequency and phase coupling. We use the normalization defined as

$$b^2(f_1, f_2) = \frac{|B(f_1, f_2)|^2}{C(f_1, f_2)P(f_1 + f_2)} \tag{2.4}$$

where $C(f_1, f_2) = \frac{1}{L}\sum_{n=1}^{L} |X^n(f_1)X^n(f_2)|^2$. (2.5)

The value of the normalized bicoherence $b^2(f_1, f_2)$ is between 0 and 1. If the frequency f_1 with phase ϕ_1 and at the frequency f_2 with phase ϕ_2 are related by quadratic phase coupling (QPC) the bicoherence value $b^2(f_1, f_2)$ in equation (2.4) is close to one at the summed frequency $f_3 = f_1 + f_2$. If the two frequencies are not phase coupled (i.e. the phase $\phi_3 \neq \phi_1 + \phi_2$ at frequency f_3) the bicoherence is low (see [4]). Therefore, the information of harmonics revealed by frequency triplets is different compared to the power spectrum. For comparisons with conventional Lofargram we use a projection of the bispectrum and the bicoherence as

$$B(f_H, f_2) = \frac{1}{H}\sum_{n=1}^{H} B(f_n, f_2) \tag{2.6}$$

where the selected frequency band along the f_1 axis is $f_n \in \{0, \ldots, f_N\}$ and H is the total number of frequency bands for averaging. This gives us the possibility of using the bispectrum projection in a time-frequency display for comparison with the conventional Lofargram.

The bispectral estimates are restricted to the non-redundant part of the inner triangle (IT), $f_2 \geq 0, f_1 \geq f_2, f_1 + f_2 \leq f_N$ (see [5] and Fig. 1).

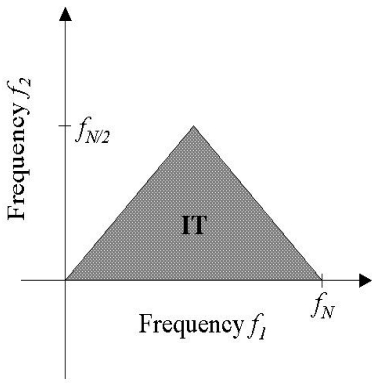

Figure 1. The non-redundant part IT of the principal domain used for bispectral estimations. f_N is the Nyquist frequency.

III. METHOD

For estimation of passive underwater target features such as spectral lines in the Lofargram it is important to use as significant values as possible. If the sonar data contain short-time disturbances, with unknown amplitude, arrival and duration time, the estimated spectra lines may be distorted. In this case it is difficult for a limited time and frequency resolution to achieve significant estimates. We use a stepwise outlier rejection algorithm for reduction and removal of disturbances, see [2]. The assumptions for the outlier rejection are; the estimates at each bifrequency are independent and if no transients are present in the estimation window the bispectral values follow a bivariate, normal distribution with unknown mean and variance. We estimate the individual bispectrum B_n for each block n=1,…, L in the estimation window and the averaged bispectrum $B(f_1, f_2)$ as in (2.3). The difference for each frequency triplet from the global mean is compared with a statistical table at the required significance level. If the value is larger than the threshold it is considered an outlier, and is rejected, removed from the bispectral estimate and replaced by a value depending on the chosen imputation method. The procedure is repeated until all values are considered as inliers to form the modified bicoherence used in the projection in (2.6) to form a modified Lofargram. The different imputation methods we use are summarized in Table 1. Method A is based on replace each outlier value in the bispectrum domain by a zero value. Instead of zeros as replaced values the other methods B to D and F use the nearest neighbor values NN in the bispectrum domain as in Fig. 2. Around the outlier value at a distance of at least one value from the bispectral manifolds the number of nearest neighbor values are eight. For method B we estimate the mean of the eight values and for method C and D we estimate the median and the minimum value. For method E and F we use a slice by holding the value of frequency f_1 constant, i.e. a slice along the frequency f_2 axis. We use three values apart from the outlier value in both direction

and take the mean of the six values. For method F we estimate the mean for all values along the slice.

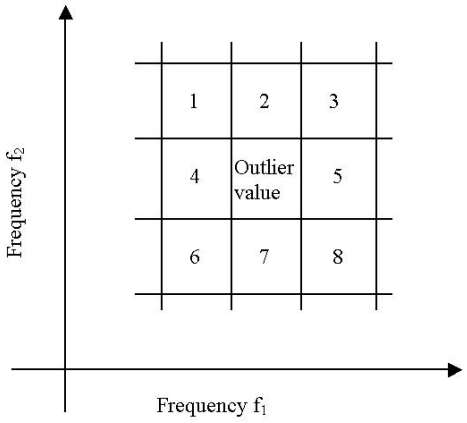

Figure 2. The nearest neighbor (NN) of an outlier value in the bispectral domain used by method B, C, D and F.

Method	Replaced outlier value
A	Zero
B	Mean of nearest neighbor NN
C	Median of NN
D	Minimum of NN
E	Mean in a global slice
F	Mean in a NN slice

Table 1. Used imputation methods for replacement of outlier values.

IV. EXPERIMENTAL DATA SETUP

The sonar data we use were recorded in a shallow bay in the Baltic Sea with a water depth of about 30 m. The trials were performed using a 23-ft. fiberglass motorboat with a 4-cyl. 4-stroke diesel engine as a sound source. The small boat started at a distance of about 600 m from the array of the bottom-mounted hydrophones. The boat was held on straight track runs with constant speed approaching and passing the array by a distance of about 100 m. The engine was held to run constantly at 2712 rpm during the recordings. The radiated underwater sound was recorded by four bottom-mounted hydrophones. The sampling rate was 25 kHz for all recording channels. For more details about the sea trial and recording procedure see [7] and [8].

V. DATA ANALYSIS AND RESULTS

For the data analysis we use hydrophone recordings. The length of a complete recording is about 100 sec. In the analysis we divided the data into time frames of 15 sec. Very little information about the source is found above 1 kHz so the data is lowpass filtered and down sampled to 2.5 kHz. The frames of data are segmented into 36 nonoverlapping blocks of 1024 samples each. The estimation is performed in 0.2 sec steps of the time frame. An example of hydrophone time series with its power spectra in the middle of a run is displayed in Fig. 3. Several peaks are clearly seen in the power spectrum. We can also see the amplitude variations in the time series during a time frame of 30 sec. In Fig. 4 the Lofargram from the same run as in Fig. 3 is displayed. Several spectral lines are visible at a lapse time between 50 and 80 sec.

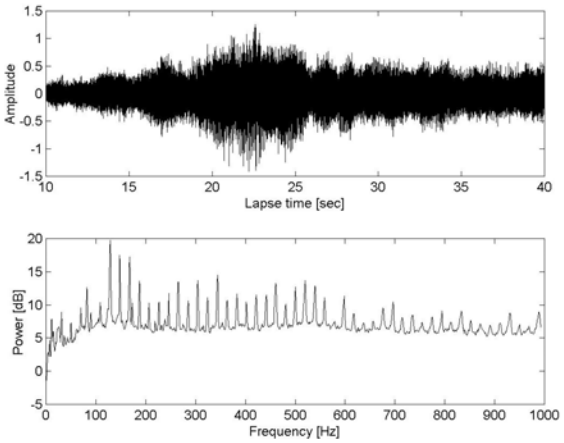

Figure 3. Example of time series (top) and power spectrum (bottom) recorded by a bottom-mounted hydrophone.

In Fig. 5 the displayed bicoherence is estimated from the same time frame of hydrophone data as in Fig. 3. The harmonic patterns from the boat are difficult to explore in the bicoherence domain. If we apply the outlier rejection algorithm and the imputation methods (see section III) new features will appear. In Fig. 6 and 7 the outliers are replaced by zeros according to imputation method A and B. The Lofargram in Figs. 8 to 11 display the final result with data modified by outlier rejection and imputation methods A, B, D and E presented as a lofargram estimated by the bicoherence (2.6) projection. The spectral lines are more stable for the Lofargram based on the modified data throughout the entire run.

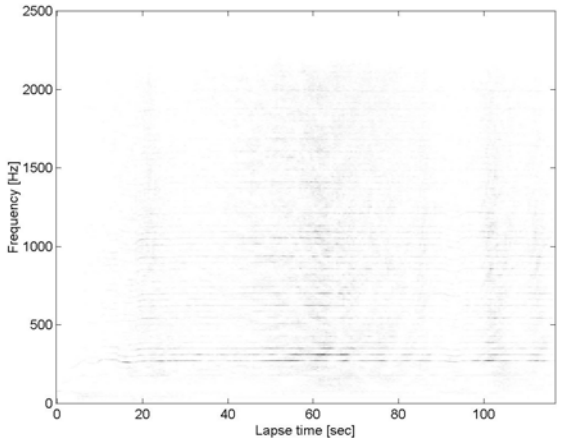

Figure 4. Time-frequency display (Lofargram) estimated from a complete recording of a boat run with a bottom-mounted hydrophone.

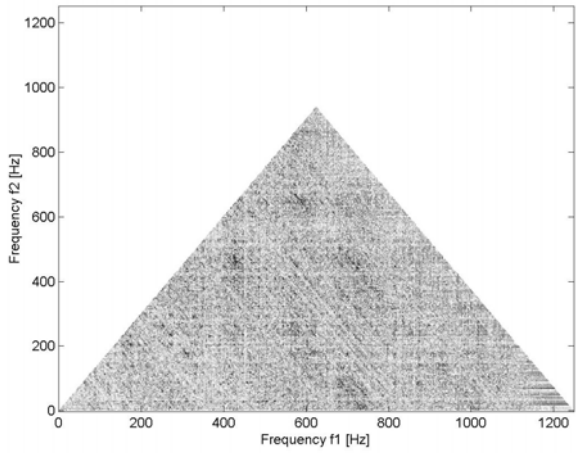

Figure 5. Bicoherence estimated from the same time frame as in Fig. 3.

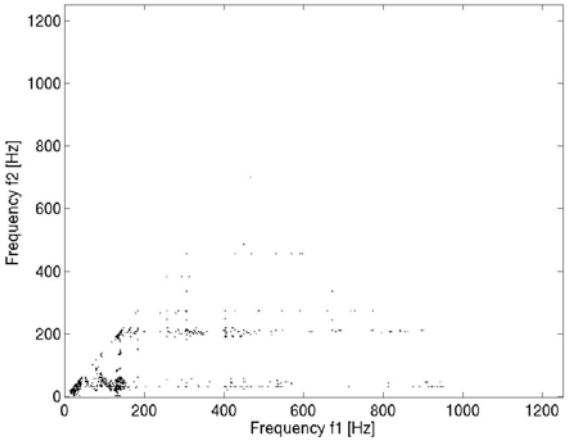

Figure 6. Bicoherence estimated with outlier rejection and imputation method A. The data are from the same time frame as in Fig. 3.

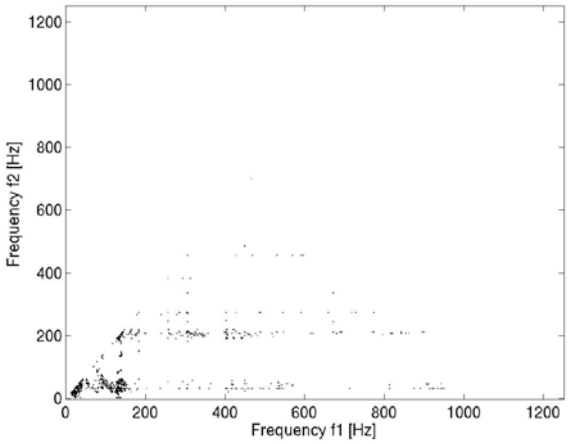

Figure 7. Bicoherence with outlier rejection and imputation method D. The data frame is as in Fig. 5.

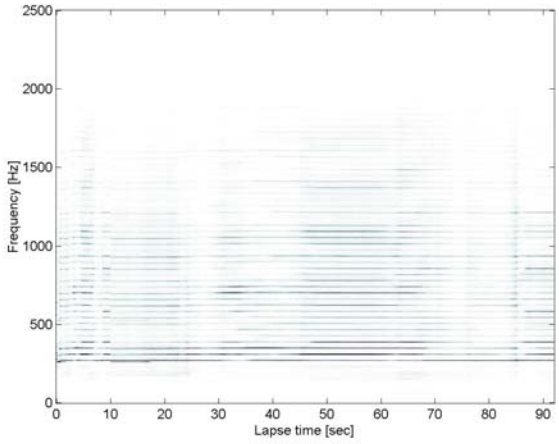

Figure 8. Time-frequency display (Lofargram) by bicoherence projection with outlier rejection and imputation method A. The estimate is from the same data as in Fig 4.

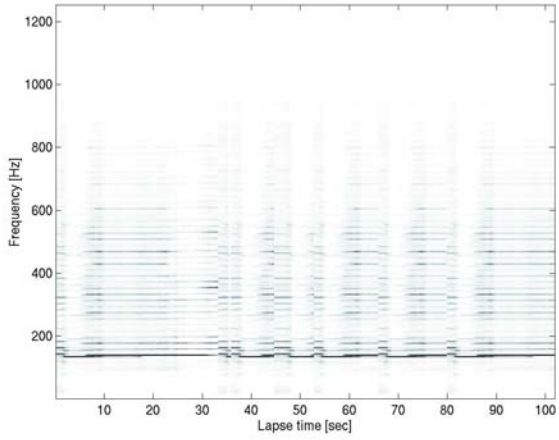

Figure 9. Time-frequency display (Lofargram) by bicoherence projection with outlier rejection and imputation method B. The estimate is from the same data as in Fig 4.

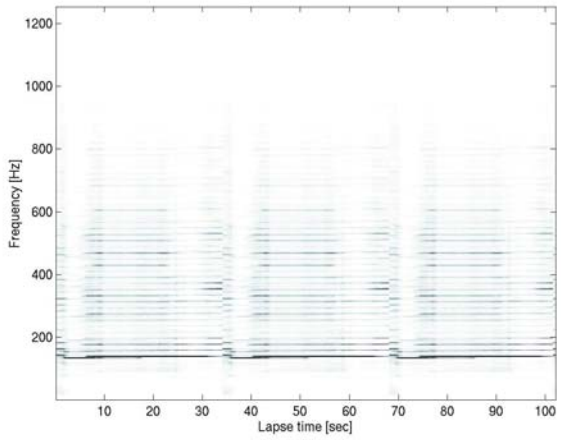

Figure 10. Time-frequency display (Lofargram) by bicoherence projection with outlier rejection and imputation method D. The estimate is from the same data as in Fig 4.

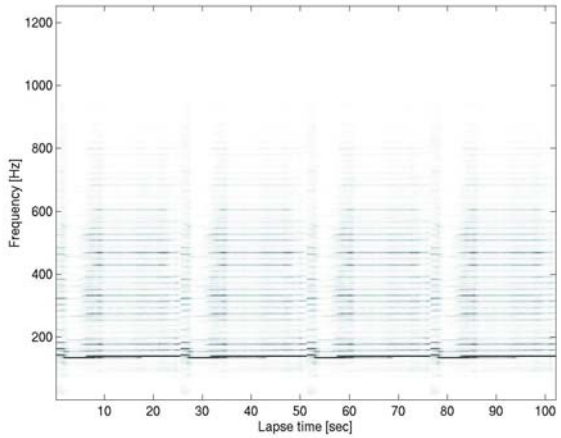

Figure 11. Time-frequency display (Lofargram) by bicoherence projection with outlier rejection and imputation method E. The estimate is from the same data as in Fig 4.

VI. CONCLUSIONS

In previous work [7] and [8] different bispectral based methods were performed for target signature analysis on the same data set as here. Relations to harmonic couplings between the engine and the drive were presented. Here, we perform conditioning of sonar data by using both outlier rejection in the bispectrum domain and imputation methods for replacement of rejected data values. The outlier rejection correction reduces the frequency components with nonstationary properties and the imputation methods replace the values. The objective is to improved narrowband spectral source patterns in passive sonar data. The imputation methods by using values based on nearest neighbor in the bispectrum domain seems to produce the most pronounced spectral lines in the Lofargram. The performance of the conditioning method is largest in parts with low signal-to-noise ratio. The harmonic patterns we found in the modified Lofargram by using the modified bicoherence projection are related to the signature of the used boat in the experiment.

Acknowledgments

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