Improving the DEMON analysis using Independent Component Analysis

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***Abstract*—Passive sonar systems used in submarines, performs the direction of arrival (DOA), the detection and classification of targets signals that are impinging on the hydrophones from a particular direction of interest. In some situations, depending on the resolution of the beamformer (hydrophones array) and when the signals are at too close bearings, a cross interference may bring difficult on the target identification by the operator of sonar. This paper aims at using independent component analysis (ICA) as preprocessing on DEMON analysis to improve the targets identification.The FastICA algorithm was used, which was applied to the simulated data, and performance was measured both, qualitatively and quantitatively.**

I. Introduction

Sonar Sound Navigation and Ranging [1] systems use the sound propagation in underwater environments for detection, communication and navigation. The main purpose of these systems is to analyse the underwater acoustic waves received from different directions by a sensor system and identify the type of target that is detected in a given direction. Sonar systems may be active or passive. The active sonar transmits an acoustic wave that is reflected by the target and signal detection, parameter estimation and localization can be obtained through the corresponding echoes [1], [2]. On the other hand, passive sonar systems perform signal detection and estimation using the noise radiated by the target [2], [3]. Both passive and active sonar systems are mainly employed in military settings, although they are also used in commercial and scientific applications, i.e., detecting shoal fishes, performing tomography on sea to exploit a given area, to measure the depth of a region, and so on [4]. On the other hand, a increased awareness of environmental issues has also stimulated the development of passive sonar techniques for detecting schools of fish and whales, as well as the detection of oil and gas in depth waters. The major difficulty in passive sonar systems, on military applications, is that often target detection is performed under huge background noise conditions and in some situations interference caused by others ships in a scenario.

The passive sonar system aims at carrying out detection and classification (target identification) of acoustic signals in underwater environments from a target. A way to perform the detection and classification of the target is trough its propeller noise. The target identification may be done using the DEMON (Detection Envelope Modulation On Noise) analysis [2] that allow the identification of the shaft rotation and the blade rate of the target. But, in some situations, when the targets are on closed bearings a cross interference may difficult the identification by the sonar operator. Due to this, it is necessary perform a preprocessing on the DEMON analysis, to improve the signal-to-interference ratio (SIR), thus facilitating the contact identification by the sonar operator.

This preprocessing is implemented using the ICA algorithms [5], [6]. The algorithm used in this work was the FastICA. The performance evaluations of the algorithm will be done qualitatively and quantitatively, using analysis graphical in the field of observations and estimated components. The quantitative performance will be realized using the Kullback-Leibler divergence as figure of merit [7].

II. Propulsion Identification

In order to accomplish contact identification at some direction of interest, the DEMON analysis may be used to detect the propulsion of the target. DEMON is a narrow band analysis that operates on cavitation noise in order to identify the number of axis, the rotation frequency and the blade rate of a contact [2] and [8]. With this analysis will be enable to perform the detection and identification of a contact on a direction of interest by the sonar operator. The Figure 1 shows the block diagram of the classical DEMON analysis. At a particular bearing, the signal is band limited by a bandpass filter, for the frequency band where cavitation is more pronounced. The cavitation frequency range goes from hundreds to thousands of Hertz [9]. However, in a certain frequency bandwidth, cavitation is more emphasized, that is, the modulation index is higher, facilitating the identification of the contact. In our case, the bandwidth was chosen to be within 1 and 2 kHz [4]. After filtering, the signal is demodulated to obtain the contact propulsion. As the sampling frequency of the signal is so high with respect to the propulsion band, a resampling is performed so that the signal is transposed to the propulsion range where the propeller characteristics are more evident [10]. Then, a fast Fourier transform (STFFT - Short Time Fourier Transform) [11] is implemented to reach the spectrum. A normalization is implemented to perform the frequency peak equalization [2].

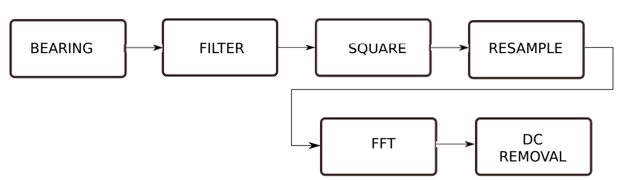

Figure 1. Block diagram of the classic DEMON analysis.

A. Data Acquisition

The data used in this work were acquired by simulation from a collaboration with the Brazilian Navy. The sampling rate was maintained at $f_s = 31,250$ Hz and the signals were split into time windows of 60 s. This choice of the windows lengths is by the fact that in the resampling process, it is necessary at least, approximately 20 s for a good resolution on a FFT of $1,024$ frequency bins, which is performed during the analysis DEMON analysis. Then, were chosen three time windows to implement the analysis.

As mentioned early, the data were acquired through a passive sonar simulator for training sonar operators and each of them have $1,020$ s (17 minutes). In this simulation, it was created a scenario where two ships are operating in permanent cavitation regime, beginning at distinct bearings (B1 and B2) and some time afterwards, they start to get close enough, so that there is an interference among them. This interference begins, approximately, at fourteenth window and the SIR decreases until the seventeenth window. The main feature of these data is the high level of cavitation, which allows the identification of the contact propulsion through the DEMON analysis.

Next will be shown the ICA algorithm and the methodology that was used to implement the blind separation.

III. Blind Source Separation

The purpose of blind source separation (BSS) is to estimate sources that were mixed in some unknown way. BSS intends to emphasize the absence or almost no knowledge about the sources which gave rise to the observations [6]. The observations (the data mixed) that are completely known, will be the starting point and object of the work. Several methods are used for solving the problem of blind source separation [12] and [13]. In this work will be used the independent component analysis.

A. Independent Component Analysis

Independent components means that, the value of a component does not provide any information about the value of any other, whereas the original components are statistically independent. Then the aim is to extract the components from observations.

The independent component analysis considers a set of N observed signals, $\mathbf{x}(t) = [x_1(t), ..., x_N(t)]^T$, is generated by a linear combination of signal sources, $\mathbf{s}(t) = [s_1(t), ..., s_N(t)]^T$, as show in Equation 1, where $\mathbf{A}$ is a mixture matrix [12].

$$\mathbf{x(t)} = \mathbf{As(t)} \tag{1}$$

The purpose on this problem is estimate the sources, $\mathbf{s}(t)$, using only the observations, $\mathbf{x}(t)$. A solution can be reached calculating the inverse of mixture matrix $\mathbf{B} = \mathbf{A}^{-1}$ and applying this matrix on the observations to obtain the original sources, as shown in Equation 2, where $\mathbf{y}(t)$ is the estimative of $\mathbf{s}(t)$. To estimate the unmixed matrix will be used the FastICA algorithm.

$$\mathbf{y(t)} = \mathbf{Bx(t)} \tag{2}$$

1) FastICA algorithm: This algorithm uses the principle of the maximization of non gaussianity in terms of kurtosis and negentropy [12], [14]. Considering a observation $\mathbf{x}_i$, it is possible to perform the estimation of independent components through a cost function, as shown in Equations 3 and 4, where $\mathbf{W}$ is a weighting matrix, and $\mathbf{z}$ is the whitened data vector by a matrix $\mathbf{V}$, i.e., $\mathbf{z}$ = $\mathbf{Vx}$. In order to make the algorithm faster, the gradient is carried out as shown in Equation 5:

$$\mathbf{x} = \mathbf{W}^T\mathbf{z} \tag{3}$$

$$\begin{aligned} \frac{\partial|kurt(\mathbf{W}^T\mathbf{z})|}{\partial\mathbf{W}} &= 4sign\left[kurt(\mathbf{W}^T\mathbf{z})\right]\dots \\ \dots E\left\{\mathbf{z}(\mathbf{W}^T\mathbf{z} - 3\mathbf{W}\|\mathbf{W}\|^2)\right\} \end{aligned} \tag{4}$$

$$\Delta\mathbf{W} \propto sign(kurt(\mathbf{W}^T\mathbf{z}))E\left\{\mathbf{z}(\mathbf{W}^T\mathbf{z}\right\} \tag{5}$$

The classical approach using negentropy is based on higher order cumulants and polynomial expansion of the input values $G(\mathbf{x}) = \log\left[\cosh(\mathbf{x})\right]$ or $-\exp(\frac{\mathbf{x}^2}{2})$ [15]. Using a gradient algorithm based on this method, the polynomial functions, mentioned above, may be applied in FastICA algorithm as shown in Equation 6. The matrix $\mathbf{W}$ must be normalized, $\mathbf{W} \longleftarrow \dfrac{\mathbf{W}}{\|\mathbf{W}\|}$, to avoid an algorithm divergence.

$$\mathbf{W} \longleftarrow E\left\{\mathbf{z}g(\mathbf{W}^T\mathbf{z}\right\} - E\left\{g^*(\mathbf{W}^T\mathbf{z})\right\}\mathbf{W} \tag{6}$$

The FastICA algorithm may estimated the independent components, all at a time or one-by-one. In this work, the estimation was performed using the deflation method that extract the components one-by-one.

IV. Performance Measurements

There were used two ways to measure the performance of the algorithm. The SIR among the signals were measured before and after the estimation of the components, to verify if there was an improvement upon the SIR estimation with ICA. Quantitatively, it was calculated the Kullback-Leibler divergence [16], as shown in Equation 7, among the spectra of the observations and among the spectra of the estimated components. Then, may be possible to verify the efficiency of the algorithm on the separation.

$$D_{kl}(\mathbf{p},\mathbf{q}) = \sum_i \ln\left(\frac{p_i}{q_i}\right)p_i \tag{7}$$

V. RESULTS

The DEMON analysis usually goes of 0 until $1,500$ rpm, that normally correspond to the range of the contact propulsion. In the case of simulated data, that were used in this work, as the propulsion range of each the contact is on the range of 380 and 480 rpm respectively, the processing and graphical representation were performed at the range of 350 tilun 550 rpm. Due to this, the components that are not of interest will be already eliminated.

As the simulated data are fully controlled, due to prior knowledge of their behaviour, it was assumed a benchmark of quality for each of the contacts. The benchmark choice was the first time window of each bearing. This choice was by fact that, at the first window, the contacts are more separated. Measurements were performed among the spectra of the benchmarks, and the observations and estimated components by the FastICA.

The last time window (window 17) contains information where the contacts are more closer, corresponding to higher interference. The ICA algorithm have been applied in each one of the time windows, in order to improve the interference among the signals facilitating the contacts identification by the sonar operator. Only the last three time windows analysis will be shown, since, these windows suffer the greatest interferences.

The ICA was applied on the DEMON analysis, on the time domain, after the signals resampling as shown in Figure 2. Due to the fact that the ICA is being performed in the propulsion domain, some components that are not of interest just will be eliminated.

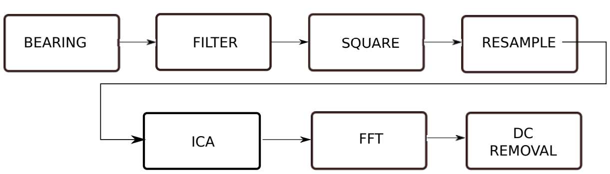

Figure 2. Block diagram of the ICA in the DEMON analysis.

A. Results with FastICA Algorithm

The Figures 3, 4 and 5 show the DEMON analysis regarding the last three time windows and their respective components.

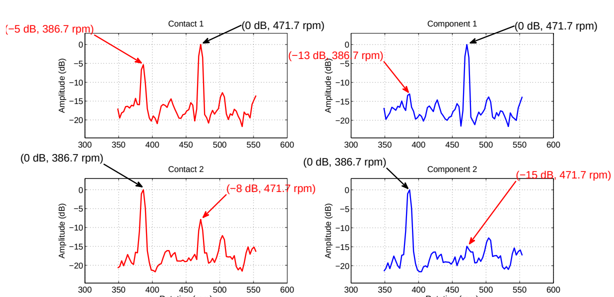

Figure 3. DEMON analysis of the contacts and the components of the time window 15.

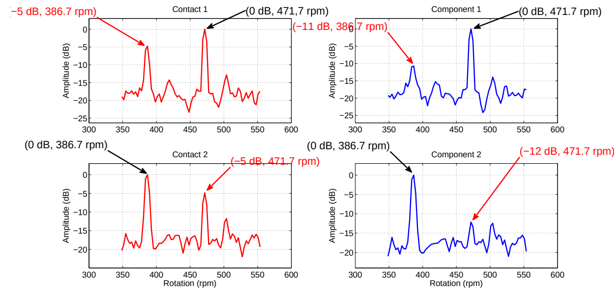

Figure 4. DEMON analysis of the contacts and the components of the time window 16.

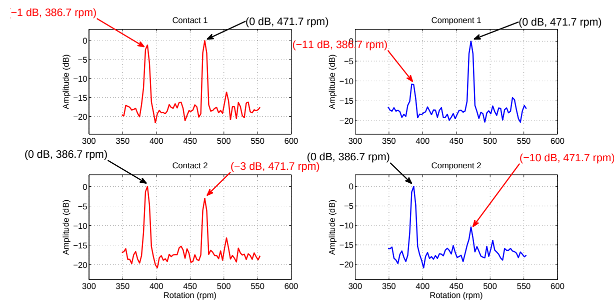

Figure 5. DEMON analysis of the contacts and the components of the time window 17.

The Figure 3 shows that, the SIR of the contact have 5 and 8 dB respectively. After the components estimations, may be observed that the SIR at each of the components reached 13 and 15 dB, respectively, showing that the SIR increases among the components. On the Figures 4 and 5, the algorithm performed the attenuation in interference among the contacts, improving the SIR.

Quantitatively, the measure of the Kullback-Leibler (KL) divergence was chosen to measure the algorithm performance [7]. First, the KL divergence was implemented at each time window, among the contacts (observations) and among the components, as shown in Figure 6.

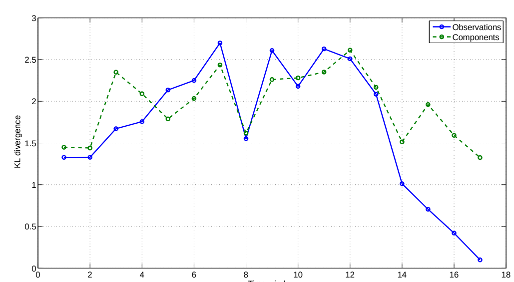

Figure 6. KL divergence among observations and among the components estimated by the FastICA algorithm.

May be observed the efficiency of the separation by comparing the curves of kl divergence, among the observations and the components. From first until the thirteenth time window, where the signals are not suffering cross interference, the KL divergence among observations and components, remain at the same level, suffering only variations due to noise fluctuations.

These time windows may serve to calibrate the behaviour of the algorithm. From the thirteenth time window, when begins the interference, the KL divergence among the observations, begins to decrease, going toward zero, while the KL divergence among components remain in values next to 1.6. This shows that the KL divergence of the components are with the values next to the divergence of the initial time windows. May be concluded that the algorithm is separating the signals and returning to values next of the initial observations.

Another way to verify the FastICA algorithm performance is to measure the KL divergence among the benchmarks time windows and the respective contacts, and among benchmarks and their respective components, as shown in Figure 7.

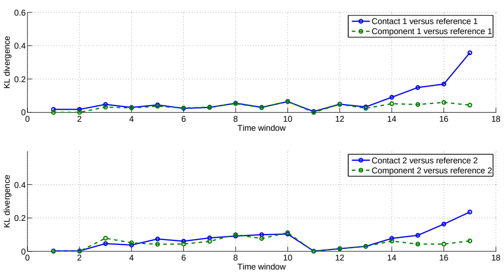

Figure 7. KL among the benchmarks and contacts, and benchmarks and components by FastICA algorithm.

The KL divergence among the benchmarks and observations remain nearly zero from the first until the thirteenth time window. From the fourteenth window upward, there is an increasing of the divergence due to the interference. While the divergence among the benchmarks and the components, remain around zero in all windows, ensuring that the algorithm performed the separation.

VI. Conclusion

Independent component analysis may be used as a important tool on passive sonar signals separation that are suffering cross interference among them. In this work the independent component analysis was used as preprocessing on the DEMON analysis with the purpose of emphasize the propulsion detection of a contact on time domain, improving the contact identification by the sonar operator. Simulated data was used to verify the behaviour of ICA the algorithms. The algorithm used in this work was the FastICA, using the negentropy as cost function and the deflation method to reach the independent components.

The performance, of the algorithm, was investigating by the use of two index. Qualitatively, the SIR was measured among the contacts(observations) and the components. May be observed that SIR after the estimation by the algorithm suffered a substantial increment showing that the algorithms searched an efficient separation.

Quantitatively, it was measured the KL divergence among the contacts (observations) and among the components estimated by the FastICA and it was observed the behaviour of the curves. The KL divergence of the components, on time windows that have less SIR, remained on values next the initial temporal windows, showing that the algorithm returned to values on which the contacts are most separated unless of noise fluctuations. When the SIR decrease, from the thirteen time window ahead, the KL divergence among the contacts goes toward zero, while the divergence among the components remains in turn of the values of the time windows that are not suffering interferences. This indicates that there was a contacts separation. Finally, another way measuring quantitatively the algorithm performance was through a benchmark. May be observed that in all time windows, the components remain next zero, providing the the algorithms implemented the separation.

Then, may concluded that the FastICA algorithm had a good performance in the separation of contacts improving the SIR on the time domain. Future works can be implemented using others ICA algorithms and applying the independent components in another domain of the DEMON analysis.

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