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Passive Sonar Signal Detection and Classification Based on Independent Component Analysis

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1. Introduction

Sonar 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 has been detected in a given direction. Sonar systems may either be passive or active. Both passive and active sonar systems are mainly employed in military settings, although they are also used in commercial and scientific applications, e.g. detecting shoal fishes, performing tomography on sea to exploit a given area, to measure the depth of a region, and so on (Burdic, 1991).

In order to detect and classify signals against background noise, passive sonar systems (Waite, 2003) listen to the noise radiated by targets (ships or submarines) using an array of hydrophones. The background noise may be produced by the sea ambient noise or the self-noise of the sonar platform. From the acquired signals, the direction of arrival (DOA) is estimated, in order to inform the eventual presence of a target in a determined direction (bearing). After DOA estimation, relevant features of the target may be extracted from a given direction.

There are two types of analysis that can be implemented to obtain the signal relevant features: DEMON (Detection Envelope Modulation On Noise) (Nielsen, 1991) and LOFAR (Low Frequency Analysis and Recording) (Di Martino, 1993). The DEMON is a narrowband analysis that furnishes the propeller characteristic: number of shafts, shaft rotation frequency and blade rate of the target. On the other hand, LOFAR, which is a broadband analysis, estimates the noise vibration of the target machinery. Both analysis are based on spectral estimation and support detection and classification of targets.

Depending on the bearing resolution, signal interference may occur for neighbour directions, which contaminates the acquired signals and makes even more difficult the target detection and classification tasks. To minimize these interferences, algorithms using ICA (Independent Component Analysis) (Hyvarinen, 2001), (Jutten, 2004) may be applied to recover the original sources of the resulting signal mixture and obtain optimal target detection and classification for each direction.

The detection is implemented using the classical signal demodulation to obtain the propeller characteristics. On the other hand, efficient classification is often obtained through neural

networks (Soares Filho, 2001). For both DEMON and LOFAR analysis, a signal preprocessing using ICA may be implemented to reduce the signal interference in neighbour directions.
On the other hand, underwater acoustic signals suffer fluctuations as a function of the sea features (salinity, temperature, and so on). In addition, noise radiated from targets may vary according to operational conditions. As a consequence, the stationarity of passive sonar signals may be affected. Therefore, it is necessary to monitor changes in the statistics of the passive sonar signals in real time. When changes are detected, the independent component extraction phase may be reloaded for updating the feature extraction procedure. An unsupervised clustering method using a modified ART (Adaptive Resonance Theory) neural network can perform such monitoring task.
The chapter is organised as it follows. In section 2, both DEMON and LOFAR analysis are detailed. Section 3 addresses signal interference and its removal in frequency-domain using ICA. Section 4 briefly presents the independent component analysis and the algorithm that was used to implement the blind source separation scheme. Section 5 gives some signal detection and classification results from experimental data, which were acquired from a passive sonar system that has been installed in a submarine. Finally, Section 6 presents conclusions and the perspectives for passive sonar signal processing.

2. Spectral analysis

In this section, both DEMON and LOFAR analysis are described. Their aim is to detect and classify the targets from a given DOA.

2.1 DEMON analysis

For signal detection, DEMON analysis is normally applied. DEMON is a narrowband analysis that operates over the cavitation noise of the target propeller (Nielsen, 1991). As resulting parameters provide a detailed knowledge of the target propellers (the propeller noise is characteristic for each target), often efficient detection is achieved. Figure 1 shows the block diagram of classical DEMON analysis.

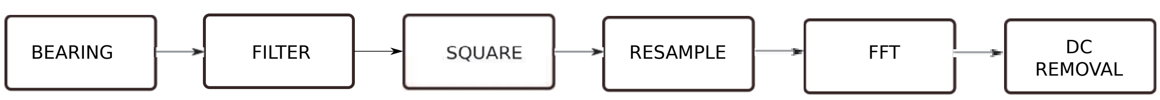


Fig. 1. DEMON analysis block diagram.

Given a direction of interest (bearing), a bandpass filter is implemented to limit the cavitation frequency range (Burdic, 1991). The cavitation frequency goes from hundreds until thousands of Hz. Therefore, it is important to select the cavitation band and obtain the maximum information for ship identification. Following, the signal is squared as in traditional demodulation (Van Trees, 2001), (Yang, 2007). In most cases, the signal sampling rate is relatively high, so that the band of interest is sampled with coarse resolution with respect to observation needs. Thus, it is necessary to decimate the signal for better observation in the range of interest (Rabner, 1983), as shown in Figure 2. The signal is sampled at a frequency

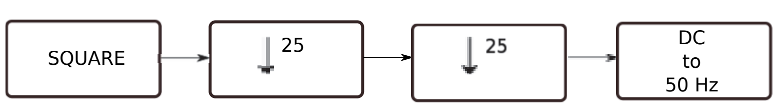


Fig. 2. Signal decimate.

of $31,250$ Hz. When the first decimate by a factor of 25 is applied the down sampling goes to $1,250$ Hz. In the sequence, a further decimate by a factor of 25 is realized and the range from DC to 50 Hz is searched for. This range contains the rotations of interest that go from 0 to $1,500$ (rpm). Finally, a short-time Fast Fourier Transform algorithm (Diniz, 2010) is applied for performing signal analysis in frequency-domain and the TPSW (Two Pass Split Window) algorithm is used to reduce the background noise (Nielsen, 1991).

2.2 LOFAR analysis

The LOFAR (Waite, 2003) is a broadband analysis that provides the machinery noise to the sonar operator and goes from DC to 15,625 Hz. The block diagram of the LOFAR analysis is shown in Figure 3.

Fig. 3. LOFAR analysis block diagram.

After bearing, the signal is multiplied by a Hanning window to emphasize the frequency range of interest (Diniz, 2010). Then, the signal is separated in blocks of 1,024 samples, which are transformed into frequency-domain using a short time Fourier transform. A spectrum module is implemented and the spectra are normalized using the TPSW algorithm. The normalization may be implemented estimating the background noise that is present at each spectrum and computing a normalized frequency bin using this estimation as normalization factor. This estimation removes the spectrum bias and equalizes the spectrum amplitude (Soares Filho, 2011).

3. Signal interference

A passive sonar system is typically used by submarines to realize the surveillance in a determined operation area. The beamforming aims at estimating the direction of arrival (DOA) from a given target. The Figure 4 shows the beamforming display. The main purpose of the DOA is to estimate the target energy for a particular direction of interest. The horizontal axis represents the bearing position (-180^o to 180^o) and the vertical axis represents time (waterfall display). In this case, an acquisition window of one second was considered (Krim, 1996).

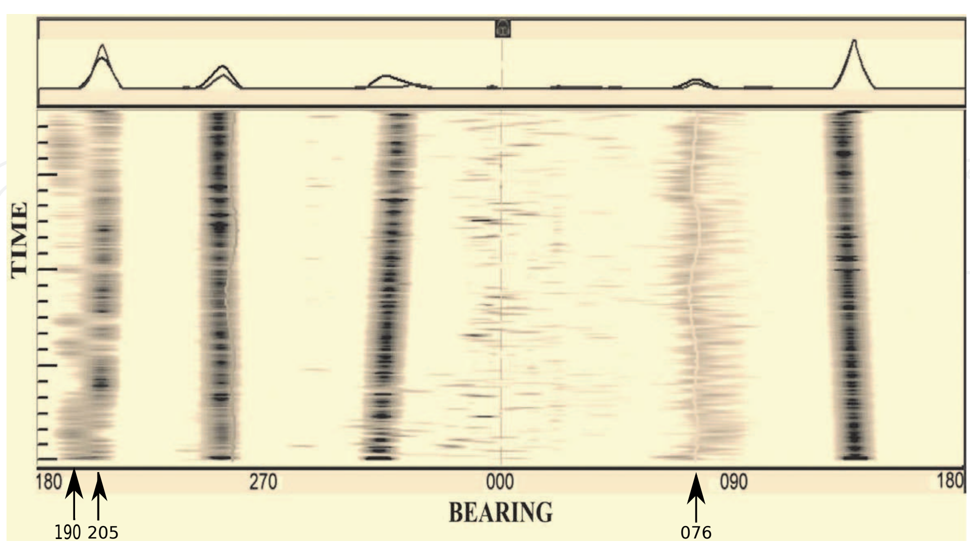


Fig. 4. Bearing time display of a passive sonar system.

When signal interference from neighbor bins occurs, as it may be the case for bearings 190° and 205° (see Figure 4), the original target features may be masked and both target detection and classification efficiencies may be affected. Beyond that, the self-noise, bearing 076°, may interfere on the detection of both targets by the sonar operator. Thus, a preprocessing scheme may be developed aiming at reducing signal interferences, facilitating target identification and classification. Here, signal preprocessing is addressed by independent component analysis (Hyvarinen, 2001), which is performed in frequency-domain (see Figure 5). After beamforming a spectral analysis is implemented at each direction of interest and an algorithm to extract the independent components is implemented. Then both DEMON and LOFAR analysis are performed over the independent sources (ICA space).

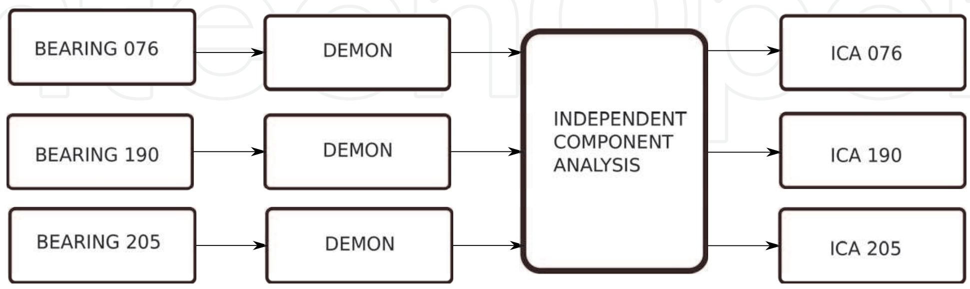


Fig. 5. Interference removal in frequency-domain.

4. Independent component analysis

The ICA provides a linear representation of nongaussian data, so that components are statistically independent, or as much independent as possible (Hyvarinen, 2001), (Yan, 2000). The basic ICA model assumes the existence of n independent signals $s_1(t), ..., s_n(t)$ and the observation of as many linear and instantaneous mixtures $x_1(t), ..., x_n(t)$, as shown in equation 1:

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

where $\mathbf{s}(t) = [s_1(t), ..., s_n(t)]^T$ is a nx1 column vector corresponding to the source signals, and $\mathbf{x}(t)$ similarly collects the n observed signals. $\mathbf{A}$ is the mixing matrix that contains the mixture coefficients. The ICA problem consists in recovering the source vector $\mathbf{s}(t)$ using only the observed data $\mathbf{x}(t)$, with the assumption of independence between the entries of the source vector $\mathbf{s}(t)$. The ICA problem may also formulated as the estimation of a nxn demixing matrix $\mathbf{B}$, which allows original sources to be recovered:

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

where $\mathbf{y}(t)$ becomes the estimated source vector.
Due to the well known central limit theorem (Barany, 2007), the ICA estimates can be obtained from the determination of the directions for which the nongaussianity is maximum. Efficient algorithms are available today (Hyvarinen, 2001), among which Newton-like algorithm has been claimed to be very efficient (Akuzawa, 2001).

4.1 Multiplicative newton-like algorithm for ICA

This ICA algorithm was proposed by Akuzawa and Murata (Akuzawa, 2000). Using kurtosis as the cost function, this method applies second order optimization (through a Newton-like algorithm) in the search for independent components (instead of first-order gradient iterations used in most ICA algorithms). Kurtosis is a fourth-order cumulant that measures the shape of the distribution. For a zero-mean random variable $\mathbf{x}$, kurtosis is defined as (Kim, 2004):

$$K_4 = E\{\mathbf{x}^4\} - 3[E\{\mathbf{x}^2\}]^2 \tag{3}$$

This ICA algorithm does not require pre-whitening and thus operates directly over the data. Modifications on the method have also been proposed (Akuzawa, 2000) aiming at reducing the computational cost by substituting the pure-Newton optimization by quasi-Newton iterations (Akuzawa, 2001).

5. Experimental results

The raw data used here were acquired from a passive sonar system that is installed in a submarine of the Brazilian Navy. Raw data were processed according to Figure 5, in which the ICA block was performed by the Newton-like algorithm. Performance is evaluated for both signal detection using DEMON analysis and signal classification from LOFAR analysis.

5.1 Signal detection

From Figure 4, one may observe that bearings 190^0 and 205^0 suffer from mutual interference. Figure 6 displays the DEMON analysis for each of these directions. For bearing 190^o the largest peak is at 146.4 rpm, which corresponds to the target shaft rotation. The next harmonic represents the target blade rate. But interferences are also observed at 120.1 rpm and 304.7 rpm, which are relative to the 205^o and the self-noise (076^o), respectively. Similarly, interference is seen at 304.7 rpm for 205^o, which is the peak of the self-noise.

Figure 7 shows the resulting DEMON analysis from ICA preprocessing. In general it is noted that the baseline noise is reduced for bearings 190^o and 205^o, which reflects in a better signal-to-noise ratio. Additionally, interferences from others bearings and the self-noise are reduced.

A manner to measure the independence between signals is the mutual information, which may quantify how much independent are the components that were extracted by the Newton-like algorithm.

5.1.1 Mutual information

Assuming we have two random variables $\mathbf{v}$ and $\mathbf{w}$ with marginal distribution $p(\mathbf{v})$, $p(\mathbf{w})$ and joint distribution $p(\mathbf{v}, \mathbf{w})$, the mutual information (Hild, 2001), (Hoffmann, 2006) is a measure of the amount of information that the variable $\mathbf{v}$ has about the variable $\mathbf{w}$, as shown in Equation 4. The mutual information $I(\mathbf{v}, \mathbf{w})$ must be non-negative. When $I(\mathbf{v}, \mathbf{w}) = 0$, $\mathbf{v}$ and $\mathbf{w}$ are independent.

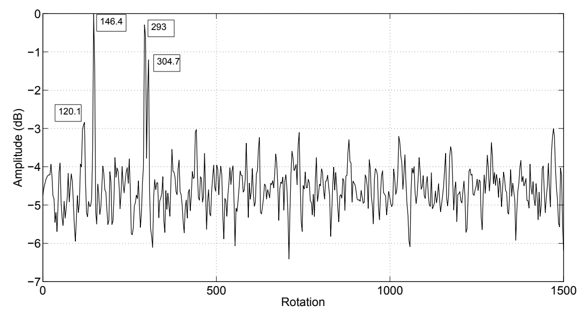
$$I(\mathbf{v}, \mathbf{w}) = \sum_{v_i \in \mathbf{v}} \sum_{w_j \in \mathbf{w}} p(v_i, w_j) \frac{\ln p(v_i, w_j)}{p(v_i) p(w_j)} \tag{4}$$

As it can be seen from equation 4, it is necessary to compute the probability density function (pdf) of the variables. To estimate the variable pdf, a non-parametric method (Kernel estimation) may be applied (Peng, 2005). Suppose $v_1, \ldots, v_n$ independent identically distributed (i.i.d.) variables, then, the kernel density approximation of its probability density function may be given by:

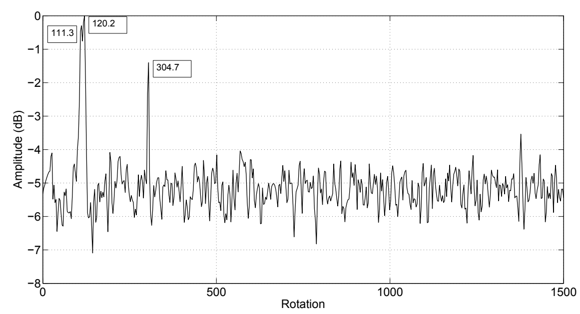
$$\hat{p}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{v - v_i}{h}\right) \tag{5}$$

where K is some kernel function and h is a smoothing parameter called the bandwidth. Here, K is taken to be a standard zero-mean Gaussian function having unitary variance.

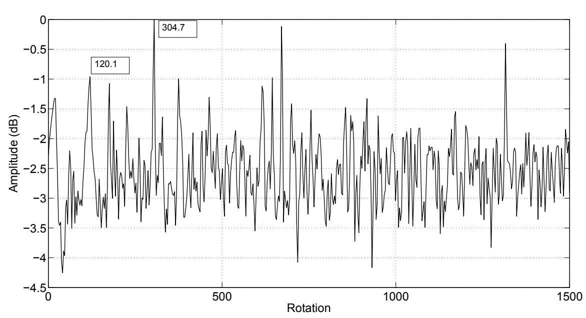
For comparison, the mutual information is computed before and after the interference removal process (see Figure 5). For controlling artificially the amount of signal interference, a weighting matrix is created:



(a) Bearing 190.



(b) Bearing 205.



(c) Bearing 076.

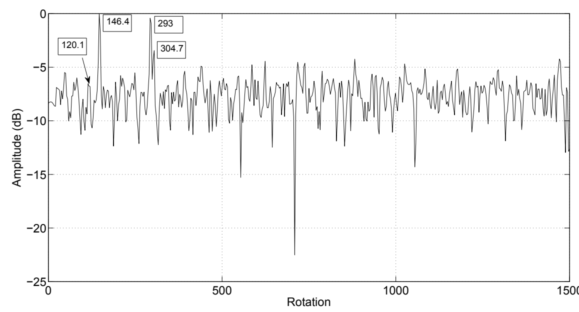
Fig. 6. Standard DEMON analysis for: (a) 190^o, (b) 205^o and (c) 076^o directions.

$$W = \begin{bmatrix} p & 1 \\ 1 & p \end{bmatrix} \tag{6}$$

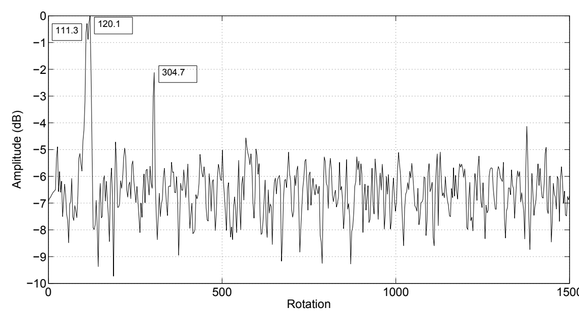
The p parameter varies from 0 to 1 with steps of 0.01. With such weighting process, it is possible to control the mixture on signals and components. This allows to calibrate the measure of the mutual information. Figure 8 shows the mutual information between bearings 190^o and 205^o as a function of weighting value. Although the components are multiplied by the weighting matrix, the mutual information is always smaller for extracted components than for the original mixing signals. Thus, despite increasing the interference through the weighting matrix, ICA outputs remains less susceptible to interferences.

5.2 Signal classification

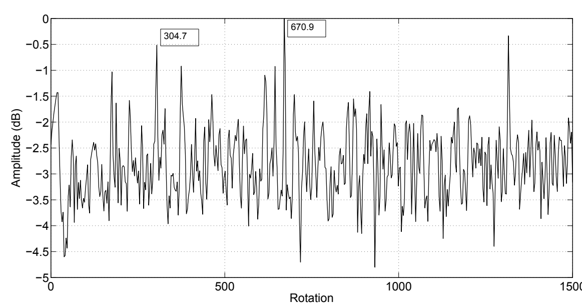
For classification tests, data from two bearings 31^o and 146^o were chosen (see Figure 9). As it may be observed from Figure 9, during around the first three minutes, signals from these two



(a) Bearing 190.



(b) Bearing 205



(c) Bearing 076

Fig. 7. Preprocessed DEMON analysis for: (a) 190^o, (b) 205^o and (c) 076^o.

bearings are well separated. This will make a good characterization of the contacts in their bearings for the neural training. In the sequence, the detected target at 31^o approaches the one in 146^o, causing mutual interferences.
The signal classification was implemented through spectra acquired from the LOFAR analysis (see Figure 3). Figure 10 shows the lofargram for both bearings 31^o and 146^o, which shows that target characteristics can be extracted through the this analysis.
For evaluating neural classification robustness based on independent component information signals were combined through a mixture matrix A (Equation 7). The matrix A corresponds to the beamforming obtained for these bearings.
After the mixture, a Gaussian noise at each bearing that correspond a signal-noise ratio of about 10 dB . The neural network was tested with these signals to verify the performance of the classify.

$$A = \begin{bmatrix} 0.2 & 0.8 \\ 0.8 & 0.2 \end{bmatrix} \tag{7}$$

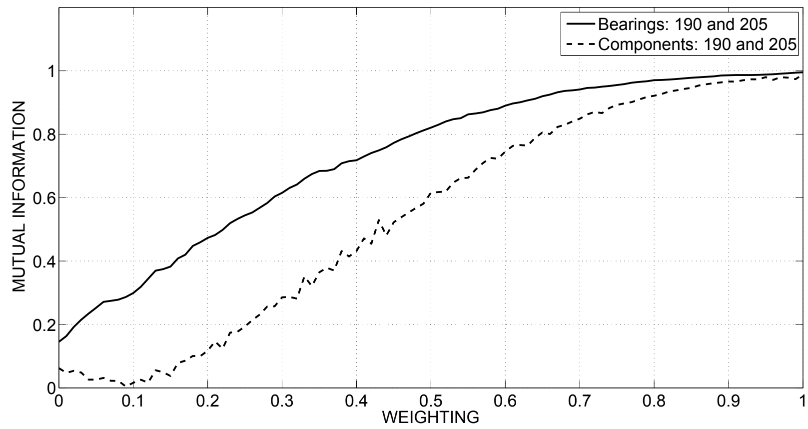


Fig. 8. Mutual information between the bearings 190 and 205 for original signal and extracted from ICA.

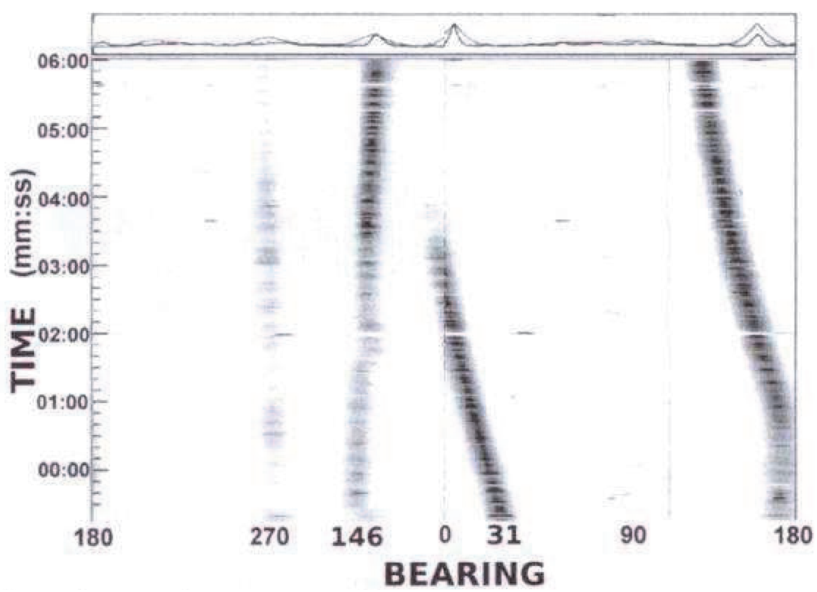


Fig. 9. Bearing time display of a passive sonar system (classification example).

- First, the classifier was tested with the separated signal;
- Next, noise was added to bearings;
- In sequence, bearing signals were mixed;
- Finally, the bearings were mixed, noise was added and the ICA algorithm, was applied, in order to recover from mixture.

5.2.1 Neural classifier

The neural classifier is based on MLP - Multi-Layer Perceptron topology (Haykin, 2008), comprising three layers without feedback. This neural network was designed with one input layer having 256 nodes, a single hidden layer with 4 neurons and an output neuron, which was trained for assigning $+1$ for data from bearing 31^o and -1 for 146^o. The neurons from both hidden and output layers have hyperbolic tangent as the activation function. The training

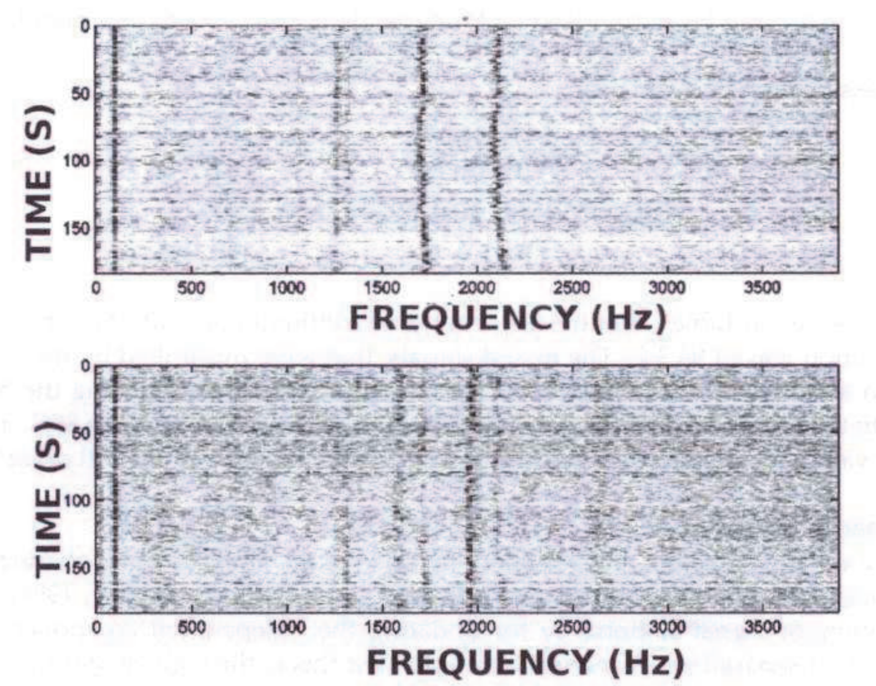


Fig. 10. LOFAR analysis for bearings 31^o (top) and 146^o (bottom), respectively.

phase has been performed in batch and used half of the spectra data from both targets. The training algorithm was backpropagation. After training, the classification performance is evaluated from the testing set (the other half of data that did not participate in the training step).

Test signal	94.3
Without mixer and with noise	89.0
With mixer	**82.7**
With ICA	**88.0**

Table 1. Classification performance (see text).

From original unmixed signals the classification efficiency was 94.3%. Adding noise reduces efficiency, which reaches 82.7%. Mixing signals provides a further reduction in classification efficiency and applying ICA, efficiency is recovered, setting back to 88%.

5.3 Stationarity analysis

The passive sonar signals are not stationary due to the ambient noise characteristics and external conditions. Then, signal stationarity monitoring is required and when the statistics changes an update of the independent component estimation may be requested for signal processing. A manner to implement this is through clustering using neural networks.

5.3.1 Clustering

Clustering may be based on non-supervised training. The main idea is to receive spectra from the DEMON analysis and observe when a change may occur on data statistics. The spectra information is from the DEMON analysis. The input spectra comprises of 513 frequency bins. Principal component analysis (PCA) (Chen, 2000), (Soares Filho, 2001) is firstly applied for

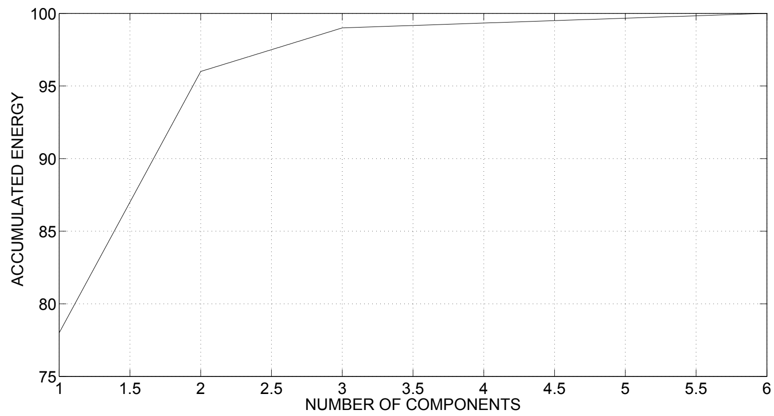


Fig. 11. Accumulated energy in principal components for PCA.

data dimensionality reduction. The Figure 11 displays the accumulated energy curve which shows that the clustering process may be realized projecting data onto only two components. For clustering, a modified ART (Adaptive Resonance Theory) (Vassali, 2002). The training is competitive and based on a Kohonen layer, attaching a neuron at each new input pattern. The control parameters are the cluster vigilance radius and the learning rate. The vigilance radius of the cluster is defined by the most probable value obtained from measuring the distance of all input data patterns.
The conceptual model of the clustering consists in:

- Information obtained from the sonar operator points out that the passive sonar signal must be evaluated at each 10 seconds to verify a statistical change. How the DEMON analysis presents each line in 500ms then, it was acquire 20 FFT windows through that corresponds to these 10 seconds;
- As data dimension is very high, a PCA was applied to reduce data dimension;
- Clusters are formed from these 20 windows;
- Changes on number of clusters are evaluated, in conjunction with possible shifts of the center of these clusters; and
- The statistical changes are then identified.

A signal of the bearing 190^o with 200 seconds was recorded to system development. As mentioned early the spectra were obtained through the DEMON analysis. Specialists indicate that the passive sonar signal must be evaluated at each 10 seconds to verify if a statistical changes have been occurred. Then 20 spectra were chosen as a start point to network parametrization.
Because of the high dimension of the input data and having the knowledge the clustering presents better results in reduced dimensions (Duda, 2000), principal components analysis (Soares Filho, 2001) was implemented. The Figure 11 shows the accumulated energy in principal components for PCA. It may be noted that only with the first two components were obtained from 95% of the variance of the process. Therefore, the clustering was implemented using in the input net the data projections of the two principal components.
Clustering is to give one neuron to each cluster from the similarity between each input pattern, which represents an FFT window. Figure 12 shows the evolution of the number of clusters. This information states that there was a new cluster or more than one. May be observed that there was the forgotten one or more clusters and this is very important to indicate that there was a statistical change in the process. For example, one can notice that there was a great

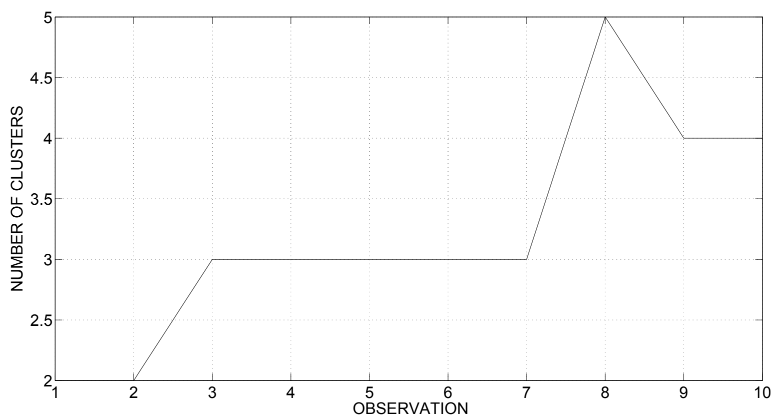


Fig. 12. Number of clusters after clustering at each observation.

increase in observation 7 to 8, since the number of clusters jumps from 3 to 5. This is a strong indication that the statistics of the signal changed significantly.

6. Conclusions

The passive sonar system aims at detecting and classifying targets from given directions. Additional difficulties arise when interferences occur in neighbour directions Therefore, a preprocessing scheme may be developed for reducing interferences and facilitating detection and classification tasks for the sonar operator. This preprocessing step may be implemented using the independent component analysis in frequency-domain and improvements in both detection and classification efficiencies have been observed from experimental data.

As original sources have to be estimated blindly, the stationarity of the passive sonar signals should be monitored. When statistics change, the preprocessing data chain may be reloaded for updating the source estimation.

Other algorithms of blind source separation may be implemented to improve the signal noise interference removal in passive sonar systems. Among them, the nonnegative matrix factorization (NMF) (Chichocki, 2009) which uses similarity measures to extract the original free of interference signals looks attractive. Additionally, algorithms of blind source separation using nonstationarity and convolutive mixture may be used.

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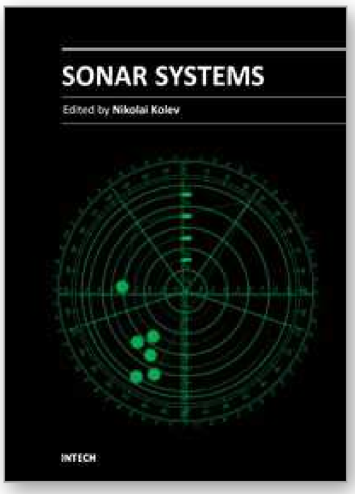

Sonar Systems

Edited by Prof. Nikolai Kolev

ISBN 978-953-307-345-3
Hard cover, 322 pages
Publisher InTech
Published online 12, September, 2011
Published in print edition September, 2011

The book is an edited collection of research articles covering the current state of sonar systems, the signal processing methods and their applications prepared by experts in the field. The first section is dedicated to the theory and applications of innovative synthetic aperture, interferometric, multistatic sonars and modeling and simulation. Special section in the book is dedicated to sonar signal processing methods covering: passive sonar array beamforming, direction of arrival estimation, signal detection and classification using DEMON and LOFAR principles, adaptive matched field signal processing. The image processing techniques include: image denoising, detection and classification of artificial mine like objects and application of hidden Markov model and artificial neural networks for signal classification. The biology applications include the analysis of biosonar capabilities and underwater sound influence on human hearing. The marine science applications include fish species target strength modeling, identification and discrimination from bottom scattering and pelagic biomass neural network estimation methods. Marine geology has place in the book with geomorphological parameters estimation from side scan sonar images. The book will be interesting not only for specialists in the area but also for readers as a guide in sonar systems principles of operation, signal processing methods and marine applications.

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