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Independent Component Analysis for Passive Sonar Signal Processing

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1. Introduction

Systems employing the sound in underwater environments are known as sonar systems. SONAR (Sound Navigation and Ranging) systems have been used since the Second World War (Waite, 2003), (Nielsen, 1991). These systems have the purpose of examining the underwater acoustic waves received from different directions by the sensors and determine whether an important target is within the reach of the system in order to classify it. This gives extremely important information for pratical naval operations in different conditions. Fig. 1 shows a possible scenario for a sonar operation, in which two targets: the ship that is a surface contact and another submarine. In this case, the submarine's hydrophones are receiving the signals from the two targets and the purpose is to identify both targets.

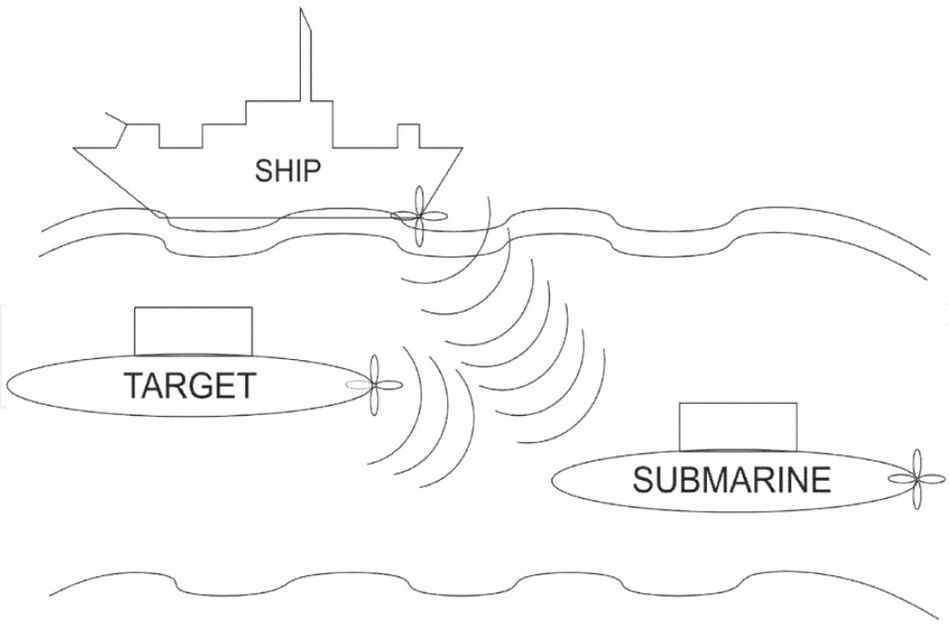


Fig. 1. Possible scenario for sonar operation

Depending on the sonar type, it may be, passive or active. The active sonar system transmits an acoustic wave that may be reflected by the target and signal detection, parameter estimation and localization can be obtained through the corresponding echoes (Nielsen,

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1991), (Waite, 2003). A passive sonar system performs detection and estimation using the noise irradiated by the target itself (Nielsen, 1991) (Clay & Medwin, 1998), (Jeffsers et al., 2000). The major difficulty in passive sonar systems is to detect the target in huge background noise environments. As much in active and passive mode, the sonar operator, (SO) listens to the received signal from one given direction, selected during the beamforming, envisaging target identification. This chapter focus on passive sonar systems and how the received noise is analysed that may arise. In particular, the signal interference in neighbour directions is discussed. Envisaging interference removal, Independent Component Analysis (ICA) (Hyvärinen, 2000) is introduce and recent results obtained from experimental data are described. The chapter is organised as it follows. In next Section, the analysis performed by passive sonar systems is detailed described. Section 3 introduces ICA principles and algorithms. Section 4 shows how ICA may be applied for interference removal. Finally, a chapter summary and perspectives of passive sonar signal processing are addressed in Section 5.

2. Passive sonar analysis

A passive sonar system is typically made from a number of building blocks (see Fig. 2); described in terms of its aim and specific signal processing techniques that have been applied for signal analysis.

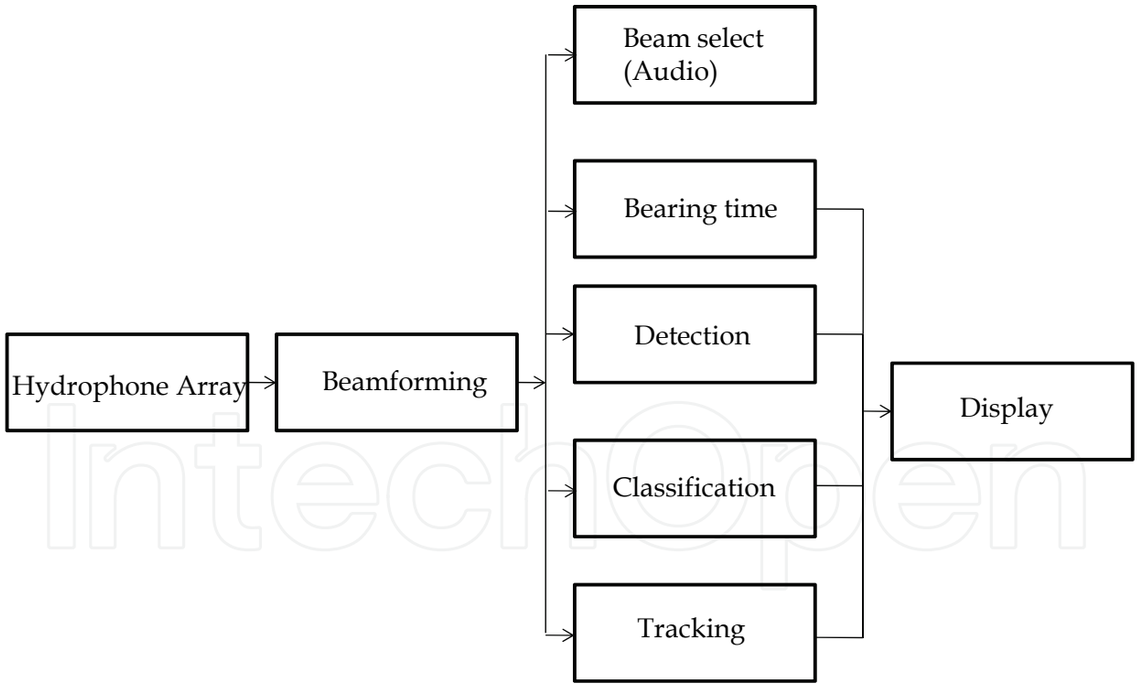


Fig. 2. Blocks diagram for passive sonar system

2.1 Sensors array

The passive sonar systems rely very much on the ability of their sensors in capturing the noise signals arriving in different directions. Typically, sensors (hydrophones) are arranged in arrays for fully coverage of detection directions The hydrophone array may be linear,

planar, circular or cylindrical. For the experimental results in Section 4, signals, were acquired through a cylindrical hydrophone array (CHA) while realizing an omnidirectional surveillance. This type of array comprises a number of sensor elements, which are distributed along staves. Therefore, the design performance depends on the number of staves, the number of hydrophones and the number of vertical elements in a given stave. For instance, the CHA from which the experimental tests were derived has 96 staves.

2.2 Beamforming

The beamforming operation aims at looking at a given direction of arrival (DOA) with the purpose of observing the target energy of a given direction through a bearing time display (Krim & Viberg, 1996). The signals are acquired employing the delay and sum (ds) technique to realize the DOA, allowing omnidirectional surveillance (Knight et al., 1981). In case of the experimental results to be described in Section 4, the directional beam is implemented using 32 adjacent sensors as it is shown in Fig. 3. A total of 32 adjacent staves were used to compute the direction of interest which gives an angular resolution of 3.75º.

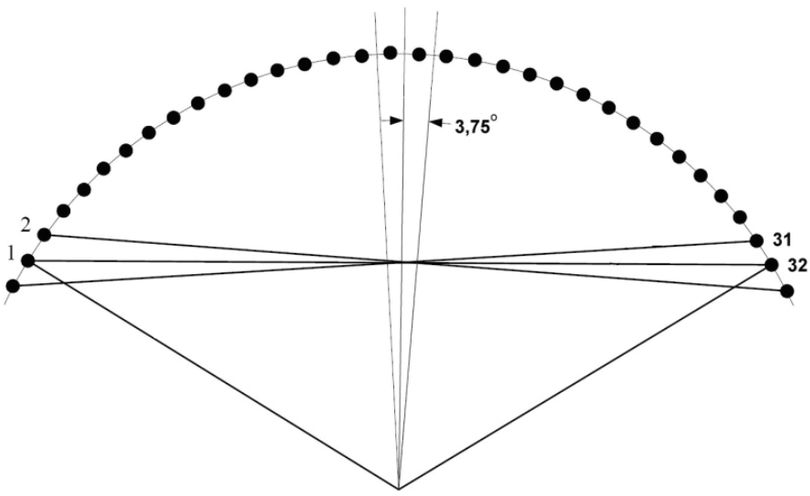


Fig. 3. Arrange of hydrophones for beamforming on a determined direction

Fig. 4 shows a bearing time display. In this figure, the horizontal axis represents the bearing position (full coverage, -180 to 180 degrees) and the vertical axis represents time, considering one second long acquisition window. This corresponds to waterfall display. The energy

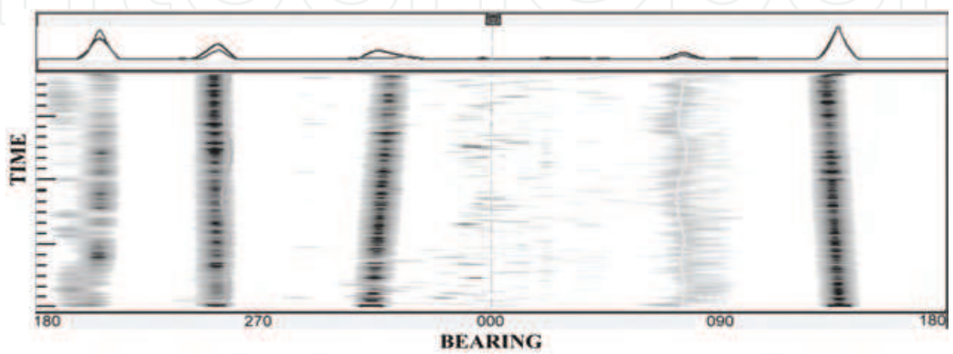


Fig. 4. A bearing time display

measurement for each bearing at each time window has a gray scale representation. The sonar operator relies very much on the bearing time display, the sonar operator relies very much on the in the time display for possible target observation. An audio output permits the operator to listen to the target noise from a specific direction of interest.

2.3 Signal processing core

After beamforming, passive sonar signal processing comprises detection, classification and, in some situations, target tracking. For detection, two main analysis are performed; LOFAR (LOw Frequency Analysis and Recording) and DEMON (Demodulation of Envelope Modulation On Noise). The LOFAR analysis is also used for target classification.

2.3.1 LOFAR analysis

The LOFAR is a broadband spectral analysis (Nielsen, 1991) that covers the expected frequency range of the target noise as, for instance, machinery noise. The basic LOFAR block diagram is shown in Fig. 5.



Fig. 5. Block diagram of the LOFAR analysis

As it can be depicted from Fig. 5, at a given direction of interest (bearing), the incoming signal is firstly multiplied by a Hanning window (Diniz et al., 2002), In the sequence, short-time Fast Fourier Transform (FFT) (Brigham, 1988) is applied to obtain signal representation in the frequency-domain (Spectral module). The signal normalization follows typically employing the TPSW (Two-Pass Split Window) algorithm (Nielsen, 1991) for estimating the background noise (see Fig. 6).

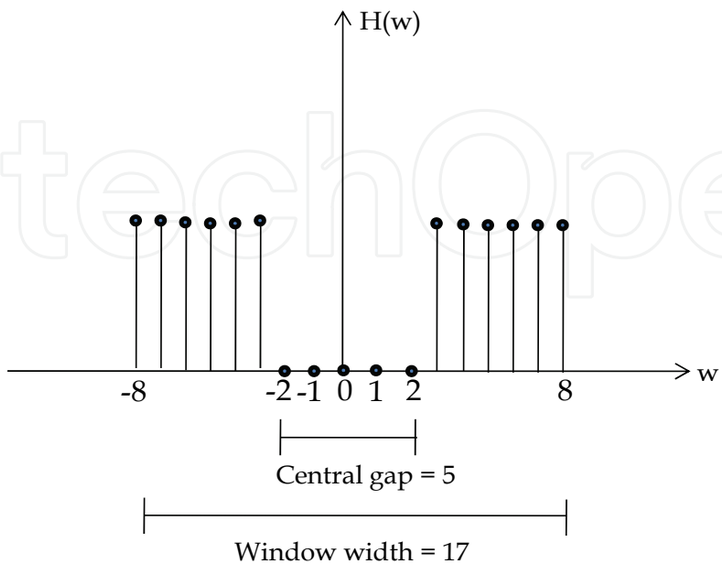


Fig. 6. TPSW window.

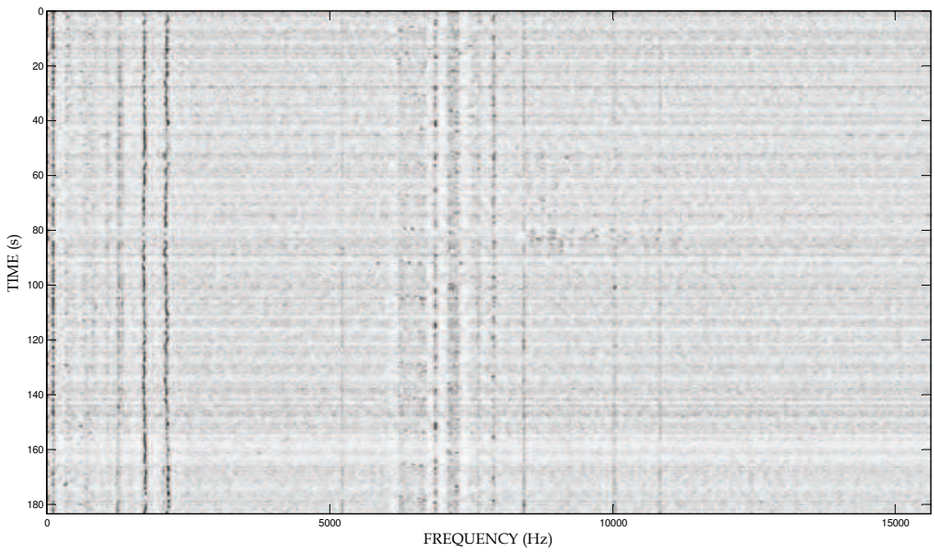


Fig. 7. Typical LOFAR display.

This window will slide along the signal and performing a local average to achieve the removal of background noise and making a sign of normalization. This TPSW normalization aims at estimation a mean spectrum by computing a local mean for each sample. This makes it possible to remove the bias and perform peak equalization, so that the amplitudes in all spectrums present similar values.
Fig. 7 shows a typical display from LOFAR analysis. The horizontal axis corresponds to frequency, in this case covering range of 0 to 15.625 Hz, and the vertical axis represents time. In this case, 200 acquisition windows (one second long each were accumulated). As can be seen in Fig. 7, some rays of often persist over time, thus characterizing the type of target being identified.

2.3.2 DEMON analysis

DEMON is a narrowband analysis that operates over the cavitation noise of the target propeller with the purpose of identifying the number of shafts, shaft rotation frequency and the blade rate (Nielsen, 1999), (Trees, 2001). As these parameters provide a detailed knowledge about the target propellers and normally the propeller noise is characteristic of each contact, this analysis shows good detection capabilities. Fig. 8 shows the block diagram of classical DEMON analysis.

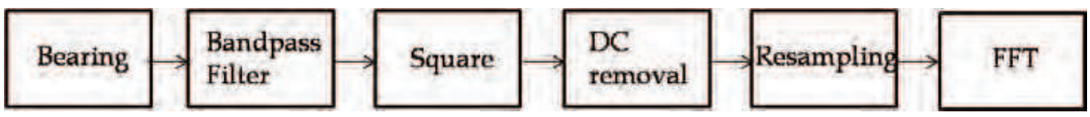


Fig. 8. Block diagram of the DEMON analysis

Given a direction (bearing) of interest, noise signal is bandpass filtered to limit the cavitation frequency range. 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. In sequence, the signal is squared as in traditional demodulation (Yang et al., 2007) (Trees, 2001) and the TPSW algorithm is used to reduce the background noise (Nielsen, 1991). Using TPSW, it is possible to emphasize target signal peaks. 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 resample the signal for better observation in the range. Finally, a short-time Fast Fourier Transform algorithm is applied to observe the peaks in frequency domain. Fig. 9 shows a typical DEMON plot. The horizontal axis represents the rotation scale (in RPM) while the vertical axis correspond to signal amplitude (in dB). This allows target identification, as shaft rotation and the number of blades may be obtained. The largest amplitude reveals the speed of shaft rotation, while the subsequent harmonics indicate the number of blades. In this example, the shaft rotation is about 148 RPM and next hamonics are, 293.6, 441.8, 587.1 and 735.3 RPM, from which the number of blades can be obtained.

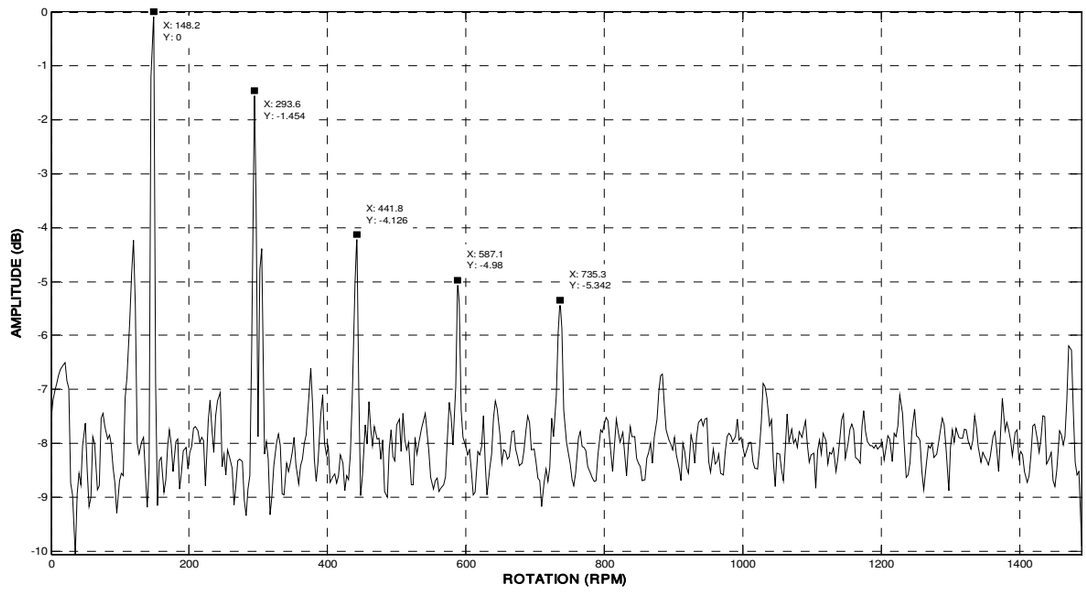


Fig. 9. typical DEMON display.

2.3.3 Classification

Another important task for passive sonar systems is target classification. Usually classification is based on extracting relevant features that characterize target classes and using such features to decide whether a detected target belongs to a given class. As already mentioned, features are typically extracted in frequency domain using the LOFAR analysis. But the stress, many directions of interest and high number of classes, automatic classification often uses computational intelligence algorithms to obtain the target class. Neural networks (Haykin, 2001) have successfully been used for passive sonar signal classification. (Moura, 2007), (Torres., 2004);(Seixas, 2001) and (Soares Filho, 2001). Other signal processing techniques have been applied to realize the classification task.(Peyvandi, 1998) used a hidden Markov model with Hausdorff similarity measurement to detect and classify targets. Another way to perform the detection and classification of targets is to use the Prony's method (Marple, 1991), which

provides an alternative time-frequency mapping (signals are modelled through a sum of damped sinusoidal components) suitable to acoustic signals.

2.3.4 Tracking

Eventually, tracking a target over time may be important. Usually this is perfomed after target detection at a specific direction. In some situations, the sonar operator performs tracking manually, but modern sonars have an automatic system to support this task. Although Kalman filters (Lee, 2004) have often been used to implement passive tracking (Rao, 2006), other techniques, (Mellema, 2006) have also been obtaining good results in target tracking application.

2.3.5 Interference

As it may be depicted from Fig. 9, interference from neighbour bins, as it is the case for bearings 190º and 205º, and the self-noise produced by the submarine in which the sonar system is installed may mask the original target features. Thus, when such is the case, a preprocessing scheme may be developed aiming at reducing signal interference, facilitating target identification.This procedure is addopted in Section 4 using the ICA (Hyvärinen, 2001).

3. Independent component analysis

The Independent Component Analysis (ICA) considers that a set of N observed signals $\mathbf{x}(t) = [x_1(t), ..., x_N(t)]^T$ is originally generated from a linear combination of signal sources $\mathbf{s}(t) = [s_1(t), ..., s_N(t)]^T$:

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

where, $\mathbf{A}$ is the NxN mixing matrix (Hyvärinen et al., 2001). Formulated this way, ICA is also referred to as Blind Source Separation (BSS) (Cardoso, 1998) and its purpose is to estimate the original sources $\mathbf{s}(t)$ using only observed data, $\mathbf{x}(t)$. A solution can be obtained if we find the inverse of the mixing matrix $\mathbf{B} = \mathbf{A}^{-1}$ and apply this inverse transformation on the observed signals to obtain the original sources.

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

A general principle for estimating the matrix $\mathbf{B}$ can be found by considering that the original source signals are statistically independent (or as independent as possible). High-order statistics (HOS) information is required during the search for independent components. There are many mathematical methods for calculating the coefficients of matrix $\mathbf{B}$. The nonlinear decorrelation and the maximally nongaussianity are among the most applied ones (Hyvärinen & Oja, 2000). There are some indeterminacies in the ICA model, the order of extraction of the independent components can change and scalar multipliers (positive or negative) may be modifying the estimated components. Fortunately these limitations are insignificant in most applications (Hyvärinen et al., 2001).

3.1 Statistical independence

Considering two random variables $\mathbf{x}$ and $\mathbf{y}$, they are statistically independent if and only if (Papoulis, 1991):

$$p_{x,y}(\mathbf{x},\mathbf{y}) = p_x(\mathbf{x})p_y(\mathbf{y}) \tag{3}$$

where $p_{x,y}$ (**x**, **y**), p_x (**x**) and p_y (**y**) are, respectively, the joint and marginal probability density functions (pdf) of **x** and **y**. Equivalent condition is obtained if for all absolutely integrable functions g(**x**) and h(**y**) the expression on Eq. 4 holds:

$$E\{g(\mathbf{x})h(\mathbf{y})\} = E\{g(\mathbf{x})\}E\{h(\mathbf{y})\} \tag{4}$$

where E{.} is the expectation operator (Hyvärinen et al., 2001).
In typical blind signal processing problems, there is very little information on the source signals and so direct estimation of the pdfs is a very difficult task. Eq. 4 gives an alternative independence measure and is the origin of a class of ICA algorithms that searches for nonlinear decorrelation.
Independent variables are uncorrelated, although, the reciprocal is not always true. Linear correlation is verified by second order statistics, while independence needs higher order information. In the nonlinear decorrelation methods, nonlinear functions introduce high-order statistics, making it possible the search for independent components.
As from Eq. 4, two random variables are statistical independent if they are nonlinearly uncorrelated. As it is not possible to check all integrable functions g(.) and h(.), estimates of the independent components are obtained while guaranteeing nonlinear decorrelation between a finite set of nonlinear functions (Hyvärinen et al., 2001).
For example, a well known linear ICA algorithm, proposed by Cichocki and Unbehauen in (Hyvärinen & Oja, 2000), searches for independent components while providing decorrelation between a hyperbolic tangent and a polynomial function, both applied to the input signals (observations).

3.1.1 Non-gaussianity and independence

The ICA/BSS model described in Eq. 1 can be re-written as:

$$x_i = \sum_{j=1}^{N} a_{ij} s_j \qquad i = 1,...,N \tag{5}$$

Considering the central limit theorem (Spiegel et al., 2000): "The sum of two (independent) random variables is always closest to a Gaussian distribution than the original variables distributions". As described in Eq. 5, the observed signals x_i are formed by an averaged summation of the sources s_i. Thus, x_i is closer to Gaussian-distributed variables than s_i. In other words, the independent components can be obtained through maximization of non-gaussianity (Hyvärinen et al., 2001).
The gaussianity (and consequently the statistical dependence) of a random variable can be measured through higher order cumulants. Considering a random vector **x**, the moment α_k and central moment μ_k of order k are defined by (Spiegel et al., 2000):

$$\alpha_k = E\{\mathbf{x}^k\} = \int_{-\infty}^{\infty} \mathbf{x}^k p_x(\mathbf{x})dx \tag{6}$$

$$\mu_k = E\{(\mathbf{x} - \alpha_1)^k\} = \int_{-\infty}^{\infty} (\mathbf{x} - \alpha_1)^k p_x(\mathbf{x})dx \tag{7}$$

where $\alpha_1=m_x$ is the mean of **x**. If the random variable **x** is zero mean ($m_x=0$), than for all k holds: $\alpha_k=\mu_k$.
The cumulant κ_k of order k is defined as a function of the moments (Spiegel et al., 2000). For a zero mean random variable **x**, the first four cumulants are:

$$\kappa_1 = 0; \qquad \kappa_2 = E\{\mathbf{x}^2\} = \alpha_2; \qquad \kappa_3 = E\{\mathbf{x}^3\} = \alpha_3; \tag{8}$$

$$\kappa_4 = E\{\mathbf{x}^4\} - 3[E\{\mathbf{x}^2\}]^2 = \alpha_4 - 3\alpha_2{}^2$$

The third and fourth order cumulants are called respectively skewness (κ_3) and kurtosis (κ_4) (Kim & White, 2004). Cumulants of order higher than four are rarely applied in practical ICA/BSS problems. Some interesting properties of cumulants are:

$$\begin{aligned} \kappa_k(\mathrm{x}+\mathrm{y}) &= \kappa_k(\mathrm{x}) + \kappa_k(\mathrm{y}) \\ \kappa_k(\mathrm{x}) &= 0, \text{for k} > 2 \text{ if xis Gaussian} \end{aligned} \tag{9}$$

Therefore, cumulants of order higher than two may be applied to estimate data gaussianity. The skewness value, for example, is related to pdf symmetry ($\kappa_3=0$ indicates symmetry). Spanning the interval [−2, ∞), kurtosis is zero for a Gaussian variable. Negative values of kurtosis indicate sub-gaussianity (pdf flatter than Gaussian) and positive values super-gaussianity (pdf sharper than Gaussian) (Spiegel et al., 2000). Examples of Gaussian, sub and super-gaussian distributions are illustrated in Figure 10. Kurtosis can be easily computed from data substituting expectations in Eq. 8 by sample means. One disadvantage is that kurtosis can be seriously influenced by outliers (observations that are numerically distant from the rest of the data), in extreme situations the kurtosis value may be dominated by a small number of points (Kim & White, 2004). Some studies are been conduced with the purpose of obtaining robust estimation of high order cumulants, specially the kurtosis (Welling, 2005).
Alternative gaussianity measures can be obtained from information theory (Cover & Thomas, 1991). These parameters are usually more robust to outliers than cumulant based ones (Hyvärinen et al., 2001).

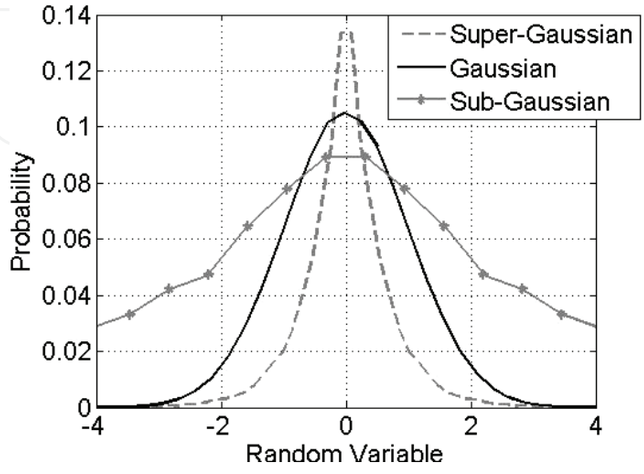


Fig. 10. Examples of Gaussian, sub and super-Gaussian distributions.

For instance, **Negentropy** of a random variable **x** is calculated through (Cover & Thomas, 1991):

$$J(\mathbf{x}) = H(\mathbf{x}_{gauss}) - H(\mathbf{x}) \tag{10}$$

where H (.) is the entropy, and $\mathbf{x}_{gauss}$ is a Gaussian random variable with the same mean and variance of **x**. Entropy is one of the basic concepts of information theory and can be interpreted as the level of information contained in a random variable. Entropy H(**x**) can also be viewed as the minimum code length needed to represent the variable **x**, considering a discrete random variable, entropy is defined as (Shannon, 1948):

$$H(\mathbf{x}) = \sum_i P(\mathbf{x} = a_i) \log P(\mathbf{x} = a_i) \tag{11}$$

where a_i are the possible values assumed by the variable **x**, and P(**x**=a_i) is the probability that **x**=a_i.

An important result is that the Gaussian variables have maximum entropy among variables of same variance (Hyvärinen et al., 2001). So both entropy and negentropy can be used as gaussianity measures. The advantage of J(**x**) is that it is always non-negative and zero when variable **x** is Gaussian. A problem with the computation of J (.) and H (.) in blind signal processing is the pdf estimation (see Eq. 10 and 11). To avoid this, approximations using high order cumulants or non-polynomial functions shall be applied (Hyvärinen et al., 2001; Hyvärinen, 1998).

Another statistical independence measure can be obtained through mutual information. The **Mutual Information** I(x_1, x_2, ..., x_m) between m random variables **x** = [x_1, x_2, ..., x_m] is obtained through (Hyvärinen et al., 2001):

$$I(x_1,..., x_m) = \sum_{i=1}^{m} H(x_i) - H(\mathbf{x}) \tag{12}$$

It is proved elsewhere (Cover & Thomas, 1991) that, more efficient codes are obtained while using the set of variables **x** instead of the individual ones x_i, unless when the variables are independent ((x_1, x_2, ..., x_m)=0). So, minimization of mutual information leads to statistical independence.

The **Kullback-Leiber (KL) divergence**, defined through Eq. 13 (Hyvärinen et al., 2001):

$$C_{KL}(Q,P) = \int Q_x(\mathbf{x}) \log \frac{Q_x(\mathbf{x})}{P_x(\mathbf{x})} dx \tag{13}$$

measures the distance between the two probability densities P_x(**x**) and Q_x(**x**), as it is always nonnegative with minimum value zero when both densities are the same. If one pdf is Gaussian, maximizing C_{KL} is equivalent to maximize non-gaussianity. The KL divergence is proved to be equivalent to mutual information (Hyvärinen et al., 2001).

Using one of these statistical independence measures, several routines have been proposed to find the **B** matrix (Hyvärinen et al., 2001). Here we consider two which are among the most successful ICA algorithms.

3.2 JADE algorithm

The start point for JADE (Joint Approximate Diagonalization of Eigenmatrices) algorithms is the realization that BSS (Blind Source Separation) algorithms generally require an estimation of the distributions of independent sources or have such an assumption built into the algorithm (Cardoso, 1998). It is also noted that, optimising cumulant approximations of data implicitly perform this, leading to present a number of approximations to information theoretic algorithms that operate on second and fourth order cross cumulant.
The cumulant tensor is a linear operator defined by the cumulant of fourth order cum(x_i, x_j, x_k, x_l) (Hyvärinen et al., 2001). This linear operation generates a matrix in form of Eq. 14. In this algorithm, the eigenvalue decomposition is considered as a preprocessing.

$$\mathrm{F}_{ij}(\mathbf{M}) = \sum_{kl} m_{kl} cum(x_i, x_j, x_k, x_l) \tag{14}$$

Where, m_{kl} is an element of the matrix **M** that is transformed and **x** is an nx1 random vector. The second order cumulant is used to ensure that data are white (decorrelated) (Cardoso, 1998). A set of cumulant matrices is estimated from the whitened data, as shown in Eq. 4.Then **F**(**M**) is made diagonal through **W** for some $\mathbf{M}_i$.

$$\mathbf{Q} = \mathbf{W}\,\mathrm{F}(\mathbf{M}_i)\mathbf{W}^T \tag{15}$$

The minimization of the sum of the squares of the non-diagonal elements of Eq. 15 is equivalent to maximization of the sum of squares of the diagonal elements, because an orthogonal matrix **W** does not change the total sum of squares of a matrix. The maximization of JADE is a method that gives an approximate joint diagonal of $\mathbf{F}(\mathbf{M}_i)$.

$$J_{JADE}(\mathbf{W}) = \sum_i \| \, diag(\mathbf{W}\,\mathrm{F}(\mathbf{M}_i)\mathbf{W}^T \, \|^2 \tag{16}$$

3.3 FastICA algorithm

Independent components can be extracted from a mixture implementing the principles of maximization of nongaussianity, described in terms of kurtosis or negentropy (Hyvärinen et al., 2001; Hyvärinen & Oja, 2000; Shaolin & Sejnowski, 1995). Considering a mixture **x**, one defines kurtosis in Eq. 8, where **W** is the weight matrix, and **z** is a component vector. There is a whitening step as a preprocessing, and thus, **z = Vx**, where **V** is the whitening matrix and the correlation matrix **z** is equal to identity, $\mathrm{E}\{\mathbf{z}\mathbf{z}^{\mathrm{T}}\} = \mathbf{I}$. So using kurtosis, it is possible to estimate the independent components from the cost function presented in Eq. 17.

$$\mathbf{x} = \mathbf{W}^{\mathrm{T}}\mathbf{z}$$

$$\frac{\partial \, |\,\mathrm{kurt}(\mathbf{W}^T\mathbf{z})\,|}{\partial \mathbf{W}} = 4\,\mathrm{sign}[\mathrm{kurt}(\mathbf{W}^T\mathbf{z})]\,\mathrm{E}\{z(\mathbf{W}^T\mathbf{z} - 3\mathbf{W}\,\|\,\mathbf{W}\,\|^2)\} \tag{17}$$

To make the algorithm faster, the gradient computation is changed to Eq. 18 a normalization was implemented to avoid a **W** overflow.

$$\Delta\mathbf{W} \propto \mathrm{sign}(\mathrm{kurt}(\mathbf{W}^{\mathrm{T}}\mathbf{z}))\,\mathrm{E}(\mathbf{z}(\mathbf{W}^{\mathrm{T}}\mathbf{z})^3$$

$$\mathbf{W} \leftarrow \mathbf{W}/\,\|\,\mathbf{W}\,\| \tag{18}$$

Then, the FASTICA (PEACH, 2000) optimizes Eq. 19.

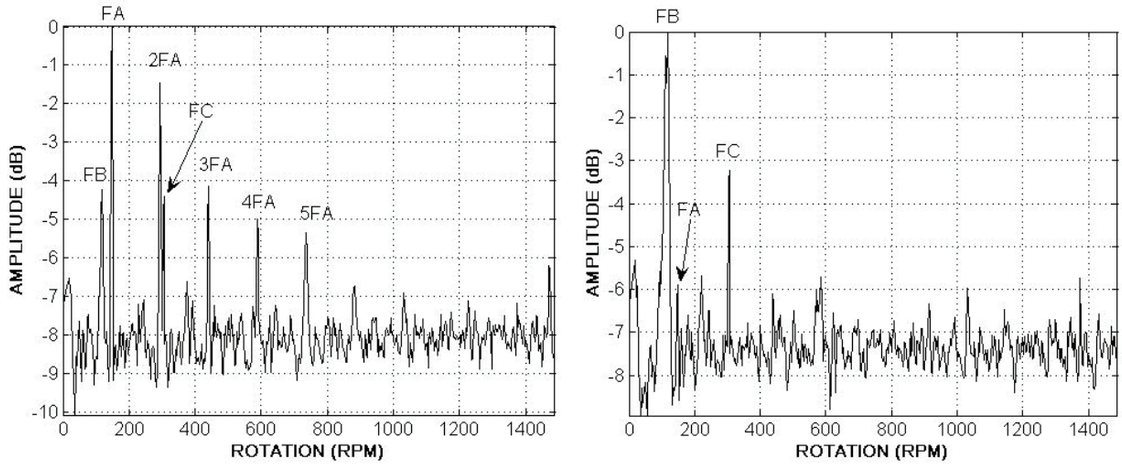
$$\mathbf{W} \leftarrow E\{(\mathbf{W}^T\mathbf{z})\} - 3\mathbf{W} \tag{19}$$

Another possibility for maximizing non-gaussianity is negentropy (Hyvärinen, 1999). The classic method of approximating negentropy is using higher order cumulants and polynomial density expansions, like G(**x**) = log[cosh(**x**)] or –exp(**x**²/2). Using a gradient based method, function derivatives (g) can be chosen to be applied in FASTICA.

$$\mathbf{W} \leftarrow E\{\mathbf{z}g(\mathbf{W}^T\mathrm{z})\} - E\{g'(\mathbf{W}^T\mathrm{z})\}\mathbf{W} \tag{20}$$

4. Interference removal

As already mentioned in Section 2, passive sonar signals detected at adjacent bearings may be masked by cross-channel interference. The complexity of the target identification task increases proportionally to the interference level. Considering this, blind source separation methods (Cardoso, 1998) may be useful as a preprocessing step in passive sonar signal analysis as they project the observed signals into directions of maximum independence.



(a) (b)

Fig. 11. DEMON analysis at (a) 190° and (b) 205°.

Consider a particular problem where two targets are present at adjacent directions (190° and 205°). As illustrated in Fig. 11, the frequency components of 190° target (F_A=148 RPM and its multiples) are mixed together with information from the 205° direction (F_B=119 RPM). The same problem exists in the signal measured at bearing 205°. It was also observed that both signals (190° and 205°) are contaminated by F_C=305 RPM that is the main frequency present at direction 076°, see Fig. 12. It is known from the experimental setup that the last bearing (076°) contains information from the noise radiated by the submarine where the hydrophones array is allocated (self-noise). It can also be verified that, signal measured at direction 076º presents interference from target at 205° (F_B).

Independent component based methods are applied in the following sub-sections aiming at reducing signal interference and thus, allow contact identification through DEMON analysis performed over cleaner data. Signal processing may be performed in both time-domain and

frequency-domain. The main advantage of frequency-domain methods is that, after DEMON, the signal-to-noise ratio is significantly improved, producing better separation results.

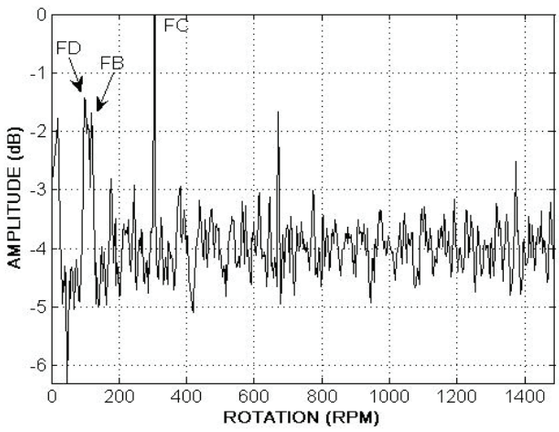


Fig. 12. DEMON analysis at 076°.

Performance comparisons between ICA algorithms applied to passive sonar signal separation were conduced in (Moura et al. 2007b) and it was observed that JADE presents slightly better performance. Considering this, the results presented in the next sections were derived through the application of JADE algorithm to perform ICA.

4.1 Time-domain BSS

A simple and straightforward implementation is to perform independent component analysis over raw-data. Signals measured at each direction (076°, 190° and 205°) are put together in order to compose a three component observation vector. An ICA algorithm (JADE) is applied to estimate three (time-domain) independent components, which will further be used as inputs to DEMON analysis block. The method is illustrated in Fig. 13.

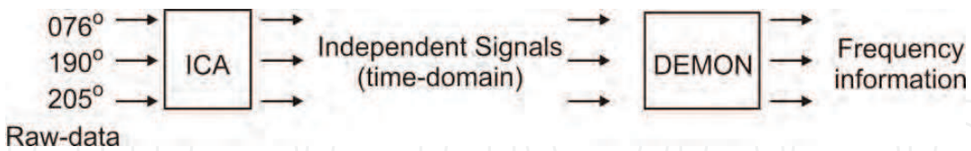


Fig. 13. Time-domain blind signal separation method.

To obtain quantitative measures of the signal separation performance, the peak amplitude values of each frequency component (after DEMON analysis) are compared for both raw-data and separated signals. Moreover, useful information is also obtained from the full-width at half of the peak value (Full-Width of Half Maximum - FWHM) of a certain frequency component *Fx*. This measure indicates whether *Fx* is accurately estimated (shorter FWHM) or not (larger FWHM). When ICA is applied, can be observed, from Fig. 14, that, considering direction 205°, the amplitudes of interfering frequencies F_A and F_C were reduced from -5.9dB and -3.2dB (in raw-data) up to, respectively, -9.1dB and -4.2dB. The background noise level (estimated from the high frequency components amplitude) was also reduced from -7dB up to -8.5dB.

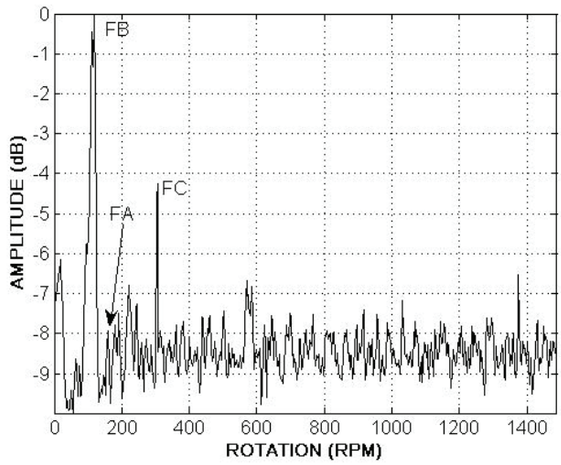


Fig. 14. DEMON analysis at 205°, for independent signal estimation.

Unfortunately, through this method, at directions 076° and 190° no significant signal separation was observed. The half-peak bandwidths were not modified either.

A main limitation of this approach is that raw-data is usually corrupted by additive underwater acoustic environment noise. It is known that, standard ICA algorithms present poor performance in the presence of noise (Hyvärinen et al., 2001). Modifications on the traditional ICA model in order to consider additive noise may increase the algorithms accuracy and thus produce better separation results (Hyvärinen, 1998b).

4.2 Frequency-domain BSS.

An alternative approach is to perform signal separation in the frequency domain. As illustrated in Fig. 15, DEMON analysis is initially performed over raw-data and frequency information from the three directions are used as inputs for an ICA algorithm, producing the independent (frequency-domain) components.

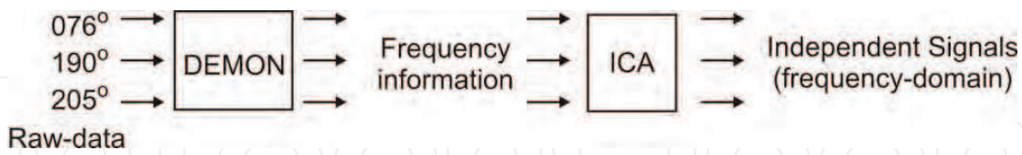


Fig. 15. Frequency-domain blind signal separation method.

As described in Section 2, DEMON analysis basically consists in performing demodulation and filtering of acoustic data in order to obtain relevant frequency information for target characterization. Most of noise and nonrelevant signals are eliminated by DEMON, allowing more accurate estimation of the independent components.

A particular characteristic is that DEMON analysis is usually performed over finite time-windows (approximate length = 250ms) and the frequency components are estimated within these windows. Aiming at reducing the random noise generated in time-frequency transformation, an average spectrum is computed using frequency information from these time slots.

In Independent Component Analysis algorithms the order and the amplitude of the estimated components are random parameters and thus different initializations may lead to

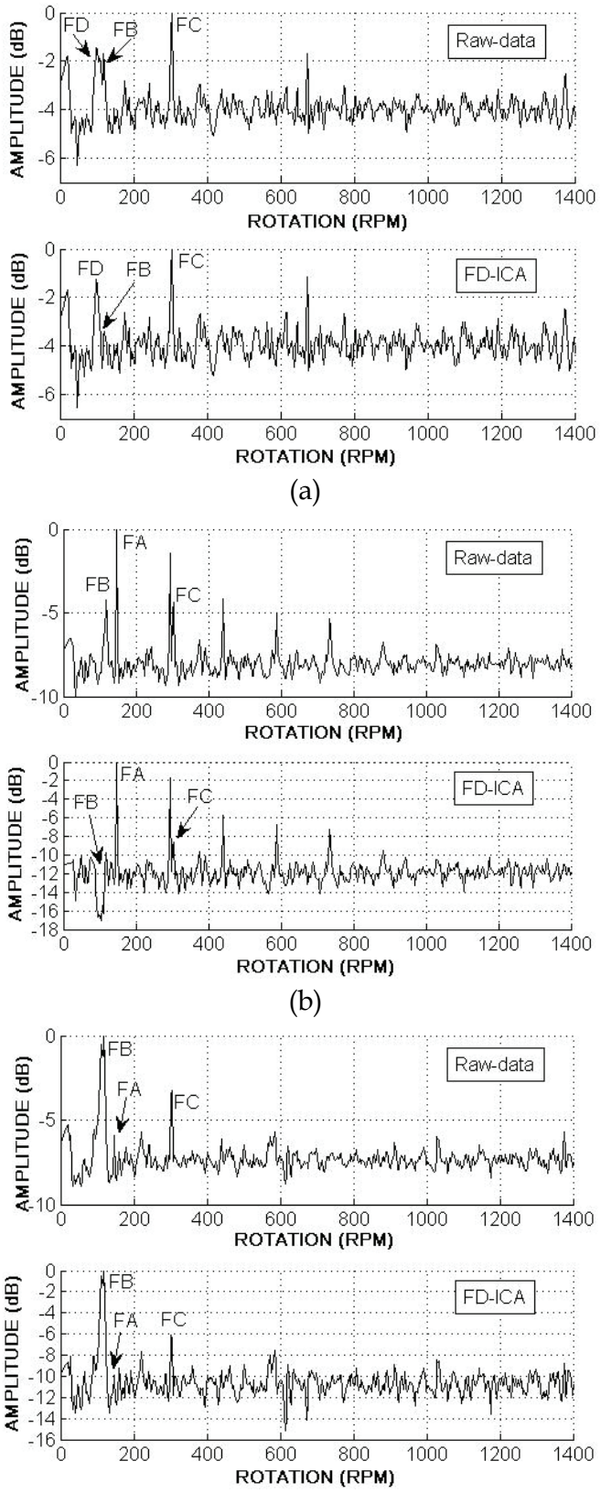


Fig. 14. DEMON analysis for both raw-data (measured acoustic signal) and frequency domain independent components (FD-ICA) at bearings (a) 076°, (b) 190° and (c) 205°.

different scaling factors and ordering (Hyvärinen et al., 2001). As in the frequency-domain BSS approach the ICA algorithms are executed after DEMON estimation at each time window, independent components from a certain direction may appear in different ordering at adjacent time-windows in this sequential procedure. Before generating the average spectrum, the independent components must be reordered (to guarantee that the averages are computed using samples from the same direction) and normalized in amplitude. The normalization is performed by converting signal amplitude into dB scale. The reordering procedure is executed by computing the correlation between independent components estimated from adjacent time slots. High correlation indicates that these components are related to the same direction.

Separation results obtained through this approach are illustrated in Fig. 14. It can be seen that, the interfering frequencies were considerably attenuated at the independent components from all three directions. The higher frequency noise levels were also reduced.

The results obtained from both time (ICA) and frequency domain (FD-ICA) methods are summarized in Table 1 (when *Fx* frequency width is not available it means that half of *Fx* peak amplitude is under the noise level). It can be observed that, for FD-ICA both the interference peaks and the width of the frequency components belonging to each direction were reduced, allowing better characterization of the target. The time domain method (ICA) produced relevant separation results only for 205° signal.

		Peak (dB)			Width (RPM)		
	Freq.	**Raw-data**	**ICA**	**FD-ICA**	**Raw-data**	**ICA**	**FD-ICA**
Direction 076	**FB**	-1,7	-0,8	-3,6	-	-	-
	FC	0	0	0	8	7,9	8,4
	FD	-1,4	-3,1	-1,3	-	-	-
Direction 190	**FA**	0	0	0	4,9	4,9	4,3
	2FA	-1,4	-1,4	-1,7	5,3	5,3	4,3
	3FA	-4,1	-4,1	-5,7	8,8	8,8	6,2
	4FA	-5	-5	-6,7	-	-	7,4
	5FA	-5,3	-5,4	-7,2	-	-	11
	FB	-4,2	-4,1	-9,8	16,6	15,8	-
	FC	-4,4	-4,4	-8,6	7,7	7,7	-
	FD	-8,7	-8,6	-16,5	-	-	-
Direction 205	**FA**	-5,9	-9,1	-9,9	-	-	-
	FB	0	0	0	16,8	16,3	15,2
	FC	-3,2	-4,2	-6,4	7	6,6	6,5
	FD	-5,6	-5,8	-9,3	-	-	-

Table 1. Separation results summary

4.4 Extensions to the basic BSS model

In order to obtain better results in signal separation and thus higher interference reduction, more realistic models may be assumed for both the propagation channel and measurement system.

For example, it is known that, signal transmission in passive sonar problems may comprise different propagation paths, and thus the measured signal may be a sum of delayed and

mixed versions of the acoustic sources. This consideration leads to the so-called convolutive mixture model for the ICA (Hyvarinen et al., 2001), for which the observed signals $x_i(t)$ are described through Eq. 10:

$$x_i(t) = \sum_{j=1}^{n} \sum_{k} a_{ikj} s_j(t-k), \quad for\ i = 1,...,n \tag{10}$$

where s_j are the source signals. To obtain the inverse model, usually a finite impulse response (FIR) filter architecture is used to describe the measurement channel.
Another modification that may allow better performance is to consider, in signal separation model, that sensors (or propagation channel) may present some source of nonlinear behavior (which is the case in most passive sonar applications). The nonlinear ICA instantaneous mixing model (Jutten & Karhunen, 2003) is thus defined by:

$$\mathbf{x} = F(\mathbf{s}) \tag{11}$$

where $F(.)$ is a $R^N \rightarrow R^N$ nonlinear mapping (the number of sources is assumed to be equal to the number of observed signals) and the purpose is to estimate an inverse transformation G : $R^N \rightarrow R^N$:

$$\mathbf{s} = G(\mathbf{x}) \tag{12}$$

so that the components of $\boldsymbol{y}$ are statistically independent. If $G = F^{-1}$ the sources are perfectly recovered (Hyvärinen & Pajunen, 1999).
Some algorithms have been proposed for the nonlinear ICA problem (Jutten & Karhunen, 2003), a limitation inherit to this model is that, in general, there exists multiple solutions for the mapping G in a given application. If **x** and **y** are independent random variables, it is easy to prove that f(**x**) and g(**y**), where f(.) and g(.) are differentiable functions, are also independent. A complete investigation on the uniqueness of nonlinear ICA solutions can be found in (Hyvärinen & Pajunen, 1999). NLICA algorithms have been recently applied in different problems such as speech processing (Rojas et al., 2003) and image denoising (Haritopoulos et al., 2002).
Although these extensions to the basic ICA model may allow better signal separation performance, the estimation methods usually require considerable large computational requirements, as the number of parameters increases (Jutten & Karhunen, 2003) e (Hyvarinen., 2001). Thus, an online implementation (which is the case in passive sonar signal analysis) may not always be possible.

5. Summary and perspective

Sonar systems are very important for several military and civil underwater applications. Passive sonar signals are susceptible to cross-interference from acoustic sources present at different directions. The noise irradiated from the ship where the hydrophones are installed may also interfere with the target signals, producing poor performance in target identification efficiency. Independent component analysis (ICA) is a statistical signal processing method that aims at recovering source signals from their linearly mixed versions. In the framework of passive sonar measurements, ICA is useful to reduce signal interference and highlight targets acoustic features.

Extensions to the standard ICA model, such as considering the presence of noise, multiple propagation paths or nonlinearities may lead to a better description of the underwater acoustic environment and thus produce higher interference reduction. Another particular characteristic is that the underwater environment is non-stationary (Burdic, 1984). Considering this, the ICA mixing matrix becomes a function of time. To solve the non-stationary ICA problem recurrent neural networks trained using second-order statistic were used in (Choi et al., 2002) and a Markov model was assumed for the sources in (Everson & Roberts, 1999).

6. References

Brigham, E. (1988). *Fast Fourier Transform and Its Applications*. ISBN10: 0133075052, Ed. FACSIMILE. 1988.

Burdic, W. S. (1984) *Underwater Acoustic System Analysis*, Prentice-Hall, ISBN 10- 0932146635.

Cardoso, J.-F. (1998). "Blind signal separation: Statistical principles", *Proceedings of IEEE*, pp. 2009-2025, vol. 86 no. 10, October 1998.

Choi, S. ; Cichocki, A. and Amari, S-I (2002). Equivariant nonstationary source separation, *Neural Networks*, vol. 15, no. 1, pp. 121-130, January.

Clay, C. and Medwin, H. (1998). *Fundamentals of Acoustical Oceanography*. ISBN:0-12-487570-X. Academic Press.

Cover, T. M. and Thomas, J. A. (1991). *Elements of Information Theory*. Wiley.

Diniz, P. S. R., Silva, E., Lima Netto, S. (2002). *Digital Signal Processing*, ISBN: 0-521-78175-2, Cambridge University Press.

Everson, R. and Roberts, S. J. (1999) Non-stationary Independent Component Analysis *Proceedings of the IEE conference on Artificial Neural Networks*, 7 - 10 September.

Haritopoulos, H.; Yin, H. and Allinson, N. M. (2002) Image denoising using self-organizing map-based nonlinear independent component analysis, *Neural Networks*, pp. 1085-1098, 2002.

Haykin, S. (2001). *Neural Networks, Principles and Practice*. Bookman, ISBN: 9780132733502.

Hyvärinen, A. (1998a). New approximations of diferencial entropy for independent component analysis and projection pursuit, *Advances in Neural Information Signal Processing*, no. 10, pp. 273-279.

Hyvärinen, A. (1998b) Independent component analysis in the presence of Gaussian noise by maximizing joint likelihood. *Neurocomputing*. Volume 22, Issues 1-3, November , Pages 49-67.

Hyvärinen, A. and Pajunen, P. (1999). Nonlinear independent component analysis: Existence and uniqueness results, *Neural Networks*, vol. 12, no. 3, pp. 429-439.

Hyvärinen, A. and Oja, E. (2000). *Independent component analysis: Algorithms ans applications*. Helsinki University of Technology, P. O. Box 5400, FIN-02014 HUT, Filand. Neural Networks, 13 (4-5): 411-430. 2000.

Hyvärinen, A., Karhunen, J. and Oja, E. (2001). *Independent Component Analysis*, ISBN: 0-471-40540-X, John Wiley & Sons, .inc. 2001.

Jeffsers, R., Breed and B. Gallemore (2000). Passive range estimation and rate detection, *Proceedings of Sensor Array and Multichannel Signal Processing Workshop*, pp. 112-116, ISBN: 0-7803-6339-6, Cambridge, US, March 2000.

Jutten, C. and Karhunen, J. (2003) Advances in nonlinear blind source separation, *Proceedings of the 4th Int. Symp. on Independent Component Analysis and Blind Signal Separation* (ICA2003), Nara, Japan, pp. 245-256.

Kim, T.-H. and White, H. (2004) "On more robust estimation of skewness and kurtosis," *Finance Research Letters*, vol. 1, pp. 56-73.

Knight, W. C. Pridham, R. G. Kay, S. M. (1981). Digital signal processing for sonar. *Proceedings of IEEE*, ISSN: 0018-9219 vol. 69, issue-.11, pp. 1451-1506, November. 1981.

Krim, H. and Viberg, M. (1996) Two decades of array signal processing research: the parametric approach. *IEEE Signal Processing Magazine*, vol. 13, Issue: 4, pp. 67-94, ISSN: 1053-5888.

Lee, B. J. Park, J.B. Joo, Y. H. Jin, S. H. (2004). Intelligent Kalman filter for tracking a manoeuvring target. *Radar, Sonar and Navigation, IEE Proceedings*, ISSN: 1350-2395, vol. 151 issue: 6, pp. 344-350 Dec. 2004.

Marple, L., Brotherton, T. (1991). Detection and classification of short duration underwater acoustic signals by Prony's method, *International Conference on Acoustics, Speech, and Signal Processing*, pp. 1309-1312 vol.2, ISBN: 0-7803-0003-3, Toronto, Ont., Canada, May 1991.

Mellema, G. R. (2006). Reverse-Time Tracking to Enhance Passive Sonar, *International Conference on Information Fusion*, ISBN: 0-9721844-6-5, pp. 1-8, July.

Moura, N. N.; Soares Filho, W.; Seixas, J. M. de (2007a). Passive Sonar Classification based on Independent components. *Proceedings of the Brazilian congress of neural networks, 2007*, Florianópolis, Brazil, pp. 1-5. (In Portuguese).

Moura, N. N., Seixas, J. M. Soares Filho, W. and Greco, A. V. (2007b) "Independent component analysis for optimal passive sonar signal detection," *Proceedings of the 7th International Conference on Intelligent Systems Design and Applications*, Rio de Janeiro, pp. 671-678, October 2007.

Nielsen, R. O. (1991). *Sonar Signal Processing*, ISBN: 0-89006-453-9. Artech House Inc, Nortwood, MA, 1991.

Nielsen, R. O. (1999). "Cramer-Rao lower bounds for sonar broadband modulation parameters". *IEEE Journal of Ocean Engineering*, vol. 24 no. 3, pp. 285-290, July 1999.

Papoulis,A. (1991), *Probability, Random Variables, and Stochastic Processes*. McGraw-Hill.

Peyvandi, H., Fazaeefar, B., Amindavar, H (1998). Determining class of underwater vehicles in passive sonar using hidden Markov with Hausdorff similarity measure, *Proceedings of 1998 International Symposium on Underwater Technology*, pp. 258-261,ISBN: 0-7803-4273-9, Tokyo, Japan, April 1998.

Rao, S. K. (2006). Pseudo linear Kalman filter for underwater target location using intercept sonar measurements. *Symposium of Position, location and navigation*, ISBN: 0-7803-9454-2. Pp. 1036-1039, San Diego, US, April 2006.

Rojas, F.; Puntonet, C. G. and Rojas, I. (2003) Independent component analysis evolution based method for nonlinear speech processing, *Artificial Neural Nets Problem Solving Methods*, PT II, vol. 2687, pp. 679-686, 2003.

Seixas, J. M., Mamazio, D. O., Diniz, P. S. R., Soares-Filho, W. (2001). Wavelet transform as a preprocessing method for neural classification of passive sonar signals, *The 8th IEEE International Conference on Electronic, Circuits and Systems*, pp. 83-86, ISBN: 0-7803-7057-0, Malta, September 2001.

Shannon, C. E. (1948). "A mathematical theory of communication," *The Bell System Technical Journal*, pp. 379-423, July.

Shaolin Li, Sejnowski, T. J. (1995). Adaptive separation of mixed broadband sound sources with delays by a beamforming Herault-Jutten network. *IEEE Journal of Oceanic Engineering*, ISSN: 0364-9059, vol. 20, pp. 73-79, 1995.

Soares Filho, W.; Seixas, J. M. de; Calôba, L. P. (2001) Principal Component Analysis for Classifyting Passive Sonar Signals. *IEEE International Symposium on Circuits and Systems*, 2001, Sidney, Australia.

Spiegel, M. R., Schiller, J. J. and Srinivasan, R. A. (2000). *Probability and Statistics*. McGraw-Hill, 2 ed.

Torres, R. C.; Seixas, J. M. de, Soares Filho, W. (2004) Sonar Signals Classification Through Non-linear Principal Component Analysis. *Learning and nonlinear models*. Vol. I, no. 4, pp. 208-222, 2004 (In Portuguese).

Trees, H. L. V. (2001) *Detection, Estimation and Modulation Theory – Part I*, ISBN: 0-471-09517-6, John Wiley & Sons, Inc.

Waite, A. D. (2003). *Sonar for practicing Engineers, ISBN: 0-471-49750-9,* John Wiley and Sons, New York, 2003

Welling, M. (2005) Robust higher order statistics, *Proceedings of the Tenth International Workshop on Artificial Intelligence and Statistics* (AISTATS2005), pp. 405-412,Barbados, January.

Yan, D. P. and Peach, J. (2000). Comparison of blind source separation algorithms. *Advanxes in Neural networks and applications*. Pp. 18-21. 2000.

Yang, Z., Yang, L., Qing, C., Huang, D.. (2007) An improved empirical AM/FMdemodulation method. *International Conference on Wavelet Analysis and Pattern Recognition*. ISBN: 978-1-4244-1065-1, vol. 3, pp. 1049-1053.

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The demand to explore the largest and also one of the richest parts of our planet, the advances in signal processing promoted by an exponential growth in computation power and a thorough study of sound propagation in the underwater realm, have lead to remarkable advances in sonar technology in the last years.The work on hand is a sum of knowledge of several authors who contributed in various aspects of sonar technology. This book intends to give a broad overview of the advances in sonar technology of the last years that resulted from the research effort of the authors in both sonar systems and their applications. It is intended for scientist and engineers from a variety of backgrounds and even those that never had contact with sonar technology before will find an easy introduction with the topics and principles exposed here.

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