X Congresso Brasileiro de Inteligência Computacional (CBIC'2011), 8 a 11 de Novembro de 2011, Fortaleza, Ceará

NEURAL PASSIVE SONAR SIGNAL CLASSIFICATION USING INDEPENDENT COMPONENT ANALYSIS

Eduardo F. de Simas Filho
Nondestructive Testing Research Group, IFBA
esimas@ifba.edu.br

Natanael Nunes de Moura, José Manoel de Seixas
Signal Processing Laboratory, COPPE/UFRJ
{natmoura,seixas}@lps.ufrj.br

Abstract – Sonar systems use the underwater sound propagation to detect, identify and locate targets (such as vessels or shoals of fishes). One of the most important tasks in passive sonar signal processing is target identification, which relies on sonar operators who listen to the acoustic signatures and assign to them a certain class of vessel. When there are acoustic signals from multiple targets arriving at adjacent directions, target identification becomes a harder task due to cross-channel interference. The purpose of this work is to develop a neural design support system for target identification, specially in multiple target applications. In order to improve the discrimination performance when cross-interference is present, independent component analysis (ICA) was used as a preprocessing step. It is shown that the proposed approach improved considerably the discrimination efficiency in an experimental two-target problem.

Keywords – Passive Sonar System, Spectral Analysis, LOFAR Analysis, Independent Component Analysis.

1. INTRODUCTION

Sonar systems [1] are used in several applications for military and civilian purposes such as underwater surveillance, target detection, location and identification, determination of water depth, bottom contours and composition and shoals of fishes location. Active sonar consists on emitting acoustic pulses and analyzing the received echoes. Otherwise, passive sonar systems record and process the acoustic signals emitted by other vessels aiming at target detection and identification.

In order to detect and classify signals against background noise, passive sonar systems [2] listen to the noise radiated by targets 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. For passive sonar systems, target identification is usually performed by experienced human operators (sonar operators).

LOFAR (Low Frequency Analysis and Recording) [3] which is a broadband analysis usually employed in passive sonar systems, estimates the noise vibration of the target machinery. The LOFAR analysis is based on spectral estimation and supports targets classification.

Depending on the bearing resolution and the geographical positioning of the targets, signal interference may occur for adjacent directions, contaminating the acquired signals and making even more difficult the target classification task.

As for passive sonar systems target classification is a very important task, some works have been developed in order to produce decision support systems to help sonar operators in this job. Neural networks have successfully been used in passive sonar signal classification [4–7]. Additionally, other techniques have been applied to perform the classification task, in [8] a hidden Markov model with Hausdorff similarity measurement was used to detect and classify targets. Another way to perform the detection and classification of targets is achieved through the Prony's method [9].

This work proposes a decision support system for target identification, specially in the multiple target case. For this, independent component analysis (ICA) [10] is used to minimize the cross-channel interferences. ICA transformation has been applied recently as a preprocessing step in classification problems [11–13]. By projecting the multidimensional signals into a new data space where the statistical dependency among the variables is eliminated ICA may (in some cases) favor the signal classification task. In our particular problem, ICA contributes to reduce the cross-interference between adjacent bearings, revealing the original acoustic signatures of the vessels, as demonstrated in previous works [4, 14]. Here ICA is applied after LOFAR analysis as a preprocessing step for classification, in order to recover the acoustic characteristics of the original sources and thus improve the discrimination efficiency. For automatic classification, a neural network (multi-layer perceptron architecture) [15] was used.

The paper is organized as it follows. Section 2 describes how the signals were acquired, and provides a brief description of LOFAR analysis. The proposed methodology is detailed in Section 3. Section 4 shows the results obtained before and after ICA preprocessing. Finally, Section 5 brings the conclusions.

2. THE PROBLEM

A passive sonar system is typically used by submarines to perform the surveillance in a given operation area. The beamforming purpose is to estimate the DOA from a given target as captured by the hydrophone array. The Figure 1 shows the beamforming display for a given experimental setup. 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 applied [16].

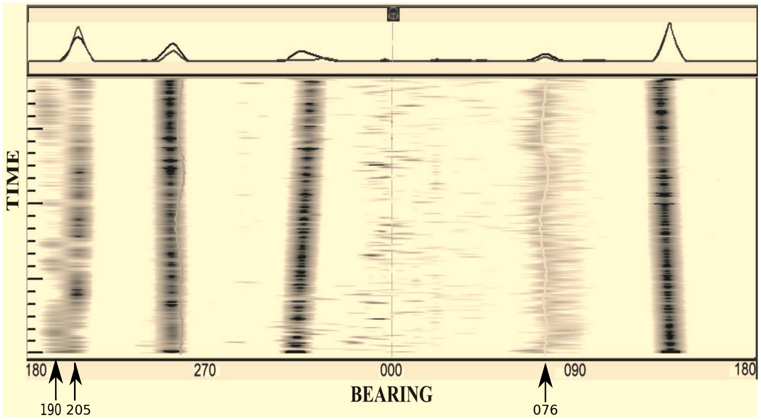

Figura 1: Bearing time display of a passive sonar system.

When there are multiple targets and signal interference at neighbor bins occurs, as it may be the case for bearings $190°$ and $205°$ (see Figure 1), the original target features may be masked and thus the target classification efficiency decreases. Beyond that, the self-noise, bearing $076°$, may interfere on both target signals. Thus, a preprocessing scheme aiming at reducing signal interferences would be attractive, as it may, facilitate target classification.

2.1 LOFAR Analysis

The LOFAR [2] is a broadband analysis that provides the machinery noise spectra to the sonar operator and goes from DC to 15,625 Hz. The block diagram of the LOFAR analysis is shown in Figure 2.

Figura 2: LOFAR analysis block diagram.

After bearing, the signal is convolved to a Hanning window to emphasize the frequency range of interest [17]. 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 [18]. The normalization was implemented by estimating the background noise that is present at each spectrum and computing a normalized frequency bin using this estimation as normalization factor. This procedure removes the spectrum bias and equalizes the spectrum amplitude [19].

3 PROPOSED CLASSIFICATION SYSTEM

In passive sonar systems, target identification is usually performed by trained operators that listen to the noise radiated in a given direction and assign it to a certain class of ship. This procedure is susceptible to human errors and becomes more difficult when additive noise or multiple targets are present. In this work it is proposed a neural network based classifier to assist sonar operators by indicating the most probable class of a acoustic signal. As illustrated in Figure 3, considering that two acoustic signals are arriving at adjacent bearings (190^o and 205^o), the received signatures are firstly processed by LOFAR analysis. The obtained average spectra are used as inputs to an ICA algorithm. The estimated independent components are then used to feed a neural (multi-layer perceptron) classifier.

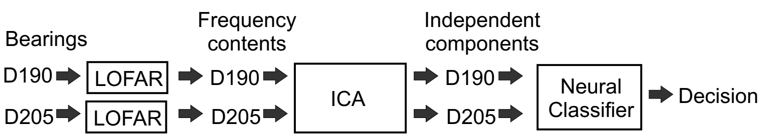

Figura 3: Proposed classifier system block diagram.

In the following subsections, the main concepts involved in both ICA and neural classification are described.

3.1 Independent Component Analysis

The basic ICA model considers that a set of $\mathbf{N}$ observed signals $\mathbf{x}(t) = [x_1(t), ..., x_N(t)]^T$ is generated by a linear combination of unknown sources $\mathbf{s}(t) = [s_1(t), ..., s_N(t)]^T$:

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

where $\mathbf{W}$ is the N×N mixing matrix [10].

Formulated this way ICA is also referred to as Blind Source Separation (BSS) and its purpose is to estimate the source signals $\mathbf{s}(t)$ using only the observed data $\mathbf{x}(t)$. A solution is obtained if one can find the inverse of the mixing matrix $\mathbf{B} = \mathbf{W}^{-1}$ and so:

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

A general principle for estimating the matrix $\mathbf{B}$ can be found by considering that the source signals are statistically independent. There are many mathematical methods for estimating the coefficients b_{ij}. The nonlinear decorrelation and the maximally nongaussianity are the most applied ones [20].

In this work, JADE algorithm [21] was used for independent components estimation. In a previous work [14], it was demonstrated that, among popular ICA algorithms (such as FastICA and Akuzawa's Newton-like method [10]) JADE presents a compromise between good separation performance and fast convergence.

3.1.1 JADE algorithm

In JADE (Joint Approximate Diagonalization of Eigenmatrices) algorithm [21], second and fourth order statistics are applied for independent component estimation through a tensorial approach. Cumulant tensors are matrices containing the cross cumulants [22]. Considering this, the second-order cumulant tensor is the covariance matrix (C) and the fourth-order tensor ($\mathbf{T_4}$) is formed by the fourth-order cross cumulants cum(x_i, x_j, x_k, x_l), that for zero mean random variables are defined as:

$$\text{cum}(x_i, x_j, x_k, x_l) = E\{x_i, x_j, x_k, x_l\} - E\{x_i, x_j\}E\{x_k, x_l\} - E\{x_i, x_k\}E\{x_j, x_l\} - E\{x_k, x_j\}E\{x_i, x_l\} \tag{3}$$

The tensor $\mathbf{T_4}$ is a four dimensional array, in which for each element $Q_{ijkl} = cum(x_i, x_j, x_k, x_l)$, the indexes i, j, k, l vary from 1 to N (where N is the number of signals).

The ICA tensorial methods are derived through a procedure analogous to the diagonalization of a covariance matrix $\mathbf{C}$, which produces signal decorrelation. Considering that $\mathbf{T_4}$ is a fourth-order counterpart of $\mathbf{C}$, independence can be achieved by diagonalizing $\mathbf{T_4}$, as for independent signals the only non-zero fourth-order cross cumulant appears when $i = j = k = l$. Analogous to the second order case, diagonalization of the fourth-order tensor can be achieved through eigenvalue decomposition (EVD) [23].

Although the idea of the ICA tensorial methods is quite simple, the diagonalization of $\mathbf{T_4}$ through an analytical procedure demands very large computational resources and is prohibitive in most applications. Considering this, JADE algorithm proposes an approximate method for diagonalization of $\mathbf{T_4}$. If the input data ($\mathbf{x}$) is pre-whitened (using for example PCA transformation [24]) it can be demonstrated that the cumulant tensor of $\mathbf{x}$ has a special structure and its eigenmatrices are described through [10]:

$$\mathbf{M} = \mathbf{w}_m\mathbf{w}_m^T \tag{4}$$

where $m = 1, ..., N$ and $\mathbf{w}_m$ are the rows of the ICA mixing matrix $\mathbf{W}$ ($\mathbf{x} = \mathbf{W}\mathbf{s}$).

JADE algorithm uses the linear transformation F_{ij} applied to $\mathbf{M}$:

$$F_{ij}(\mathbf{M}) = \sum_{kl} m_{kl}\text{cum}(x_i, x_j, x_k, x_l) \tag{5}$$

where m_{kl} is an element of $\mathbf{M}$, and searches for a matrix $\mathbf{W}$ that makes $Q = \mathbf{W}F(\mathbf{M_i})\mathbf{W}$ as diagonal as possible.

3.2 Neural Classifier

In this work, multi-layer perceptron networks with a single hidden layer were used. The number of hidden neurons was chosen after testing exhaustively the discrimination performance of each network.

The particular experimental setup comprises two distinct acoustic signatures (two ship classes) arriving at adjacent directions. Considering this, the designed classifier has a single output neuron (with training target output 1 for class 1 and -1 for class 2).

For training, the resilient back-propagation algorithm (RPROP) [25] was used. In order to account for statistical variations in the available signals, a cross-validation procedure was adopted by restarting the training procedure 10 different times using different sample arrangements into training, validating and testing sets.

4. RESULTS

An experimental run comprising the recordings of approximately 220 seconds was used. Two ships (targets) were detected at adjacent directions (190^o and 205^o). LOFAR analysis was performed using time-windows of $\sim$6 ms in length (resulting in $\sim$3600 windows). The average LOFAR spectra, considering all time windows, was computed for both directions and is illustrated in Figure 4-(left). The JADE algorithm was applied to the time-windowed LOFAR spectra and two frequency-domain independent components were estimated for each time-window (Figure 4-(right) illustrates the average LOFAR+ICA spectra). It can be observed that the LOFAR spectra for both directions present similar characteristics (probably due to the existing cross-interference). After ICA, the frequency contents in different bearings are quite different, favoring the target classification task.

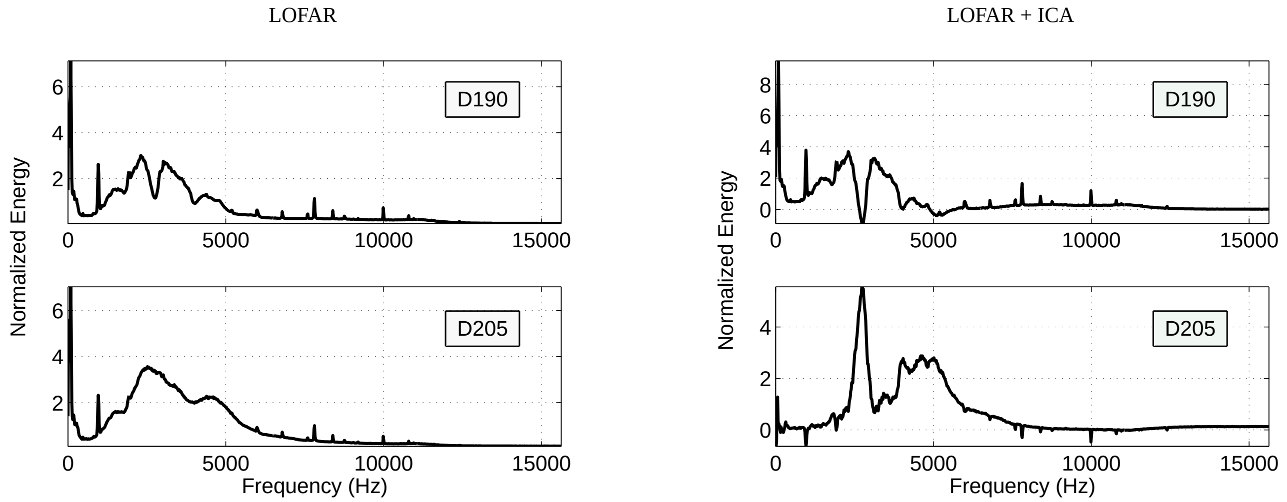

Figura 4: LOFAR analysis (average spectrum) applied to raw data (left) and after ICA (right).

For designing the classifiers, the available LOFAR time windows ($\sim$3600) were split into training, validation and testing sets. In order to evaluate the effects of ICA pre-processing, the neural classifier was trained using both LOFAR spectra and the frequency-domain independent components (LOFAR+ICA).

In order to compare both classifier design approaches, discrimination performance was evaluated through both ROC (Receiver Operating Characteristic) curve [26] and SP product. The ROC illustrates how both the detection (P_D) and false alarm (P_F) probabilities vary with respect to the decision threshold. The SP product index is defined as [27]:

$$SP = \frac{Ef_1 + Ef_2}{2} \times \sqrt{(Ef_1 \times Ef_2)} \tag{6}$$

where $Ef_1 = P_D$ is the detection efficiency for class 1 and $Ef_2 = (1 - P_F)$ is the corresponding efficiency for class 2. The threshold value that maximizes the SP tend to produce both high P_D and low P_F.

In order to chose the optimum number of hidden neurons for the MLP classifiers an iterative procedure was employed. Initially a neural network with a single hidden layer was trained and the efficiency estimated (through SP). New neurons are added to the hidden layer and the training procedure restarted until the SP index stabilizes near its maximum. As illustrated in Figure 5, for the classifiers based on LOFAR the maximum SP was achieved for five hidden neurons and in the LOFAR+ICA approach three neurons were enough to reach the maximum efficiency. It can also be observed that the use of ICA results on higher discrimination efficiency.

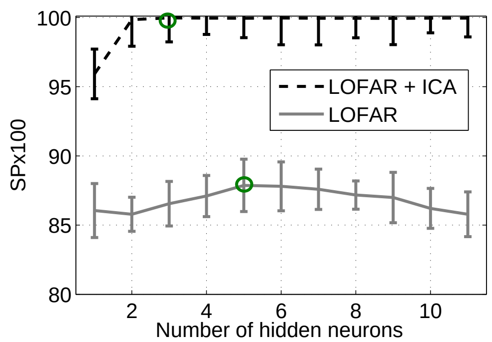

Figura 5: Discrimination efficiency (SP$\times$100) variation as the number of hidden neurons is increased.

Figure 6 illustrates the neural network outputs (considering the number of hidden neurons that produced higher discrimination efficiencies) for classifiers based on LOFAR and LOFAR+ICA. One can see that ICA favors the separation of distinct classes, which implies on a higher area under the ROC curve as shown in Figure 7. Table 1 summarizes the obtained results.

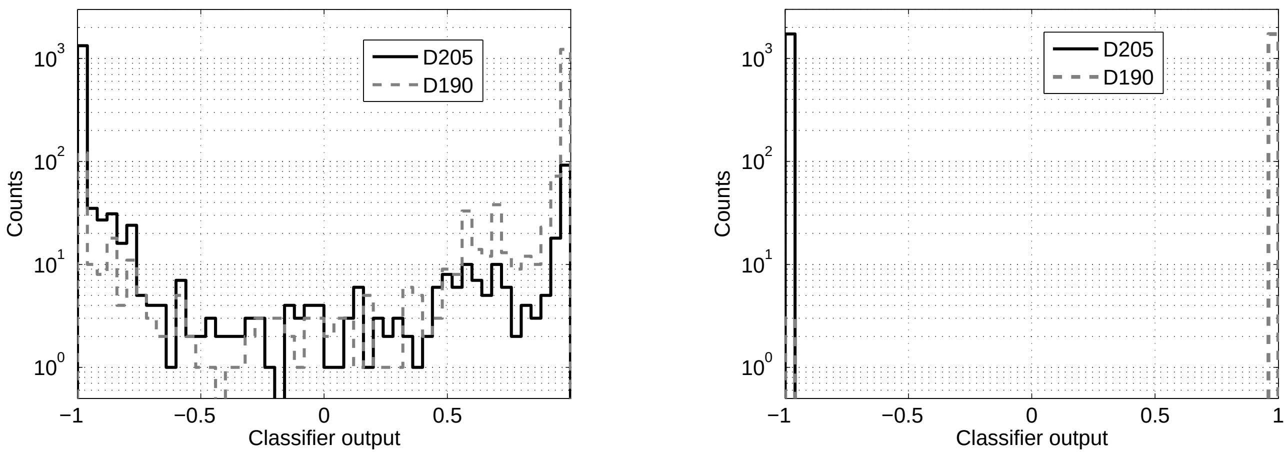

Figura 6: Neural classifier outputs using LOFAR (left) and LOFAR+ICA (right).

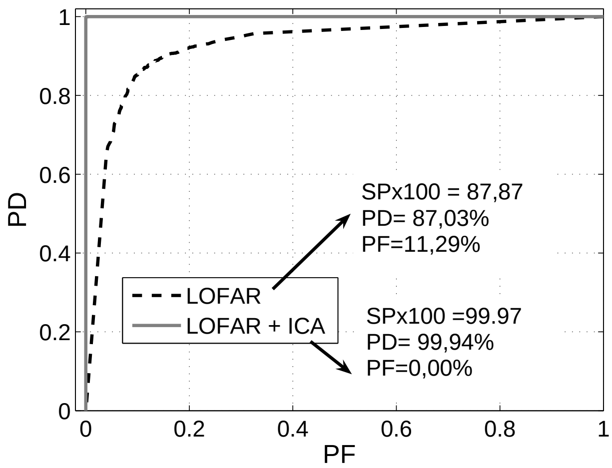

Figura 7: ROC curves for both classifiers.

Tabela 1: Discrimination efficiency obtained for both classifiers

Preprocessing	**SP×100**	**Eff. Clas 1** (%)	**Eff Clas 2** (%)
LOFAR	87.87	87.03	88.71
LOFAR+ICA	99.97	99.94	100.00

5. CONCLUSIONS

Sonar systems are widely used in military and civilian applications. In passive sonar, target identification is usually performed by trained human operators which listen to the acoustic signatures and also analyze frequency information obtained from LOFAR analysis. The identification tasks becomes more difficult when acoustic signals from different vessels arrive at adjacent direction of the hydrophone array. In this case, either the acoustic signatures and the LOFAR spectra are distorted by the cross-interference. In this work was proposed the application of independent component analysis (ICA) in order to reduce the efects of cross-interference when targets are at adjacent directions. ICA was applied in frequency-domain after LOFAR analysis and a multi-layer perceptron classifier performed the hypothesis testing. The obtained results indicate that using a combination of LOFAR and ICA the discrimination efficiency was considerably improved, from ∼87% for class 1 and ∼89% for class 2 to for respectively ∼99.9% and 100%.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to CNPQ, CAPES and FAPESP for the financial support and to the Brazilian Navy Research Institute (IPqM) for providing the used data and for fruitful discussions concerning this work.

REFERENCES

[1] R. J. Urick. *Principles of Underwater Sound for Engineers.*. McGraw-Hill., 1983.

[2] A. D. Waite. *Sonar for practicing Engineers.*. John Wiley and Sons, Inc., third edition, 2003.

[3] J. D. Martino, J. Haton and A. Laporte. "Lofargram line tracking by multistage decision process." *IEEE International Conference on Acoustics, Speech, and Signal Processing.*, vol. 1., pp. 27–30., April. 1993.

[4] N. N. de Moura, W. S. Filho and J. M. Seixas. "Passive Sonar Classification based on Independent components." *Proceedings of the Brazilian congress of neural networks, pp. 1-5. (portuguese).*, 2007.

[5] R. C. Torres, J. M. de Seixas and W. S. Filho. "Classificação de Sinais de Sonar Utililizando Componentes Principais não-lineares." *Learning and nonlinear models.*, vol. 1., no. 4., pp. 208–222., 2004.

[6] J. M. Seixas, D. O. Damazio and W. S. Filho. "Wavelet transform as a preprocessing method for neural classification of passive sonar signals." *International Conference on Electronic, Circuits and Systems.*, pp. 83–86., September. 2001.

[7] W. S. Filho, J. M. de Seixas and L. P. Caloba. "Principal Component Analysis for Classifyting Passive Sonar Signals." *IEEE International Symposium on Circuits and Systems.*, 2001.

[8] H. Peyvandi, B. Fazaeefar and H. Amindavar. "Determining class of underwater vehicles in passive sonar using hidden Markov with Hausdorff similarity measure." *Proceedings of 1998 International Symposium on Underwater Technology.*, pp. 258–262., April. 1998.

[9] L. Marple and T. Brotherton. "Detection and classification of short duration underwater acoustic signals by Prony's method." *International Conference on Acoustics, Speech, and Signal Processing.*, vol. 2., pp. 1309–1312., May. 1991.

[10] A. Hyvarinen, J. Karhunen and E. Oja. *Independent Component Analysis*. Wiley, New York, United States, 2001.

[11] V. S. Poblador, E. M. Moreno and J. S. Casals. "ICA as a Preprocessing Technique for Classification". In *Ind. Comp. Analysis And Signal Separation, 5th Int. Conf.*, LNCS, pp. 1165–1172, Charleston, United States, Setembro 2004. Springer.

[12] F. Oveisi. "EEG Signal Classification Using Nonlinear Independent Component Analysis". In *Proceedings of the International Conference on Acoustics, Speech and Signal Processing*, volume 1, pp. 361–364, Taipei, Taiwan, 2009.

[13] E. F. Simas Filho, J. M. Seixas and L. P. Caloba. "Modified Post-Nonlinear ICA Model for Online Neural Discrimination". *Neurocomputing*, vol. 73, no. 16-18, pp. 2820–2828, 2010.

[14] N. N. Moura, E. F. Simas Filho and J. M. Seixas. *Advances in Sonar Signal Processing*, chapter Independent Component Analysis for Passive Sonar Signal Processing, pp. 91–110. In-Tech, Vienna, Austria, 2009.

[15] S. Haykin. *Neural Networks and Learning Machines*. Prentice Hall, New Jersey, United States, third edition, 2008.

[16] H. Krim and M. Viberg. "Two decades of array signal processing research: The parametric approach". *IEEE ASSP Magazine*, vol. 13., pp. 67–94, 1996.

[17] P. S. R. Diniz, E. Silva and S. L. Netto. *Digital Signal Processing: Applications and Design.*. Second edition, 2010.

[18] R. O. Nielsen. *Sonar Signal Procesing.*. Artech House Inc, Nortwood., 1991.

[19] W. S. Filho, J. M. de Seixas and N. N. de Moura. "Preprocessing passive sonar signals for neural classification." *IET Radar, Sonar and Navigation.*, vol. 6, 2011.

[20] A. Hyvarinen and E. Oja. "Independent Component Analysis: Algorithms and Applications". *Neural Networks*, vol. 13, no. 4-5, pp. 411–430, 2000.

[21] J.-F. Cardoso and A. Souloumiac. "Blind Beamforming for Non-gaussian Signals". *IEE Proceedings-F*, vol. 140, no. 6, pp. 362–370, 1993.

[22] A. Cichocki, R. Zdunek, A. H. Phan and S. ichi Amari. *Nonnegative Matrix and Tensor Factorizations Applications to Exploratory Multi-way Data Analysis and Blind Source Separation*. John Wiley & Sons, United States, 2009.

[23] G. H. Golub and C. F. V. Loan. *Matrix Computations*. Johns Hopkins Studies In The Mathematical Sciences, United States, 1996.

[24] I. Jolliffe. *Principal Component Analysis*. New York: Springer-Verlag, second edition, 2002.

[25] M. Riedmiller and H. Braun. "A direct adaptive method for faster backpropagation learning, the RPROP algorithm". *Proc. of Int. Conf. on Neural Networks*, pp. 586–591, 1993.

[26] H. L. V. Trees. *Detection, Estimation, and Modulation Theory, Part I*. Wiley, New York, United States, 2001.

[27] A. dos Anjos, R. Torres and J. Seixas. "Neural triggering system operating on high resolution calorimetry information". *Nuclear Instruments and Methods in Physics Research A*, vol. 559, no. 1, pp. 134–138, 2006.