ICA applied to passive ocean acoustic tomography

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Abstract

In last two decades, many researchers have been involved in acoustic tomography applications. Many algorithms have been developed for active tomography applications. However few algorithms have been dedicated to the passive acoustic tomography applications. Up to now, all the developed algorithms are considering the single input single output channel or some specific type of signals (narrow band with specific features or signatures in time-frequency domain).

This paper deals with the blind separation of many natural and artificial acoustic sounds, in order to simplify and improve the performance of the previously cited algorithms. First of all, the choice of some Independent Component Analysis (ICA) algorithms is discussed, then some simulation results are given and analyzed.

Key-words: Underwater Acoustic, Passive Oceanic Tomography, Blind Source Separation, Independent Component Analysis

1 Introduction

Acoustic tomography researchers are involving in many different applications for civil or military purposes as: Mapping underwater surfaces, meteorological applications (to measure the temperature, the salinity the motion and the depth of the water), to improve sonar technology, so on. Many algorithms [10, 11] have been developed to deal with active acoustic tomography. Recently, the Passive Acoustic Tomography (PAT) [9] has taken an increased importance mainly for the three following reasons: related to Submarine Acoustic Warfare applications, Ecological reasons (in passive way, we don't emit any signal. Therefore we don't perturb underwater ecological system) and Economical and logistical reasons (one don't need emitters).

The main drawbacks of PAT are the lack of information about the number, the positions and the natures of the emitted signals. With more than two sources many actual tomography algorithms can't give satisfactory results. Many other don't work well or at all when the emitted signals are large band signals [18]. Some algorithms also take into consideration the position of the acoustic sound emitters [8]. In typically real world PAT applications, underwater acoustic signals are generated by various sources in motion whose their number and their positions are hardly (impossible) identified (as in the case of shoal of fish or wave noises).

Since the early of the ninetieth, Independent Component Analysis (ICA) has been a set of many important signal processing tools [16]. By assuming that the unknown p emitted signals (i.e sources) are statistically independent from each other, ICA consists on retrieving a set of independent signals (output signals) from the observation of unknown mixtures of the p sources [15]. It was proved that the output signals can be the sources up to a factor (or filter) scale and a permutation [7]. To separate the independent unknown sources from some mixed observed signals is called the Blind Source Separation problem (BSS).

Actually, the BSS problem can be found in many different applications. such as: radio-communication (Spatial Division Multiple Access, free hand telephone set), control of nuclear reactor, the study of seismic signals, and so on. More applications have classified and cited in [16].

This paper deals with the application of ICA algorithms in PAT in order to improve and simplified the PAT algorithms as well as the processing of the received signals.

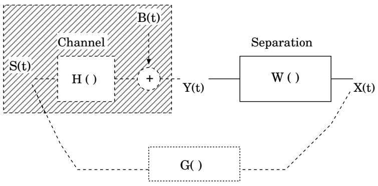


Figure 1: General Structure.

2 Channel model

Under some mild assumptions [11], acoustic submarine channel can be considered as a multiple paths which, in frequency domain, each them can be defined by a complex constant gain (i.e. a real lag τ_i and and a real gain C_i). For a classic Single Input Single Output (SISO) channel, the relationship between the emitted signal $s(t)$, which will be called later on as source or source signal, and the received (or observed) signal $y(t)$ is given by:

$$y(n) = \sum_{i=0}^{M} C_i s(n - \tau_i) + b(n) \tag{1}$$

where $b(n)$ stands for an Additive White Gaussian Noise (AWGN) and M for the channel order or the number of paths. the Let $S(t)$ is a $p \times 1$. In general case, the channel can be considered as Multiple Input Multiple Input (MIMO) channel whose mathematical model is given by the following equation:

$$Y(n) = \sum_{i=0}^{M} \mathbf{H}(i) S(n - i) + B(n) \tag{2}$$

Here $\mathbf{H}(i)$ denotes the $q \times p$ real constant matrix corresponding to the impulse response of the channel at time i (i.e. the ith path), $S(n-i)$ is the $p \times 1$ source vector at time $(n-i)$ and $B(n)$ is a AWGN $p \times 1$ vector. Fig. 1 shows a general structure of the channel, where $\mathbf{W}$ denotes the separation matrix and $\mathbf{G}$ denotes the global matrix which it can be used to show the simulation performances.

For passive acoustic tomography applications, one may be have an idea about the emitted signals, however he can not control them. Therefore Blind Source Separation (BSS) algorithms can be very helpful to deal with such situation. In BSS terminology, the above mentioned problem can be solved by considering the blind separation of linear mixed signals. In fact, two cases should be considered:

- Convolutive Mixtures: In the case, the channel is a multi-path with memory (i.e an echo channel). This type of mixture can represent the general case of acoustic underwater channel, i.e equation (2).

- Instantaneous Mixtures: This mixture model can be considered as a simplified convolutive one, specially when the channel is a memoryless channel (without echo). The later situation can be justified in deep water environment. Therefore, equation (2) can be rewritten as:

$$Y(n) = \mathbf{H}S(n) + B(n) \tag{3}$$

Convolutive mixture algorithms are generally time consuming algorithms. Few of them have been developed in the literature [15]. Most of those algorithms are dedicated to specific tasks and signals. In our knowledge, none of them has been optimized to deal with our problem. For these reasons among others which are noticed later, in the actual manuscript we consider only the instantaneous mixture. The convolutive mixture will our main future work. Thus, our study can be roughly divided in three parts:

- First of all, we select and apply some ICA algorithms in goal to better identify and characterize the features of acoustic sounds (mainly animal sounds) or acoustic noises (artificial noise as oil tanker's noise or natural one as waves' noise).

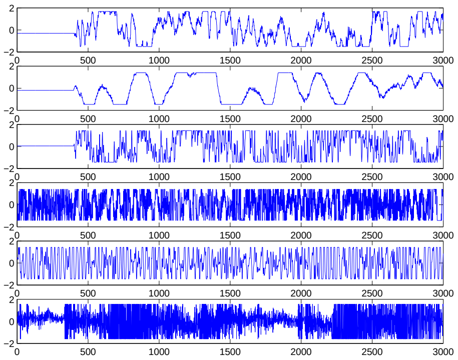
- Once the first part is achieved, many convolutive blind separation algorithms will be used to separate real observed signals. The performances of these algorithms will point out some problems related to underwater acoustic channel.

- Our final task consists on developing an optimized convolutive blind separation algorithm by taken into consideration the features of underwater acoustic channel (identified in the first and the second part of our study).

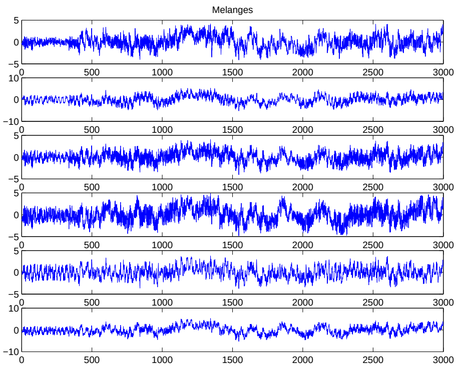
3 Selected ICA Algorithms

Actually, a huge number of ICA algorithms has been developed and proposed in the literature. Many of these algorithms are dedicated to specific applications. In addition, these algorithms are based on various criteria. To reach our gaol, many problems related to PAT applications should be considered:

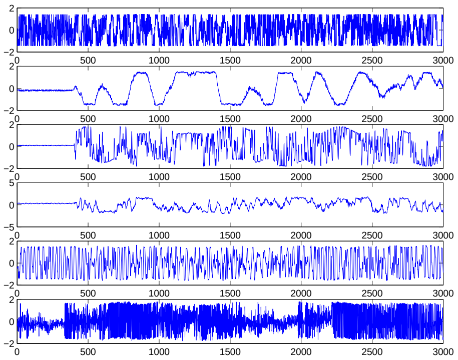
- First of all, can ICA algorithms give satisfactory results for our PAT problem?



Source Signals.



Observed Signals.



Separated Signals.

Figure 2: Separation results of FFPA applied to separate different shrimp and whale noises.

- If so, what is the influence of the propagation channel on the algorithm's performance?
- Because of the huge number of ICA used criteria and regarding our PAT application, one can ask the following question: What kind of criterion should be optimized?
- Finally, what are the features of the acoustic sounds? How can we use some of them to better achieve the separation?

The previous raised questions are addressed in the following subsections.

3.1 Validation of ICA Choice

To answer the first question concerning the choice of ICA to improve PAT algorithms, we applied some ICA algorithms to separate real acoustic signals in simulated experiments. One of these algorithm is the "Fast Fixed Point Algorithm for ICA: FFPA" proposed in [13]. This algorithm was selected for the main followin reasons:

- To separate the sources, FFPA minimize a cross normalized fourth order cumulant (i.e. *Kurtosis*).
- The originality of FFPA consists on the minimization procedure. In fact, the author update the separation matrix by an adptive way around the separation point of the criterion.
- The algorithm can be easily implemented and it is not a time consuming algorithm.

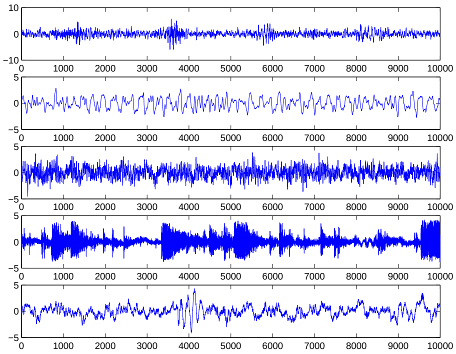
Some nice results were obtained, please see fig. 2.

3.2 Influence of Propagation Channel

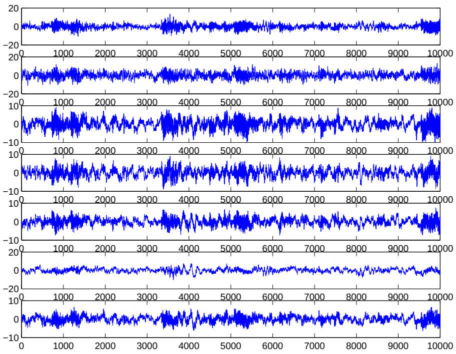
In [4], the authors propose an "Equivariant Adaptive Source Separation: EASI" algorithm. This algorithm is one of few algorithms that their performance results generally are not affected by the initial value of the mixing matrix when the last one stays a full rank matrix. This kind of algorithm should be more robust against the fluctuation of the channel parameters). The first version of EASI algorithm is a two steps separation algorithm :

- Whitening: By using Second Order Statistics (SOS) of observed signals, output signals of the first step become spatially white (i.e they are uncorrelated from each other).
- High Order Statistics (HOS) criterion: The separation is achieved by minimizing a criterion based on fourth order cross cumulant.

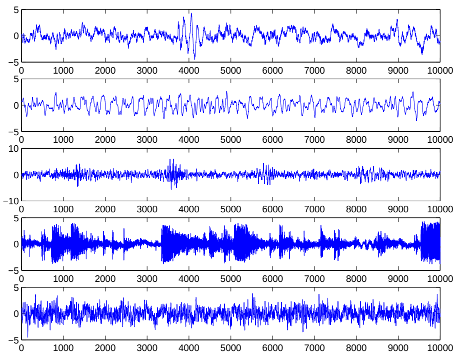
later on, the authors proposed another version of EASI in which the step can be done simultaneously. One of the advantage of EASI consists on the proposed heuristic numerical minimization algorithm which called "Relative Gradient". Same algorithm has been proposed separately by Amari and called "Natural Gradient". The basic idea of such algorithm is that the minimization is done in Riemannian space instead of Euclidian space considered in classic minimization algorithms [1].



Sources.



Received Signals



Separated signals

Figure 3: Experimental results of JADE algorithm. The source signals are the noises of: 1. Submarine immersion 2. Escort Vessel ASM 3. Killer Whales 4. Shrimps 5. Whales

EASI can separate successfully telecommunication signals (BPSK, QAM). Unfortunately, we could not obtain satisfactory results in PAT applications.

3.3 The Choice of ICA Criteria

In [16] many ICA algorithms are classified according to their criteria, mixture models or applications. To evaluate the choice impact of the selected criteria, we tested two different categories of criteria.

3.3.1 Non Linear Principal Component Analysis

J. Karhunen *et al.* in [14] propose an ICA algorithm based on Non Linear Principal Component Analysis (NL-PCA). The proposed algorithm can be considered as a generalization of classic PCA algorithm. In fact, instead of the minimization of cross correlations as in classic PCA algorithm, NLPCA minimize the cross correlation of a non linear function of output signals. Using the fact that the chosen function can be developed in Taylor series, then it is easy to prove that the proposed criteria becomes a criteria of various order statistic.

The authors performed the separation of quasi-periodical signals and some modulated signals as BPSK and QAM. One should mention that the choice of the non-linear function is very important task. Unfortunately with the proposed functions, we could separate underwater acoustic signals.

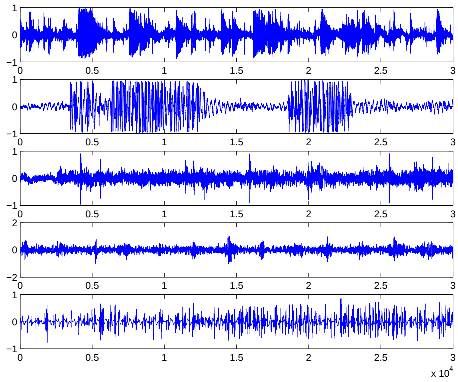
3.3.2 Blind beamforming for non-Gaussian signals

In [6], the authors propose an algorithm to perform on the simultaneous Joint Approximate Diagonalization of a set of matrices. This algorithm can be considered as the generalization of the Jacobian cyclic diagonalization [12].

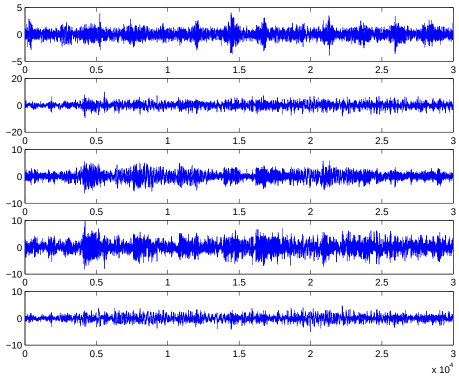
Based on the independence assumption, it is proved that the cross cumulant of any order higher than one should be equal to zero [7]. Using this property and JADE algorithm, Cardoso and Soulamiac [5] proposed an ICA algorithm based on the simultaneous diagonalization of the eigen matrices of the fourth order cross cumulant tensor. Their algorithm is called JADE "Joint Approximate Diagonalization of Eigen matrices". By using JADE, we separated successfully a large various of signals (telecommunication as well as speeches and acoustic signals), see fig. 3.

3.4 Acoustic Signals

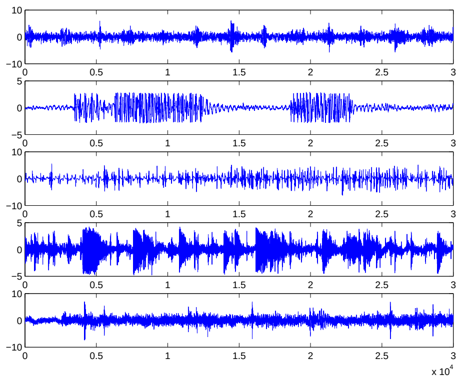
All the algorithms presented in previous sections are general ICA algorithms in the sense that they are only using the independence assumption of the sources. However in PAT applications, one should use various underwater acoustic sounds and noises. The signals can have few common features. Some of these features could be used to improve our algorithms.



Original Signals.



Received Signals.



Estimated Signals.

Figure 4: Separation results of the Geometrical algorithm. The original signals are the acoustic sounds of: 1. Shrimps 2. Lobster 3.Globicephala Dolphin 4. Submarine immersion 5. Torpedo

To identify some characteristic features of underwater acoustic signals, a statistical study has been conducted in our laboratory. Our study shows that: Some of them are non-stationary and non-Gaussian signals because wave noise are Gaussian signals. In some sense, they have some similar properties of speech signals. Therefore, we conduct some experimental study to emphasize their characteristic features.

3.4.1 Geometrical Approach

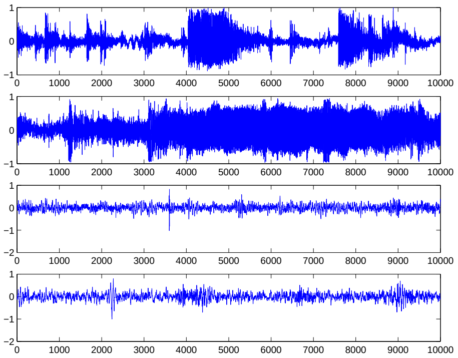
Recently, a geometrical approach for separating several speech signals has been proposed by M. Babaie-Zadeh *et al.* [2]. The last algorithm is based on "SPARSE" property of speech signals, i.e. the probability density function of speech signals can be considered as Gamma pdf [17]. In other world, the sources should have a multidimensional star shape in their scatter space (or phase space). This algorithm is optimized to separate speech signals. The convergence speed and the low cost computational function of the proposed algorithm make him a very attractive algorithm. Unfortunately, this kind of algorithms can not be easily generalized to consider the convolutive mixtures and that is its major drawback. In instantaneous mixtures, good separation results can be obtained, see fig. 4.

3.4.2 Neural Net approach

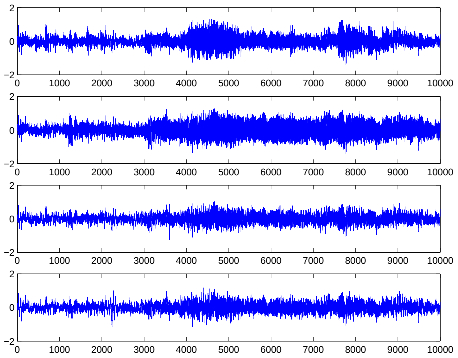
A Neural Net approach for blind separation of nonstationnary signals has been proposed by K. Matsuoka *et al.* [19]. Using the fact that the sources are non-stationary signals, one can show that the covariance matrix of such signals is a time dependent matrix. The basic idea of [19] consists on the estimation by sliding windows many covariance matrices. In addition, the authors prove that the separation of non-stationary signals can be done by minimizing an Hadamard inequality applied to the estimated covariance matrices. As well as the sources are non-stationary and non iid signals, one can separate the sources using this neural net approach. Finally, this approach can be compared to a joint diagonalization of a set of covariance matrices (i.e. the algorithm proposed by Belouchrani *et. al.* in [3]). The major drawback of the algorithm is the need to tune up some convergence parameters. Our experimental study showed that the performance as well as the stability of such algorithm can be affected by the parameter values. Unfortunately, the values of the parameters should be very well tuned in order to achieve a satisfactory separation, please see fig. 5.

4 Discussion on Experimental Results

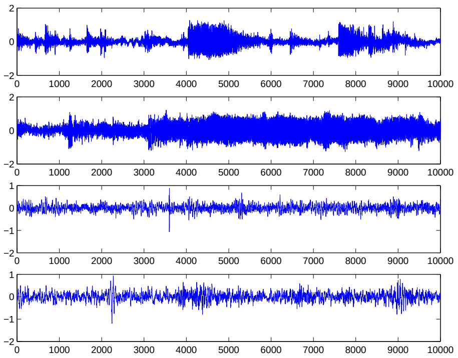
First of all, we should mention here that all the previously cited algorithms have been tested using three steps:



Input Signals.



Mixed Signals



Output Signals.

Figure 5: Results of Blind Separation of Non stationary Signals: 1. Shrimps 2. Petrol Tanker 3. Killer Whales 4. Submarine Immersion.

1. At first, we generate similar (or same) sources to the sources given in the original references. Once the separation is achieved over the mentioned sources, we go to a second test.

2. In the second step: many simulations have been conducted using real signals as speech signals in order to find best parameters of the algorithms and to measure their convergence speed and their performance using the global matrix, see fig. 1.

3. The final step consists on the application of these algorithm on PAT signals.

According to our experimental study, one can emphasize the following points:

- Simple ICA algorithm such FFPA can give satisfactory results with good convergence speeds.

- As modulated signals are far from acoustic signals, EASI or NLPCA which they have been optimized for such signals, can not give satisfactory results in PAT applications.

- With a small number of iteration, a geometrical approach can separate successfully speech and acoustic signals. Unfortunately, such approach can not be generalized for convolutive mixtures. However, the good results of this method push us to consider the Sparness properties of acoustic signals in our future work.

- Finally, approaches based on non-stationarity of the acoustic signals should be also considered in the developing of our future algorithm.

5 Conclusions

In PAT applications the signals have different origins. However a statistical study done in our laboratory shows that most of them have some common features: they are sparse quasi non-stationary signals (as they are stationary within a small time difference) and some of them are non-gaussian signals. Our experimental study shows that:

- ICA algorithm can be of great importance for PAT applications.

- ICA algorithm which they are based on HOS criteria, can achieve successfully the separation of acoustic signals.

- Better performance results and low cost criteria can be reach if we consider some features of acoustic signals (noniid, non stationary signals, Sparse, frequency band information, *etc.*).

- Some general ICA algorithms can be used to separate successfully modulated or quasi-periodic signals, but they can not achieve well the separation of acoustic signals.

Finally, our future work will focus on the identification of useful acoustic signal features as well as the separation of convolutive mixture.

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