POSTER DE RECHERCHE

Blind Source Separatiohn using Penalized Mutual Information criterion. Application to audio signals

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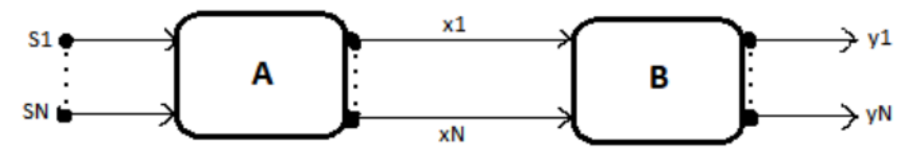
Introduction

Blind Source Separation (BSS) (see [1,2]) is one of the most atractive research topics nowadays in the field of signal processing and its has a wide range of engineering applications.
It consists of the separation of source signals set from a mixed signals set, we call it "Blind" due to the absence of information about the mixing process.
To achieve the separation, we minimize a penalized mutual information using the Gradient method



Objectif

The objective of blind source separation is to find $y(t) = Bx(t)$, an approximation of the original sources $s = (s_1, \dots\dots, s_N)$ using only the observed signals $x = (x_1, \dots\dots, x_N)$.
there is some assumptions that we suppose verifies on the sources and the mixing system :

- the components of the vector s are independent
- there is at most one Gaussian source
- the mixing system is an invertible linear operator independent of time

Method : part 1

To measure the independence of the components of the random vector $y = (y_1, \dots\dots, y_N)$, we use the mutual information :

$$\mathbf{I}(\mathbf{y}) = \int_{\mathbf{y}} \mathbf{p_y}(\mathbf{y}) \ln \frac{\mathbf{p_y}(\mathbf{y})}{\prod_i \mathbf{p_{y_i}}(\mathbf{y_i})} \mathbf{dy}$$

To resolve the problem of indeterminacy, we add a term of penalization to the mutual information :

$$\mathbf{J}(\mathbf{y}) = \mathbf{I}(\mathbf{y}) + \lambda \sum_{\mathbf{i}=1}^{\mathbf{N}} (\sigma_{\mathbf{i}}^{\mathbf{2}} - \mathbf{1})^{\mathbf{2}}$$

Method : Part 2

To calculate the gradient of the penalized mutual information, we derive with respect to the separation matrix B rather than y. For this, we apply the theorem of variation of mutual information so we get :

$$\frac{\partial J}{\partial B} = E\{\psi_y(y)x^T\} + \lambda E\{w(y)x^T\}$$

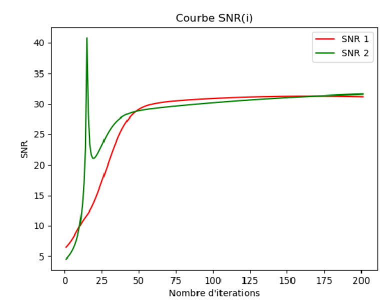
where $\psi_y(y)$ is the Marginal Score Function defined in [3].
To estimate the values of $\psi_y(y)$, we use an approach based on the method of least squares (see [2])
Then, we can calculate the matrix B using the Gradient method :

$$\mathbf{B^{k+1}} \leftarrow \mathbf{B^K} - \mu \frac{\partial \mathbf{J}}{\partial \mathbf{B}}(\mathbf{B^k})$$

Application of BSS

To show the performance of this algorithm, we take two audio and the mixed them. After that, we tried to get separated them using only the mixed signals. the results are presented in the QR code

To illustrate the performance of the method, we represent the variation of the output Signal-to-Noise-Ratio (SNR) versus the number of iterations



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References

- [1] M. El Rhabi, H. Fenniri, A. Keziou, E. Moreau, A robust algorithm for convolutive blind source separation in presence of noise, In Signal Processing, Volume 93, Issue 4, 2013, Pages 88
- [2] Y. AYYOUBI, A. Bahich, Z. Boutaleb, Z. Abou-zhar, Blind Source Separation using Penalized Mutual Information criterion, scientific project report (2A , M1 level), 18 january 2023
- [3] M. Babaie-Zadeh Malmiri. On blind source separation in convolutive and nonlinear mixtures, PhD thesis, INP Grenoble, September 2002.