Simulated Annealing, High-Order Statistics and Mutual Information for Separation of Sources

J.Solé-Casals

Grup de Processament de Senyal
Dept. Electrònica i Telecomunicacions
Universitat de Vic
jordi.sole@uvic.es

C.G.Puntonet

Departamento de
Arquitectura y computadores
Universidad de Granada
carlos@atc.ugr.es

I.Rojas

Departamento de
Arquitectura y computadores
Universidad de Granada

ABSTRACT

In this article, the fusion of a stochastic metaheuristic as Simulated Annealing (SA) with classical criteria for convergence of Blind Separation of Sources (BSS), is shown. Although the topic of BSS, by means of various techniques, including ICA, PCA, and neural networks, has been amply discussed in the literature, to date the possibility of using simulated annealing algorithms has not been seriously explored. From experimental results, this paper demonstrates the possible benefits offered by SA in combination with high order statistical and mutual information criteria for BSS, such as robustness against local minima and a high degree of flexibility in the energy function.

1. INTRODUCTION

The separation of independent sources from mixed observed data is a fundamental and challenging signal processing problem [1,2]. In many practical situations, one or more desired signals need to be recovered from the mixtures only. A typical example is speech recordings made in an acoustic environment in the presence of background noise and/or competing speakers. The task of blind signal separation (BSS) is that of recovering unknown source signals from sensor signals described by:

$$x(t) = As(t) \tag{1}$$

where $x(t)=[x_1,x_2,...,x_n]^T$ is an available *nx1* sensor vector, $s(t)=[s_1,s_2,...,s_n]^T$ is a *nx1* unknow source vector having stochastic independent and zero-mean non-Gaussian elements $s_i(t)$, and A is a *nxn* unknown full-rank and non singular mixing matrix. The BSS problem consists in recovering the source vector s(t) using only the observed data x(t), the assumption of independence between the entries of the input vector s(t) and possibly some a priori information about the probability distribution of the inputs. Statistical independence means that given one of the source signals, nothing can be estimated or predicted about any other source signal. It can be formulated as the computation of an *nxn* separating matrix W whose output u(t) is an estimate of the vector s(t) of the source signals.

$$u(t) = Wx(t) \tag{2}$$

In this article, the application of simulated annealing to the separation of sources is proposed for the optimization of the estimated mixing matrix W. Unlike many classical optimization techniques, SA do not relies on computing local first or second order derivatives to guide the search algorithm; SA is a more general and flexible method that is capable of searching wide solution spaces and avoiding local minima (i.e. it provides more possibilities of finding an optimal or near-optimal solution), including also random elements, which help to avoid getting trapped in sub-optimal solutions.

1.1. Energy Functions

Two energy functions are presented for the blind separation of sources through Simulated Annealing. The first function is based on the Hérault and Jutten criterion for source separation [3] and the second is based on the Mutual Information criterion [4].

The first algorithm for the separation of sources was the algorithm proposed by Hérault and Jutten. Motivated by this result, we propose to use equation (3) to define an energy function to carry out the separation of sources through Simulated Annealing:

$$Energy = \left| E\left[f\left(u(t)\right) g\left(v(t)\right) \right] \right| \tag{3}$$

On the other hand, one of the functions that allow to measure the independence between sources is the Mutual Information criterion. Therefore the second proposed algorithm is based on this function to carry out the source separation problem. Based on this result, we propose to use the equation (4) to define an energy function to carry out the separation of sources through Simulated Annealing:

$$Energy = \left[\sum_{i=1}^{n} H\left(y_i\right) - \log\left|\det\left(\mathbf{B}\right)\right| \right]^2 \tag{4}$$

1.2. Experimental results

In this section, we consider the cocktail party problem, assuming for the sake of simplicity that we have two microphones to receive the linear mixture of two signals that, in principal, are unknown. To provide an experimental demonstration of the validity of the proposed algorithm, 1,000 samples of two different signals were used (Fig.1). A linear mixture of the two signals was achieved, using the mixing matrix A represented by the following equation:

$$A=\begin{pmatrix}1 & -0.5\\ 0.5 & 1\end{pmatrix}\; W_{HJ}=\begin{pmatrix}1 & -0.55\\ 0.65 & 1\end{pmatrix}\; W_{MI}=\begin{pmatrix}1 & -0.47\\ 0.66 & 1\end{pmatrix}$$

The goal of the simulation was to analyse the behaviour of the algorithm and observe where the energy function thus achieved is optimised; with this aim, therefore, we studied the mixing matrix obtained by the algorithm. When the number of generations reached a maximum value, the obtained solution is selected and the estimated signals u were extracted, using the mixing matrix W. Fig.2 give the joint representation of the recovered sources, one versus the other, using the two proposed energy functions. In Fig.3 we shown the obtained signals using the Mutual Information energy function. For a numerical analysis of the results obtained, two error indices were used:

$$MSE_i=\frac{\sum_{t=1}^{N}(s_i(t)-u_i(t))^2}{N} \qquad \mathrm{Ct_i}=10\log\left(\frac{\sum_{t=1}^{N}(s_i(t)-u_i(t))^2}{\sum_{t=1}^{N}(s_i(t))^2}\right)$$

The crosstalk parameter and the mean squared error of the separated signal are presented in the following table:

Method	*Crosstalk*		*MSE*	
	Ct_1	Ct_2	MSE_1	MSE_2
HJ	-18.7078	-23.3469	0.0011	0.0023
MI	-24.8252	-22.8861	0.0003	0.0026

2. CONCLUSION

Many different approaches have been attempted by numerous researchers using neural networks, artificial learning, higher order statistics, minimum mutual information, beam forming and adaptive noise cancellation, each claiming various degrees of success. Despite the diversity of the approaches, the fundamental idea of the source signals being statistically independent remains the single most important assumption in most of these schemes. The neural network approach has the drawback that it may be trapped into local minima and therefore it does not always guarantee optimal system performance. This article discusses a satisfactory application of Simulated Annealing, to the complex problem of the blind separation of sources using two energy functions: High-Order Statistics and Mutual Information.

ACKNOWLEDGEMENT

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3. REFERENCES

[1] A.Papoulis, "Probability, random variables, and stochastic processes", McGraw-Hill, 1991.

[2] C.G.Puntonet, A.Prieto, "Neural net approach for blind separation of sources based on geometric properties", Neurocomputing, 18 (3), 1998, pp.141-164.

[3] C. Jutten, J, Hérault "Blind separation of sources, Part I: An adaptive algorithm based on a neuromometic arquitechture". Signal Processing 24, pp. 1-10, 1991.

[4] A. Bell & T.J. Sejnowski: An Information-Maximization Approach to Blind Separation and Blind Deconvolution Neural Computation 1129-59 (1995).

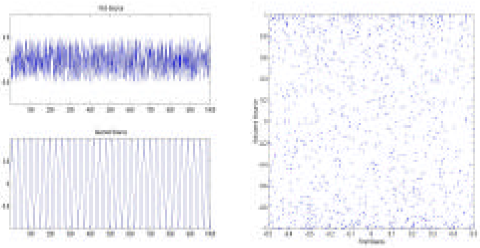

Figure 1. *Original sources and joint representation of the original sources, one versus the other*

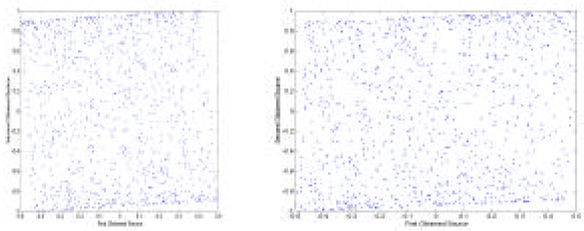

Figure 2. *Joint representation of the recovered sources, one versus the other. On the left, by means of the HJ energy function. On the right, by means of the MI energy function.*

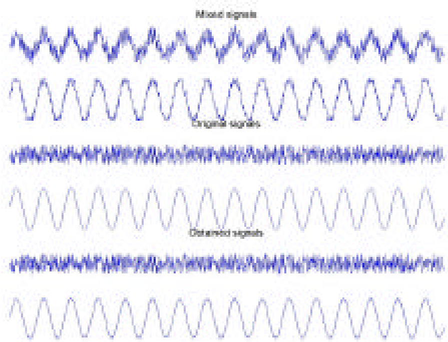

Figure 3. *On the top, the mixed signals. On the middle, the original signals. On the down, the obtained signals by means of the MI energy function.*