A fast algorithm for blind separation of sources based on the cross-cumulant and Levenberg-Marquardt method.

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Abstract

In this paper, a new algorithm for the instantaneous mixture of the blind separation of sources problem is derived. This algorithm deals with Multi-Input Multi-Output (MIMO) channels. The cost function proposed in this paper can be considered as an extension of that previously proposed by us (Mansour - Jutten [6]) for only two sources and two sensors.
The cost function is based on the cross-cumulant 2×2 and it is minimized using the Levenberg-Marquardt method. Generally, algorithm convergence was attained unless than 50 iterations and the experimental results were satisfactory even with five stationary sources and two non-stationary sources.

1 Introduction

Since 1989, blind separation of sources has been one of the important signal processing problems. Most of the blind separation algorithms deal with two kinds of mixtures: instantaneous (memoryless) mixture [1, 5, 3] or convolutive mixture (the channel effects can be modeled by a matrix of filters) [11, 4, 7, 9].

Generally, fourth order statistics are needed to separate the sources [2, 8]. In the case of only two sources, we proposed in [6] an algorithm for the blind separation of sources. The separation was achieved by minimizing the cross-cumulant 2x2 of the two output signals. This minimization was carried out using a gradient algorithm.

The new cost function, proposed here, like the old one is based on the cross-cumulant 2x2 of the output signals but the new algorithm deals with Multiple Input and Multiple Output (MIMO). This algorithm is relatively very rapid, and convergence is attained in less than 50 iterations, owing to the choice of a simple cost function which can be minimized using the Levenberg-Marquardt method. Finally, by experimental study, we observed satisfactory results even with a small number of sample data.

2 Model and Criterion

X represents $(x_i(n))$, the N zero-mean unknown sources, assumed to be statistically independent, and E represents $(e_i(n))$ observed signals. We assume in this paper that the mixture is instantaneous (see Fig. 1).

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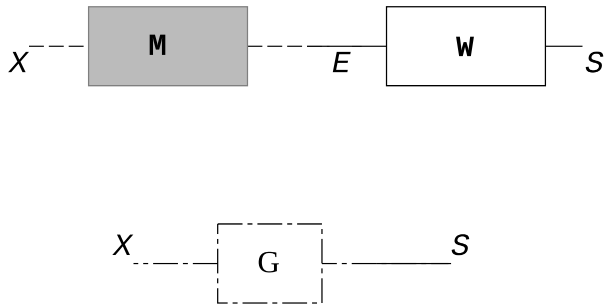

Figure 1: Channel model.

S represents the estimated signals:

$$S = WE = GX, \tag{1}$$

where M is the mixture matrix, W is the separating matrix and $G = (g_{ij})$ is the global matrix $G = WM$. The separation occurs when G becomes a general permutation matrix (i.e, $G = \Delta P$, where P is a permutation matrix and Δ is an invertible diagonal matrix [3]).

The sources can be separated by minimizing the following cost function.

$$\min_{W}\{\sum_{m>n}^{N} \mathrm{Cum}_{22}^{2}(s_m, s_n)\} \tag{2}$$

In fact, we proved in [**?**] that:

$$\sum_{m>n}^{N} \mathrm{Cum}_{22}^{2}(s_m, s_n) = 0 \Longleftrightarrow g_{mj} g_{nj} = 0, \tag{3}$$

where $(1 \leq j \leq N)$ and $m \neq n$. Using eq. (3), it is easy to demonstrate that the minimization of this cost function leads us to the following important proposition[1]:

Proposition 1: All the column vectors of the global matrix G have at most one coefficient not equal to zero.

Proposition 1 may be considered as not being adequate to separate the sources (i.e, G becomes a general permutation matrix). To force G to be a general permutation matrix, we must put one on the principal diagonal of W ($w_{ii} = 1$, where $1 \leq i \leq N$):

$$w_{ii} = 1 \Longrightarrow W_i \neq 0, \tag{4}$$

where $1 \leq i \leq N$ and W_i is the ith row of W. Using eq. (4), we can prove that G cannot have a zero row, then we can claim that:

Proposition 2: All the row vectors of G have at least one coefficient not equal to zero.

Togethers, propositions 1 and 2 give us:

Proposition 3: The global matrix is a general permutation matrix.

Finally, minimization of the cost function (2) is done according to the Levenberg-Marquardt algorithm [10, 12]. Using this algorithm, the convergence of our algorithm is attained in a small number of iterations, as the experimental results in the next section demonstrate.

3 Experimental results

In the case of stationary signals, good results are obtained (the cross-talk is about -25 dB at most of the channels).

Satisfactory results are obtained even with five stationary signals. The signal statistics are estimated over 1500 samples. The convergence is obtained after 25 iterations, as shown in fig. 2.

In the cases of two non-stationary sources, satisfactory results are obtained: the signal statistics are estimated over 300 samples and the convergence is obtained within less than 50 iterations.

[1] For example, in the case of two sources and two sensors, we proved in [6] that four possible cases can be obtained:

$$\begin{cases} g_{11} = 0 & \text{and} & g_{12} = 0 & \Rightarrow & s_1 = 0 \\ g_{11} = 0 & \text{and} & g_{22} = 0 & \Rightarrow & \text{Good solution} \\ g_{21} = 0 & \text{and} & g_{12} = 0 & \Rightarrow & \text{Solution up to permutation} \\ g_{21} = 0 & \text{and} & g_{22} = 0 & \Rightarrow & s_2 = 0 \end{cases}$$

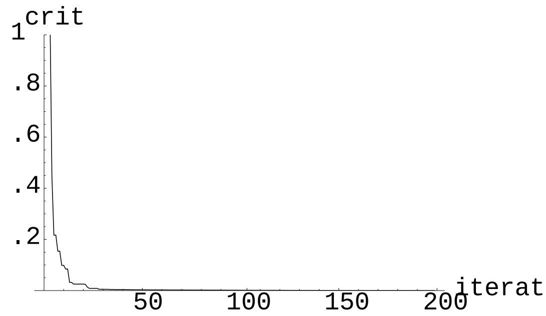

Figure 2: Criterion convergence.

For more than two non-stationary sources, the experimental results depend on the properties of the sources (the non-stationarity and the silent period). To demonstrate this, we present the results of an experiment attempting to separate three sources $N = 3$ (see Fig. 3):

- The first source is children's song (with music). This source has strong non-stationarity and a relatively low power.
- The second source is a stationary noise.
- The third source is the English phrase "Good morning" spoken by a man. This source presents a high energy into the convergence period.

All three signals were recorded in real room using a normal (non-sophisticated) microphone. The mixture was done numerically, using a PC and an instantaneous mixture model (see Fig. 3).

4 Conclusion

In this paper, we have proposed a fast algorithm for blind separation of sources. This algorithm minimizes, using the Levenberg-Marquardt method, a cost function based on the cross-cumulant 2x2. The experimental study demonstrated that the convergence is very rapid (generally, less than 50 iterations are required to reach convergence).

In the experimental studies, we have obtained good results, and even when using only if a small number of samples, the algorithm is able to converge using less than 500 samples. Also in the case of stationary signals, this algorithm can separate more than two sources.

To date, we have obtained good results in the cases of two non-stationary signals, the cross-talk is about -22 dB. Attempts to improve the algorithm to allow separation of more than two non-stationary signals are underway.

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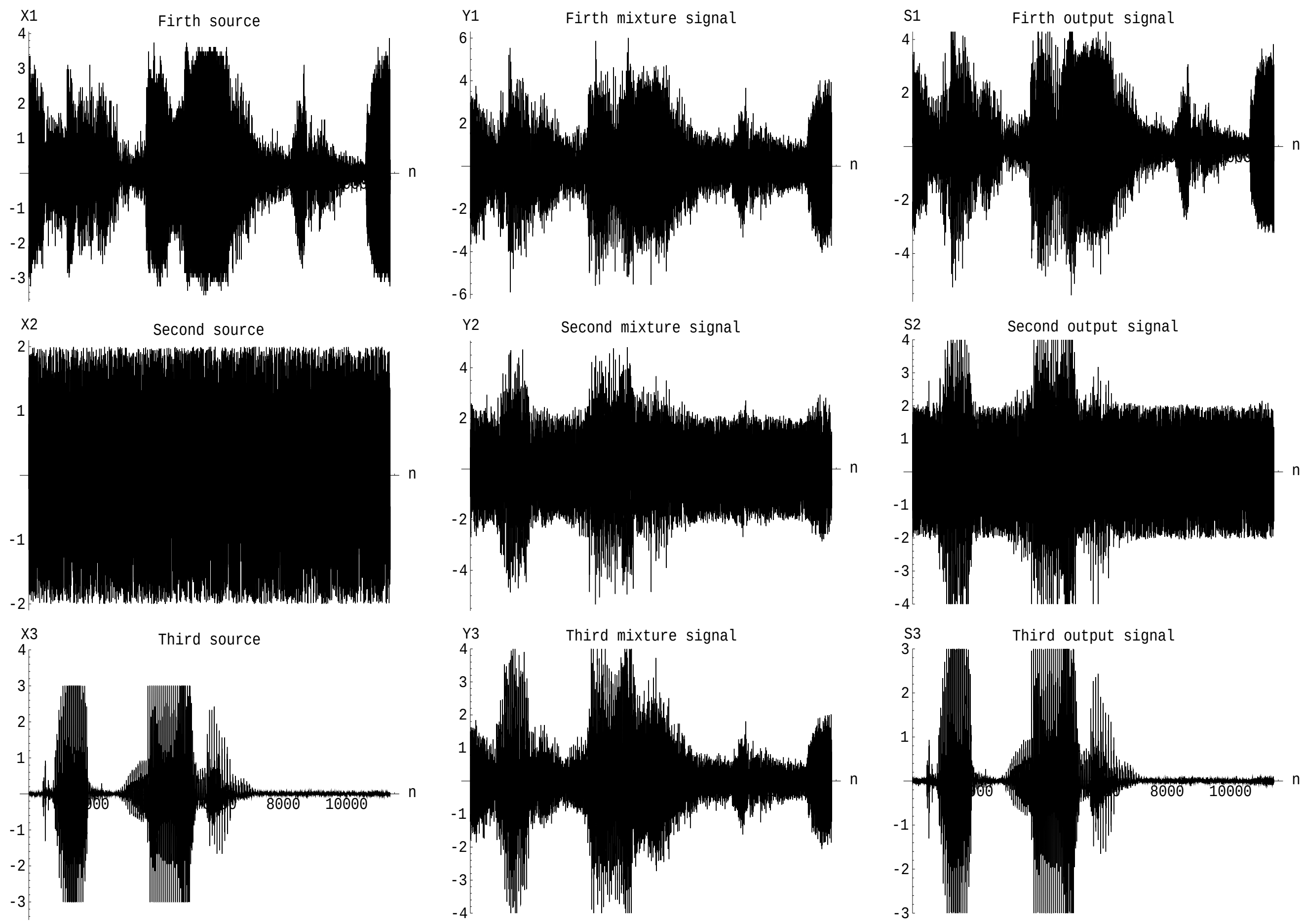

Figure 3: The experimental results: First column contains the sources, the second column contains the mixture signals and the last one contains the estimated signals.

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