

Blind Source Separation by ICA

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INTRODUCTION

This work presents a brief introduction to the blind source separation using independent component analysis (ICA) techniques. The main objective of the blind source separation (BSS) is to obtain, from observations composed by different mixed signals, those different signals that compose them. This objective can be reached using two different techniques, the spatial and the statistical one. The first one is based on a microphone array and depends on the position and separation of them. It also uses the directions of arrival (DOA) from the different audio signals.

On the other hand, the statistical separation supposes that the signals are statistically independent, that they are mixed in a linear way and that it is possible to get the mixtures with the right sensors (Hyvärinen, Karhunen & Oja, 2001) (Parra, 2002).

The last technique is the one that is going to be studied in this work. It is due to this technique is the newest and is in a continuous development. It is used in different fields such as natural language processing (Murata, Ikeda & Ziehe, 2001) (Saruwatari, Kawamura & Shikano, 2001), bioinformatics, image processing (Cichocki & Amari, 2002) and in different real life applications such as mobile communications (Saruwatari, Sawai, Lee, Kawamura, Sakata & Shikano, 2003).

Specifically, the technique that is going to be used is the Independent Component Analysis (ICA). ICA comes from an old technique called PCA (Principal Component Analysis) (Hyvärinen, Karhunen & Oja, 2001) (Smith, 2006). PCA is used in a wide range of scopes such as face recognition or image compression, being a very common technique to find patterns in high dimension data.

The BSS problem can be of two different ways; the first one is when the mixtures are linear. It means that the data are mixed without echoes or reverberations, while the second one, due to these conditions, the mixtures are convolutive and they are not totally independent

because of the signal propagation through dynamic environments. It is the “Cocktail party problem”. Depending on the mixtures, there are several methods to solve the BSS problem. The first case can be seen as a simplification of the second one.

The blind source separation based on ICA is also divided into three groups; the first one are those methods that works in the time domain, the second are those who works in the frequency domain and the last group are those methods that combine frequency and time domain methods. A revision of the technique state of these methods is proposed in this work.

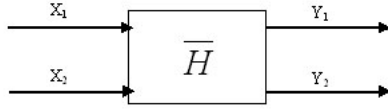
BACKGROUND

The problem consists in several sources that are mixed in a system, these mixtures are recorded and then they have to be separated to obtain the estimations of the original sources. As was mentioned above, BSS problems can be of two different types; the first one, when the mixtures are linear, see equation 3, and the second one, when the mixtures are convolutive, see equation 5.

In the first case each source signal is multiplied by a constant which depends on the environment, and then they are added. Convolutive mixtures are not totally independent due to the signal propagation through dynamic environments. This makes that the signals are not simply added. The first case is the ideal one, and the second is the most common case, because in real room recordings the mixing systems are of this type. The following figure shows the mixing system in the case of two sources two mixtures:

Where X_1 and X_2 are the independent signals, Y_1 and Y_2 are the mixing of the different X_j , and \bar{H} is the mixing system that can be seen in a general form as:

Figure 1. 2 sources – 2 mixtures system.



$$\overline{H} = \begin{bmatrix} h_{11} & \dots & h_{1j} \\ \dots & \dots & \dots \\ h_{i1} & \dots & h_{ij} \end{bmatrix} \quad (1)$$

The h_{ij} are FIR filters, each one represents an acoustic transference multipath function from source, i , to sensor, j . i and j represent the number of sources and sensors. Now it is necessary to remember the first condition that makes possible the blind source separation:

“The number of sensors must be greater than or equal to the number of sources.”

Taking this into account, the problem for two sensors, in a general form, can be represented as:

$$Y_1 = X_1 * h_{11} + X_2 * h_{12} \quad (2.1)$$

$$Y_2 = X_1 * h_{21} + X_2 * h_{22} \quad (2.2)$$

Generally, there are n source signals statistically independent $X(t) = [X_1(t), \dots, X_n(t)]$, and m observed mixtures that are linear and instantaneous combinations of the previous signals $Y(t) = [Y_1(t), \dots, Y_m(t)]$. Beginning with the linear case, the simplest case, the mixtures are:

$$Y_i(t) = \sum_{j=1}^n h_{ij} \cdot X_j(t) \quad (3)$$

Now, we need to recover $X(t)$ from $Y(t)$. It is necessary to estimate the inverse matrix of H , where h_{ij} are contained. Once we have this matrix:

$$\hat{X}(t) = \overline{W} \cdot Y(t) \quad (4)$$

where $\hat{X}(t)$ contains the estimations of the original source signals, and \overline{W} is the inverse mixing matrix. Now we have defined the simplest case, it is time to explain the general case that involves convolutive mixtures.

The whole process, which includes mixing and separation process, and that has been described before for linear mixtures, is defined as in Figure 2.

The process will be the following; first a set of source signals (X) pass through an unknown system \overline{H} . The output (Y) contains all the mixtures. Y is equalized with an inverse estimated system \overline{W} , which has to give an estimation of the original source signals (\hat{X}).

Given access to N sensors with a number of sources less than or equal to N , all with unknown direct and cross channels, the objective is to recover all the unknown sources. Here arises the second condition to obtain the source separation:

“In blind source separation using ICA, it is assumed that we only know the probability density functions of the non-Gaussian and independent sources.”

So we have to obtain \overline{W} , and it must be that:

$$\hat{X} = \overline{W} * Y \quad (5)$$

Here, as it was mentioned above, \hat{X} are the estimations of the original source signals, Y are the observations, and \overline{W} is the inverse mixing filter.

BLIND SOURCE SEPARATION BY ICA

This article presents different methods to solve the blind source separation, more exactly those that are based on independent component analysis (ICA). First, methods for the linear mixtures are going to be described, and then we are going to divide the methods for convolutive mixtures in three groups depending on the domain; frequency domain, time domain or both.

Blind Source Separation for Linear Mixtures

The blind source separation for linear mixtures is a particular case of the convolutive one. So methods

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