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Mixed Audio Signal Separation Using Independent Component Analysis

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ABSTRACT

Blind Source Separation (BSS) is a statistical approach to separating individual signals from an observed mixture of a group of signals, which relies on little assumptions of the signals and the mixing processes or media. This paper covers the general overview of Independent Component Analysis (ICA), an algorithm for achieving BSS techniques with application to real life activities. The ICA algorithm developed using MATLAB 2012, was used to separate mixture of audio signals recorded and it proved effective.

Keywords: Blind Source Signals, Independent analysis.

INTRODUCTION

Unmistakably, Blind Signal Separation is refers to as Blind Source Separation. The context is a recent chapter in the development of signal processing. The field began at a neural network conference in Utah, 1986 where Jutten and H'erault presented a paper entitled "Space or time adaptive signal processing by neural network models". Source separation has long been a topic of interest in electrical engineering. Many algorithms including Non-negative Matrix Factorization (NMF), Multichannel Blind De-convolution (MBD), Topographic ICA, Multi-dimension ICA, Kernel ICA, Tree-dependent Component Analysis and Sub-band Decomposition ICA have been developed to perform separation, but prior to BSS, major assumption were always required on the nature of the sources. The Jutten and H'erault's techniques were revolutionary in that it did not require assumptions on the nature of the signals being separated. Despite this, however, their techniques did not initially attract much attention. This is primarily because in the 1980's, neural network research focused on Hopfield networks and Jutten and H'erault's work went largely unnoticed. It was only with a much clearer formulation of BSS by Comon, 1994, that BSS became a mainstream topic of research.

Algorithm developed to perform blind source separation is given the name Independent Component Analysis algorithm; a term that is often used interchangeably with BSS. In this paper, BSS refers to the entire body of knowledge relevant to blindly separating signals, whereas ICA is reserved more specifically for algorithm that performs this separation.

The problem of source separation is an inductive inference problem. There is not enough information to deduce the solution, so one must use any available information to infer the most probable solution. The aim is to process these observations in such a way that the original source signals are extracted by the adaptive filter. The problem of separating and estimating the original source waveforms from the sensor array without knowing the transmission channel characteristics and the source can be briefly expressed as problem related to Blind Source Signals (BSS) (Ganesh et al., 2009).

A critical distinction is drawn in Blind Signal Separation research between instantaneous and convolution BSS algorithm. The distinction is based primarily on type of signal mixing being considered if mixing does not involve time delays, then instantaneous BSS is used, otherwise convolution BSS is necessary. Instantaneous BSS is better developed and widely applicable of the two. Historical development of BSS as a research field began with the instantaneous BSS. Convolution BSS is an extension of instantaneous BSS that was developed more recently to address some specific applications of instantaneous BSS (Akingbade, 2011).

Following Comon's (1994) seminar paper, there was a rapid proliferation of ICA algorithms. Algorithms were formulated based on a wide variety of principles, including mutual information, maximum likelihood and higher order statistics, to name just a few of the popular approaches. Despite such a wide variety, all ICA algorithms are fundamentally similar. ICA algorithms invariably obtain estimates of the independent signals by adopting a numerical approach (e.g gradient descent) to maximizing an "independence metric", that is a measure of the signals' independence. The main difference between ICA algorithms is in the metric that is used.

Blind Signal Separation has been applied to a number of biomedical signal processing tasks. Two among others of the biomedical application areas include Electrocardiogram and Electromyography signals.

Electrocardiogram (ECG) signals are generated by the electrical activity of the heart. These signals are recorded from the surface of the chest or abdomen and are routinely used by physicians to diagnose heart diseases. When plotted against time, an ECG signal is a series of impulses with each impulse corresponding to a heartbeat.

Electromyography (EMG) signals are also electrical signals and similar to ECG, but appears as a series of impulses when plotted against time (except impulse frequency is much higher in an EMG signal). The source of EMG signals is muscular activation, or motor unit activation to be precise. A motor unit is a group of muscles innervated by a single motor neuron. The motor neuron controls muscles activation by transmitting a pulse to each muscle fiber it is connected to (motor units comprise up to 1000 muscles fiber).

THE PROPOSED METHOD

Independent Component Analysis (ICA) is a statistical technique, perhaps the most widely used for solving the blind source separation problem. It is the mathematical algorithm that is used to perform Blind Separation problem. Blind Signal Separation is of two types, viz a viz; Instantaneous and Convolution Blind Separation. Instantaneous is a separation technique adopted by ICA without considering time delay. This method is the most popular among the two, whereas, when time delay is considered, it is said to be convolution blind signal separation.

The basic ICA approach uses the linear models as in figure 1.

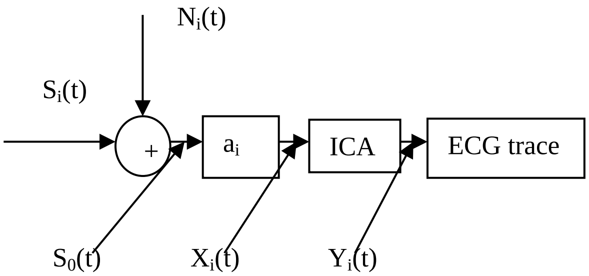

Figure 1: An ICA model with mixing signals

The general model for ICA is that the sources are generated through a linear basis transformation, where additive noise can be present. Suppose there is N statistically independent signals Si(t), i = 1…………N. It is to be assumed that the sources themselves cannot be directly observed and that each signal Si(t) is a realization of some fixed probability distribution at each time t. Also, suppose there are signal using N sensors, then a set of N observation signals Xi(t), i = 1……..,N that are mixtures of the sources. A fundamental aspect of the mixing process is that the sensors must be spatially separated (e.g. microphones that are spatially distributed around a room) so that each sensor records a different mixture of the sources. With this spatially separation assumption in mind, the mixing process with matrix multiplication can be model as follows:

$$X(t) = As(t) \qquad (1)$$

Where A is an unknown matrix called the mixing matrix and *x(t), s(t)* are the two vectors representing the observed signals and source signal respectively. Incidentally, the justification for the description of this signal processing technique as blind is that the prior information on the mixing matrix or even on the source themselves is not known.

The objective is to recover the original signals, *s(t)*, from only the observed vector *x(t)*. Its obtained estimates for the sources by first obtaining the 'un-mixing matrix" *W*, where $W = A^{-1}$. This enables an estimate y(t) of the independent sources to be obtained.

$$y(t) = Wx(t) \qquad (2)$$

Figure 2 seeks to obtain a vector *y* that approximates *s* by estimation the un-mixing matrix *W*. If the estimate of the un-mixing matrix is accurate, it obtains a good approximation of the sources.

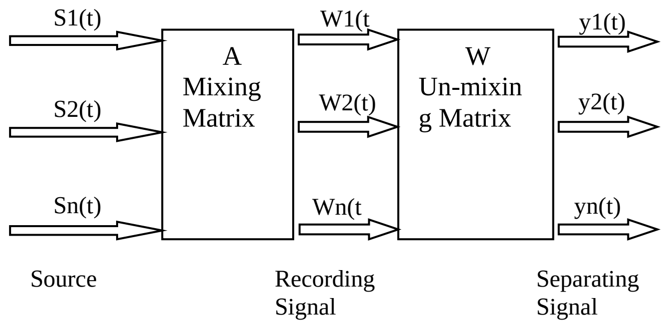

Figure 2: Blind Source Separation (BSS) block diagram

The summary of the statement so far is, let *k* be an arbitrary value observation of a set of signals which could be written as

$$S_0(t) = S_i(t) + N_i(t) \qquad (3)$$

And $$X_i(t) = S_0(t) * a_i \qquad (4)$$

In view of equation 2.1, equation 2.4 applies

$$X_i(t) = \sum_{i=1}^{k} a_i(S_i(t) + N_i(t)), \quad i = 1,2 \qquad (4)$$

where

$X_i(t) = (x_i(t) \dots\dots\dots\dots\dots x_k(t)$ is composed of *k* observed signals.

a_i is $k * k$ mixing matrix.

$S_i(t) = (s_i(t) \dots\dots\dots\dots\dots s_k(t))$ represents *k* independent sources, and *N(t)* is noise from independent sources.

Mathematically, an ICA problem can be described as a process of estimating k original signals $S_i(t) = [s_i(t)s_2(t) \dots\dots.. s_k(t)]^T$ from their k observed mixed signals $X_i(t) = [x(t)x_2(t) \dots\dots.. x_k(t)]^T$ at sensors produced by some unknown mixing function A among the *k* original source (Akingbade, 2011).

The Ica Algorithm

A very popular approach for estimating the independent component analysis (ICA) model is maximum likelihooh (ML) estimation. Maximum Likelihooh estimation is a fundamental method of statistical estimation. One interpretation of ML estimation is that the value parameters are taken as estimates that give the highest probability for the observations. Maximum likelihood is used in this paper because of its simplicity and nose free ICA model.

Density Tarnsformation

Assume now that both x and y are n-dimensional random vectors that are related by the vector mapping

$$y = g(x) \qquad (5)$$

for which the inverse mapping

$$x = g^{-1}(y) \qquad (6)$$

exit and is unique. It can be shown that the density $p_y(y)$ of the y is obtained from the density $p_x(x)$ of x as follows:

$$p_y(y) = \frac{1}{|detj_g(g^{-1}(y))|} p_x(g^{-1}(y)) \qquad (7)$$

Here, J_g is the Jacobian matrix

$$J_g(x) = \begin{bmatrix} \frac{\delta_{g1}(x)}{\delta_{x1}} & \cdots & \frac{\delta_{gn}(x)}{\delta_{x1}} \\ \vdots & \ddots & \vdots \\ \frac{\delta_{g1}(x)}{\delta_{xn}} & \cdots & \frac{\delta_{gn}(x)}{\delta_{xn}} \end{bmatrix} \qquad (8)$$

and $g_j(x)$ is the Jth component of the vector function g(x).

Deriving Maximum Likelihood Algorithm for ICA

It is not difficult to derive the likelihood in the noise free ICA model. This is based on using the well-known result on the density of a linear transform given in equation 6 according to this result, the density p_x of the mixture vector.

$$x = As \qquad (9)$$

can be formulated as

$$p_x(x) = |detB| p_s(s) \prod p_i(s) \qquad (10)$$

where

$B = A^{-1}$ and the p_i denote the densities of the independent components. This can be expressed as a function of $B = (b_1 \ldots\ldots\ldots\ldots \ldots b_n)^T$ and x, giving

$$p_x = |detB| \prod p_i(b_i^T x) \qquad (11)$$

Assume that there is T observations of x, denoted by x(1), x(2), …………..x(T). Then the likelihood can be obtained as the product of this density evaluated at the T points. This is denoted by L and considered as a function of B.

$$L(B) = \prod_{t=1}^{T} \prod_{i=1}^{n} p_i(b_i^T x(t)|detB|) \qquad (12)$$

Very often, it is more practical to use the logarithm of the likelihood, since it is algebraically simpler. This does not make any difference her since the maximum of the logarithm is obtained at the same point as the maximum of the likelihood. The log-likelihood is given by equation 13

$$\log(L(B)) = \sum_{t=1}^{T} \sum_{i=1}^{n} logp_i(b_i^T x(t) + T|detB| \qquad) \qquad (13)$$

The basis of the logarithm makes no difference, though in the following, the natural logarithm is used. To simplify notation and make it consistent to what was used in the previous notes, the sum over the sample index t can be denoted by an expectation operator, and divide the likelihood by T to obtain equation 14.

$$\frac{1}{T} logL(b) = E \sum_{i=1}^{n} \{logp_i(b_i^T x(t) + T|detB|\} \qquad (14)$$

The expression here is not the theoretical expectation, but an average computed from the observed sample. Of course, in the algorithms, the expectations are eventually replaced by sample averages, so the distinction is purely theoretical.

Simulation Result

The simulation is carried out using MATLAB 2012. First, a code was written to generate sin and sawtooth function. The mixture of these two was separated using the ICA algorithm. Figure 5, 6, and 7 show the result of these mixture of electrical signals.

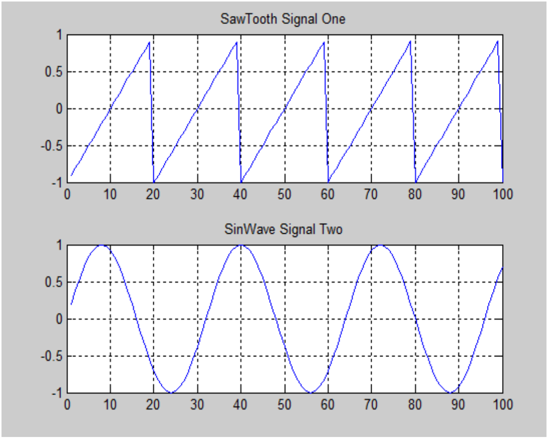

Figure 3: Electrical sin and sawtooth signals.

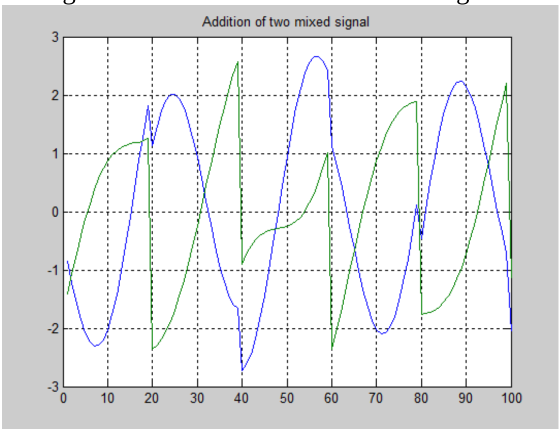

Figure 4: Mixture of the two signals

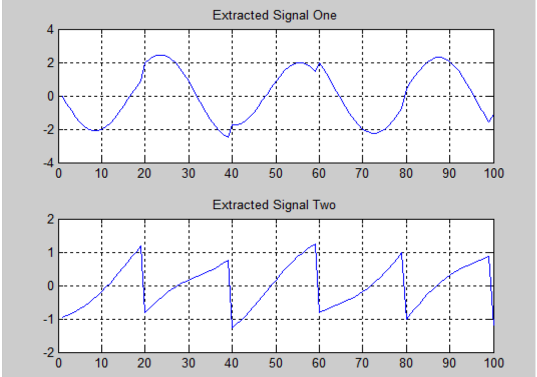

Figure 5: The extracted signals using ICA algorithm

Likewise, to demonstrate the validity of this algorithm, audio signals recorded and saved in .wav were mixed together, and the algorithm was also used to do the separation. The result is shown in figure 8, 9, and 10.

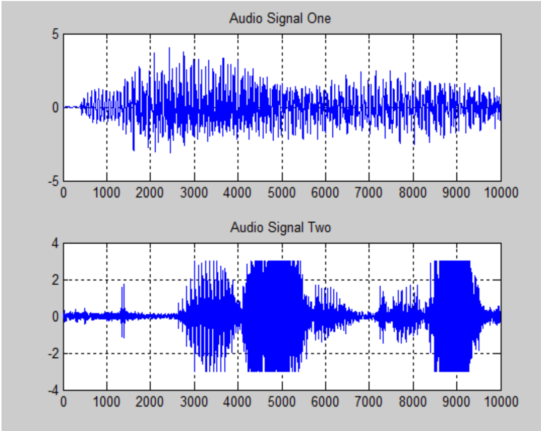

Figure 6: Independent audio signals

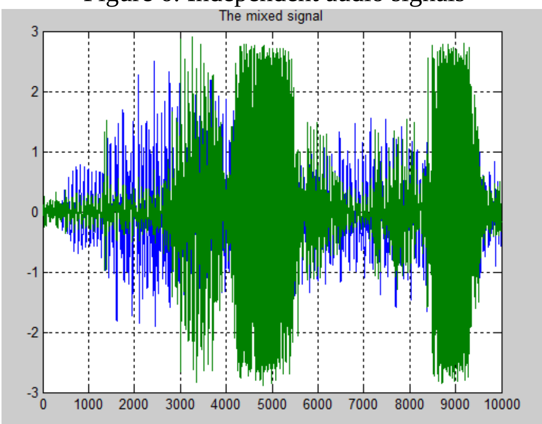

Figure 7: Mixture of the two signals

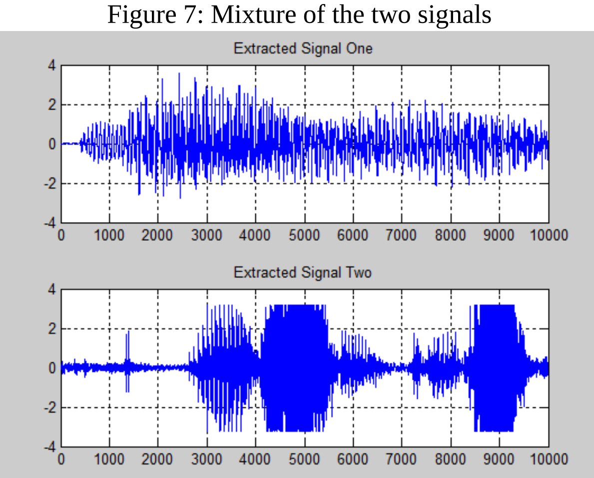

Figure 8: Separated Signals using ICA

CONCLUSION

Independent Component Analysis has the capability to separate mixed signals without the aid of information about the nature of the signals. It is therefore regarded as a powerful tool for separating a set of independent source signals without the aid of information about the nature of the signals.

The algorithm was applied in this research to separate mixture of two electrical signals and also mixture of two audio signal recorded and saved in .wav format.

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