AN LMS BASED BLIND SOURCE SEPARATION ALGORITHM USING A FAST NONLINEAR AUTOCORRELATION METHOD

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ABSTRACT

Blind source separation (BSS) is the technique that anyone can separate the latent data from their mixtures without any knowledge about the mixing process, but using some statistical properties of original source signals. In this paper we will use the nonlinear autocorrelation function as an object function to separate the source signals from the mixing signals. Maximization of the object function using the LMS algorithm will be obtained the coefficients of a basic linear filter which separate the source signals. To calculating the performance of proposed algorithm two parameters such as Performance Index (PI) and Signal to Interference Ratio (SIR) will be used. It will be shown that the proposed algorithm gives better results than other method such as Newton method which has been proposed by Shi.

KEYWORDS

BSS, LMS Algorithm, Newton Method, Nonlinear Autocorrelation, Speech Processing

1. INTRODUCTION

Blind source separation (BSS) is the technique that anyone can separate the original signals or latent data from their mixtures without any knowledge about the mixing process, but using some statistical properties of latent or original source signals.

Blind source separation (BSS) using Independent Component Analysis (ICA) has attracted great deal of attention in recent years. Important applications such as pattern recognition, speech recognition systems, speech enhancement, speech and image separation, wireless communication, image processing, telecommunications, data mining, and biomedical signal analysis and processing has been carried out using ICA [1-2]. The main objective of ICA is to identify independent sources using only sensor observation datum which are linear mixtures of unobserved independent source signals [3-5]. In fact, the ICA is an algorithm for solving the BSS problems, which assumes the source signals are non-Gaussian. The standard formulation of ICA requires at least as many sensors as sources [4].

Many algorithms for BSS have been proposed by researchers using the statistical properties of original signals such as non-gaussianity [6-14], smoothness [9,15], linear autocorrelation [10,16-17], temporal algorithms [18-20], nonstationarity [21-23], sparsity [24-27], nonnegativity [28-29] and nonlinear autocorrelation [30-33].

Tinati et al proposed a comparison method for speech signal orthogonality in wavelet and time-frequency domains [34]. Tinati et al proposed a new algorithm for selecting best wavelet packet node using LMM-EM model, finally they could obtain best results about estimation of mixing matrix [35-36]. They apply LMM model for speech mixture signals in wavelet packet domain using long-term Analysis. They also applied the wavelet packet transform in their proposed algorithm and obtained the best results [37].

DOI : 10.5121/ijcsit.2011.3315

Zhenewi Shi et al proposed a nonlinear autocorrolation of source signals for solving the BSS problems. They proposed a fixed point algorithm to solve the BSS problem based on nonlinear autocorrelation also they showed anyone can solve the BSS problem by maximizing the nonlinear temporal autocorrelation of source signals [31]. Zhenewi Shi et al also proposed a fast method for solving the BSS problems using the non-Gaussianity and nonlinear temporal autocorrelation structure assumption. They applied Newton algorithm as an iterative method for signal separation [32].

In this paper we use the nonlinear autocorrelation method based on LMS algorithm to source signal separation. The obtained results are compared with other reported results. Using the signal to noise ratio and the performance index parameter it will be shown that our obtained results are better than the Shi algorithm.

2. BACKGROUND MATERIALS

2.1. Independent Component Analysis

Independent component analysis is a statistical method expressed as a set of multidimensional observations that are combinations of unknown variables [1-2,4]. These underlying unobserved variables are called sources and they are assumed to be statistically independent with respect to each other. The linear ICA model is expressed as the following equation:

$$\boldsymbol{X}(t)=\boldsymbol{A}\times\boldsymbol{S}(t) \tag{1}$$

Where $\boldsymbol{X}(t)=[x_1(t),x_2(t),x_3(t),\ldots,x_M(t)]^T$ is an observed vector and $x_i(t)$ is the i^{th} mixture signal. $\boldsymbol{A}=[a_{ij}]_{M\times N}$ is an unknown $M\times N$ mixing matrix that operates on statistically independent unobserved variables which is defined as the following vector:

$$\boldsymbol{S}(t)=[s_1(t),s_2(t),s_3(t),\ldots,s_N(t)]^T$$

Where again $s_i(t)$ is the i^{th} source signal. It is assumed that any entry of mixing matrix $\boldsymbol{A}$ has a constant value, in other words the ICA system is an LTI system and also we assumed that the source signals have zero mean and unit energy or variance. In the case of an equal number of sources and sensors, ($M=N$), a number of robust approaches using independent component analysis have been proposed by many researchers [38-39]. In this case ICA method estimates the inverse or pseudo inverse of mixing matrixes as $\boldsymbol{W}$.

2.2. Whitening Filter

One of the important assumption of ICA method is that the observation data or signals must be have unit variance and be uncorrelated with each other. Therefore the observations signals must be processed using whitening filter such '**V**' vector as follows:

$$\tilde{\boldsymbol{X}}(t)=\boldsymbol{V}\times\boldsymbol{X}(t) \tag{2}$$

Where the '**V**' vector can be obtained as the following equations:

$$\boldsymbol{V}=\boldsymbol{D}^{-\frac{1}{2}}\times\boldsymbol{E}^T \tag{3}$$

If we define the covariance matrix of observation data as:

$$\boldsymbol{C}_X=\boldsymbol{E}\{\boldsymbol{X}\times\boldsymbol{X}^T\} \tag{4}$$

Where 'D' is the diagonal matrix defined as: D=diag($d_1\ d_2\ \ldots\ d_i\ \ldots\ d_N$) where '$d_i$' is the i^{th} eigenvalue of the covariance matrix of observation data and '$\boldsymbol{E}$' is the corresponding eigenvector matrix.

2.3. Nonlinear Autocorrelation to BSS Problem

We assume that the observation data obtained by sensors is modeled using (1) where the '***A***' is $N\times N$ square mixing matrix and it's each entries is a constant real numbers. We also assume that the original signals are mutually independent and have a nonlinear autocorrelation with each other.

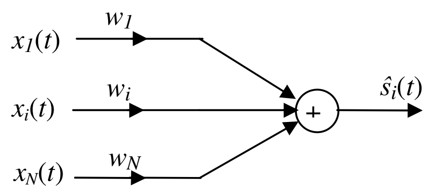

Figure 1. Basic Linear Instantaneous Filter for BSS

Using a basic linear instantaneous filter as shown in figure (1) with the tap gain vector as $\boldsymbol{W}=[w_1,w_2,\ldots,w_N]^T$ anyone can estimate the desired source signal $\hat{s}_i(t)$ as the following equation.

$$\hat{S}_i(t)=\boldsymbol{W}^T\times\boldsymbol{X}(t) \tag{5}$$

Where '**W**' is the unknown vector that must be obtained using an optimal method. With the definition of τ as some lag constant we can use the delayed version of the estimated source signal to obtaining the autocorrelation function of estimated source signal as:

$$\hat{S}_i(t-\tau)=\boldsymbol{W}^T\times\boldsymbol{X}(t-\tau) \tag{6}$$

To obtaining the '**W**' vector we will use the nonlinear autocorrelation [31-32] of estimated signals as an object function and maximizing it respect to have unit energy for the '**W**' vector. The object function can be written as:

$$max\,\underbrace{\psi(\boldsymbol{W})}_{\|\boldsymbol{W}\|=1}=E\{G(\hat{S}_i(t))G(\hat{S}_i(t-\tau))\}=E\{G(\boldsymbol{W}^T\tilde{\boldsymbol{X}}(t))G(\boldsymbol{W}^T\tilde{\boldsymbol{X}}(t-\tau))\} \tag{7}$$

Where $\tilde{\mathbf{X}}(t)$ is the whitened form of the observation data given by (2) and the 'G' operator is a differentiable nonlinear function, which measures the nonlinear autocorrelation degree of the estimated source signal. This nonlinear function can be choice such as $G(x)=x^2$ and $G(x)=\log\cosh(x)$.

3. Proposed Method

3.1. Learning Method Using the LMS Algorithm

To maximizing the objective function defined by (7), we apply the LMS method therefore the weight vector defined as '***W***' can be obtained as following equations:

$$\begin{aligned}&\boldsymbol{W}(k+1)\leftarrow\boldsymbol{W}(k)-\mu\frac{\partial\psi}{\partial\boldsymbol{W}},\quad \boldsymbol{W}\leftarrow\frac{\boldsymbol{W}}{\|\boldsymbol{W}\|}\\&\frac{\partial\psi}{\partial\boldsymbol{W}}=E\{g(\hat{S}(t))G(\hat{S}(t-\tau))\tilde{\boldsymbol{X}}(t)+G(\hat{S}(t))g(\hat{S}(t-\tau))\tilde{\boldsymbol{X}}(t-\tau)\}\end{aligned} \tag{8}$$

Where 'g' function is the derivative of 'G'.

Using the above equations given by (8) we can summarize the proposed algorithm as figure (2).

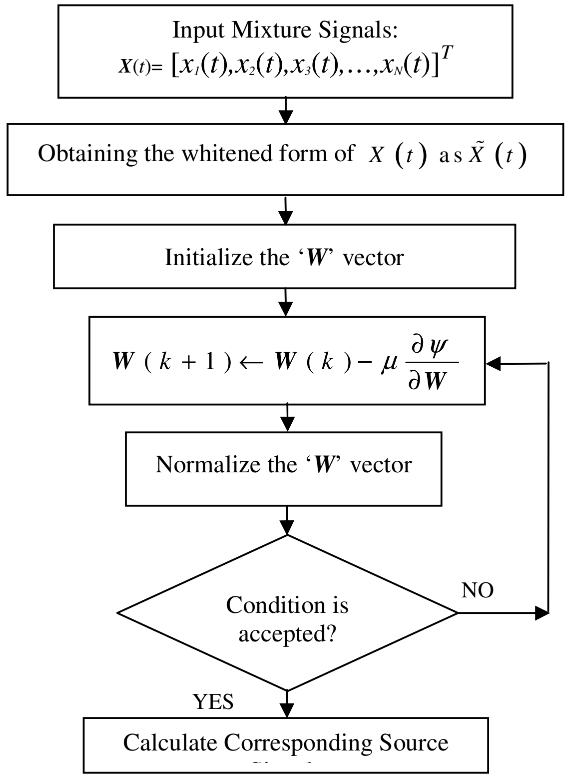

Figure 2. The Proposed Algorithm to Obtaining the Source Signals

3.2. Simulation Results

As described in proposed method, we apply the LMS algorithm for source signal separation such as speech and ECG data with considering the nonlinear functions $G(x)=x^2$ and $G(x)=\log(\cosh(x))$.

To measuring the degree of accuracy of source separation in proposed algorithm two parameters such as 1) Signal to Interference Ratio (SIR) and 2) Performance Index (PI) are considered. These parameters are defined as the following equations [32]:

$$SIR_i = 10\log\left(\frac{(s_i(t))^2}{(s_i(t)-\tilde{s}_i(t))^2}\right) \tag{9}$$

$$PI = \frac{1}{n^2}\left\{\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{|p_{ij}|}{\max_k |p_{ik}|}-1\right)+\sum_{j=1}^{n}\left(\sum_{i=1}^{n}\frac{|p_{ij}|}{\max_k |p_{kj}|}-1\right)\right\} \tag{10}$$

In the PI parameter p_{ij} is the i,j^{th} element of $P=W\times V\times A$ matrix. This matrix is the matrixes which can be separate the source signals. The larger value of PI parameter indicates that the separation is done in poorer.

Example: We consider 4 speech signals as shown in figure (3) with sampling rate 16000 sample per second which selected from TIMIT database. It is assumed that these source signals are zero mean and unit variances. These signals are mixed using a random mixing matrix and the mixing signals are obtained as an observation signals. The mixing signals are plotted in figure (4).

We apply the proposed algorithm and the estimated source signals are computed which shown as figure (5).

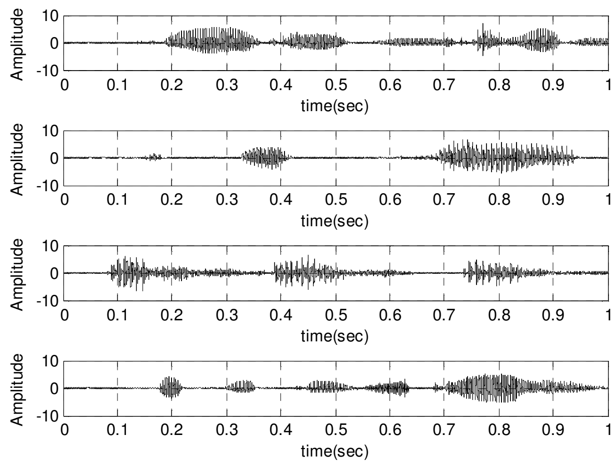

Figure 3. Speech Source Signals

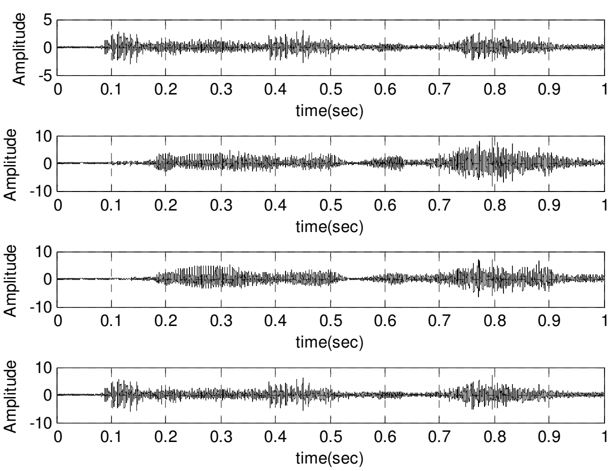

Figure 4. Mixing Signals

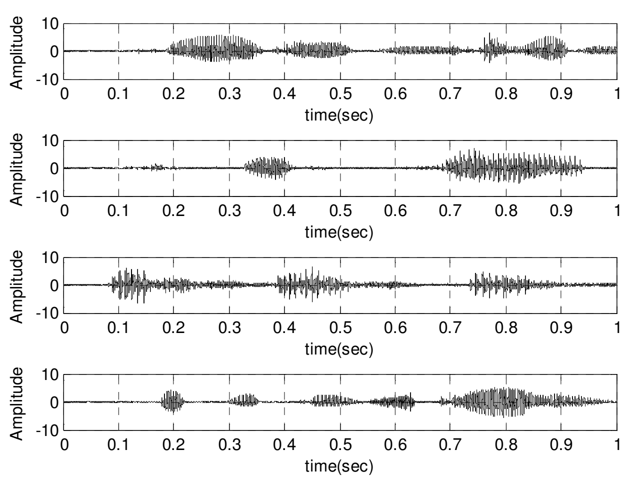

Figure 5. Estimated Speech Signals

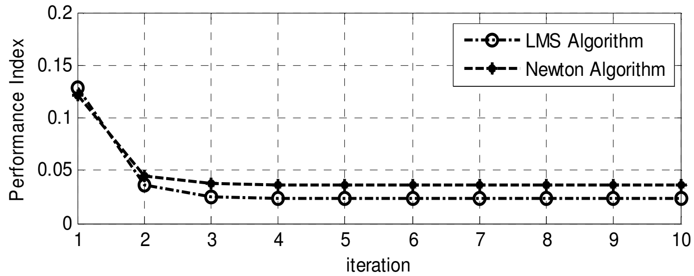

Figure 6. PI Parameter with τ=13 for LMS and Newton Methods

Table 1. SIR parameter of Estimated Speech Signals for both methods

Method	SIR_1(dB)	SIR_2(dB)	SIR_3(dB)	SIR_4(dB)
Shi	22.2134	26.6651	38.3949	21.9902
Proposed	**28.0435**	**26.4293**	**38.4228**	**31.8080**

To comparison of the proposed algorithm with the Shi algorithm (Newton Method) [32] Performance Index (PI) and Signal to Interference Ratio (SIR) parameters are computed to both methods. In figure (6) the PI Parameter for both method are plotted and it is shown that the value of PI parameter in LMS Method is better than Newton method. Also, in table (1) SIR parameter for the estimated source signal are shown in both algorithm and again the obtained results are better than other algorithm.

4. CONCLUSIONS

In this paper the nonlinear autocorrelation function as an object function is used to solving the BSS problem. With maximizing of the object function using LMS algorithm the coefficients of a basic linear filter are obtained and therefore the separation of source signal is done. To obtaining of accuracy of the proposed algorithm the performance index and SIR parameter are calculated and the obtained results are compared with the Newton method. It is shown that the proposed algorithm gets better results than the other method.

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