An algorithm for noisy Blind Source Separation with nonlinear autocorrelation and noise reduction using wavelet

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Abstract

Recently, Blind Source Separation (BSS) of received noisy signal has been great interest the in the field of signal processing. BSS can separate the original signals from their mixtures without any knowledge about the mixing process. The nonlinear autocorrelation function is used as an object function to separate the source signals from the noisy mixing signals that has to be maximized. Wavelet transform is a useful tool to maximize the nonlinear autocorrelation function and reduce the effects of noise. In this paper we will investigate the usage of wavelets to solve the BSS using LMS algorithm in the two scenarios. In the former scenario, the mixed signals were first separated and then the wavelet transform is used to eliminate noise effect. In the latter scenario, the wavelet packet transform of the mixed signal is obtained and then according to these packet signals, BSS is applied. To calculate the performance of the proposed algorithms, the parameter of Signal to Noise and Interference Ratio will be used. The source signals are selected from TIMIT database. Simulation shows wavelet in the latter scenario has better performance.

Key words: Blind Source Separations, Wavelet Packet Transform, Signal to Noise and Interference Ratio, LMS Algorithm, Nonlinear Autocorrelation

1. Introduction

In most of the signal processing, raw signals are not available, but mixed signals from various sources have been obtained. When no information about the source and mixing channel is available, the problem is called Blind Source Separation (BSS). One goal of the Blind Signal Separation (BSS) is the recovering of underlying source signals of some given set of observations obtained by an unknown mixture of the sources. Recently, independent component analysis (ICA) is used to solve the BSS. This method takes into account the independency of the signals, and tries the estimated signals to be independent from each other as possible. In this method, several objective functions are used, that are optimized by algorithms. Recently, maximizing of the nonlinear autocorrelation function of estimated signals is introduced, that become signals more independent. First time, Shi, Jiang and Zhou solved BSS problem using maximizing the nonlinear autocorrelation function [1]. Then, Mozaffari and Tinati maximized the objective function using LMS algorithm in the time domain [2]. According to this fact that noise is as a disruptive factor causes undesirable results, so preprocessing is necessary that can help to reduce noise effects. So a tool that able to reduce the processing calculations will be required. Wavelet is one of the most important tools to reduce the harmful effects of noise. In this paper, two scenarios are contained. The first scenario is related to noisy speech signal separation. Where the separation of mixed signals has been done, and the wavelet transform is applied noise reduction at the end. The next scenario is that the wavelet packet transform of the noisy mixed signal is obtained, and separation will be performed using the obtained signals. Simulation shows that the second scenario has better result and signals were estimated better. This manuscript is organized as follows. In Section 2, the materials used in algorithm such as ICA, the preprocessing, the wavelet packet transform and the noisy blind source separation are examined. In Section 3, the two algorithms for noisy blind sources separation with non-linear correlation function in the two scenarios are described, as: first, noise reducing using wavelet transform after the separation process, and second, taking account noise reduction in preprocessing, then separating using wavelet packet transform. Section 4 demonstrates the present method experiments. Conclusion is drawn in the final section.

2. Materials

In this section, we discuss materials used in algorithm such as ICA, preprocessing, and next the nonlinear autocorrelation function and BSS problem are studied. Finally, we briefly review on wavelet packet transform.

2.1. ICA

The purpose of Independent Component Analysis (ICA) [3] is to obtain a transformation matrix that separates mixed signals into statistically-independent sources signals. A direct approach to ICA is to find a transformation matrix such that independence among separated signals is maximized. Noisy linear model for ICA is shown in Eq. 1.

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

Where $X(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$ is mixed signals, $x_i(t)$ is i-th mixed signal, A is an $M \times M$ unknown mixing matrix, $S(t) = [s_1(t), s_2(t), \ldots s_N(t)]^T$ is a vector of unknown zero-mean and unit-variance source signals, and $n(t) = [n_1(t), n_2(t), \ldots n_N(t)]^T$ is the noise which is modelled as Gaussian with zero mean and covariance matrix Σ (usually $\sum = I$, I is unit matrix), where $t = 1,2,..,T$ and t is the time index.

2.2. Preprocessing

One of the important assumptions in ICA method is that mixed signals are uncorrelated and their variances equal unity. A useful preprocessing strategy in BSS is to first whiten the observed signals. The goal of whitening is to transform the observation vector X into another stochastic vector $\tilde{X}$, which has unit variance. This involves the multiplication of X with the inverse of a square root of its covariance matrix C_X. However, the effect of noise must be considered in the whitening. If the noise covariance matrix is known, we use the "quasi-whitening" operation [4] as Eq. 2.

$$\tilde{X}(t) = (C_X - \Sigma)^{-1/2} X(t) \tag{3}$$

Where $\tilde{X}(t)$ is the whitened version of signal $X(t)$, $\Sigma = E\{n(t)n(t)^T\}$ is the noise covariance matrix, and $C_X = E\{X(t)X(t)^T\}$ is the covariance matrix of the noisy mixed signal. In this paper, we will use both of the whitening and "qausi-whitening".

2.3. Nonlinear Autocorrelation Function and BSS Problem

We assume that the observed signals according to Eq. 1 are obtained by sensors, and mixing matrix is a square matrix and its components are constants. This means that the number of the observed signals is equal to number of the source signals, and the mixing channel is constant in all the sensing time. Another assumption is that original sources are mutually independent and have the nonlinear autocorrelation. For estimating a desired source signal $\tilde{s}_i(t)$, we use a linear filter described as Eq. 4.

$$\tilde{s}_i(t) = w_i^T \tilde{X}(t) \tag{4}$$

Where $w_i = [w_{i1}, w_{i2}, \ldots, w_{iN}]^T$ is an unknown vector as estimation filter coefficients, that estimates source signal $\tilde{s}_i(t)$. In order to calculate the autocorrelation function, delayed version is calculated as Eq. 5.

$$\tilde{s}_i(t-\tau) = w_i^T \tilde{X}(t-\tau) \tag{5}$$

Where τ is some lag, often equal to 1. In order to compute the estimation filter coefficients w_i, we present the following maximization problem $\psi(w_i)$ under the constraint $\|w_i\| = 1$ based on the nonlinear auto-correlation of the desired source [1,2], as Eq. 6.

$$\max \underbrace{\psi(w_i)}_{\|w_i\|=1} = E\{G(\tilde{s}_i(t))G(\tilde{s}_i(t-\tau))\} = E\{G(w_i^T \tilde{X}(t))G(w_i^T \tilde{X}(t-\tau))\} \tag{5}$$

Where G(.) is a differentiable nonlinear function, which measures the nonlinear autocorrelation degree of the desired source. Examples of choices of G(.) are $G(x)=x^2$ and G(x)=logcosh(x) [1~2,4~7].

2.4. Wavelet Packet Transform

Wavelet theory has received wide attention in various fields of signal processing, including data compression, image processing, biomedical signal analysis, coding, transient signal analysis, and other signal processing applications. Wavelet is a signal with limited energy in short time and frequency domain and compass little bandwidth. Using this tool you can specify a time interval, the signal at different scales examined, and the property is called the multi-resolution of wavelet. For wavelets, there are two functions, the mother wavelet that is produced by down sampling of the input signal using a high-pass filter, and the father wavelet or scaling function, which is created by applying a low-pass filter on the input signal.

Wavelet transform can be stated base on both low-pass and high-pass filters impulse responses. The outputs of two filters expand the next level coefficients. If the outputs the of high-pass and low-pass filters are decomposed based on filter-banks, the results will be wavelet packets, and will be called wavelet packet transform, as shown in Fig. 1 [8].

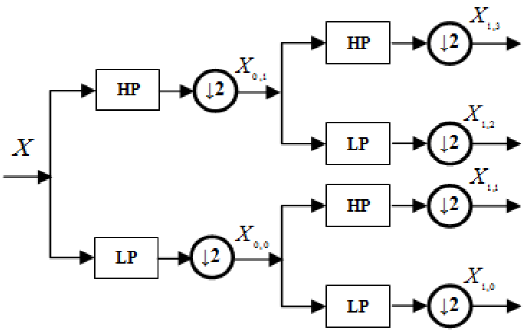

Fig 1: two-level wavelet packet decomposition [8].

3. Noisy BSS Algorithms in Two Scenarios

Here, we describe the two algorithms for noisy blind sources separation with non-linear correlation function in the two scenarios. In the former scenario, the noisy mixed signals were first separated and then the wavelet transform is used to eliminate noise effect. In other words, BSS is applied without considering noise in whitening step, and then wavelet ('db4') is used for noise reduction. In the latter scenario, wavelet packet transform of mixed signal is obtained and then according to these packet signals, BSS is applied with considering "qausi-whitening". In these scenarios (In the two scenarios), LMS algorithm is used to maximize the objective function $\psi(w_i)$. In each iterations of the algorithm, the weight vector w_i is changed so that the maximum value of the objective function is reached. So, we propose the two scenarios as follow.

3.1 Noise Reducing after Separation using Wavelet

In this scenario, the source signals are estimated without using wavelet transform. After estimation, the wavelet transform is used to reduce noise. Here, the algorithm in this scenario is described.

a) Getting the noisy mixed signals and normalize them.
b) Whitening the normalized noisy mixed signals.
c) Initializing the filter coefficients w_i
d) Computing the w_i coefficients using LMS algorithm and normalizing them
e) Reducing noise using wavelet
f) If termination condition is occurred, stopping the algorithm, and estimating corresponding source signals, else going into (d).

In each iteration, noise is reduced by wavelet to survey the performance of this scenario.

3.2. Noise Reducing before Separation using Wavelet

In this scenario, wavelet packet transform of the noisy mixed signal is obtained and then source signals are estimated according to these packet signals. It is noteworthy that for reducing the noise, "qausi-whitening" is considered in the preprocessing. Here, the algorithm in this scenario is described.

a) Getting the noisy mixed signals and normalize them.
b) Producing the wavelet packet transform of normalized mixed signals.
c) Preprocessing using "quasi-whitening" for obtained signals (b)

d) Initializing the filter coefficients w_i
e) Computing the w_i coefficients using LMS algorithm and normalizing them
f) If termination condition is occurred, stopping the algorithm, and estimating corresponding source signals, else going into (e).

Termination condition can be considered as $|W_{k+1} - W_k| < \varepsilon$, where indicate distance of estimation filter coefficients in step k and k+1, or can be specified as constant iteration number.

4. Experimental Result

In this section we discuss the results of the two algorithms introduced in Section 3. We chose three source signals from TIMIT database [9], with length of about 1.4 seconds that was sampled with 16KH rate. Then we mix them by a 3×3 random mixing matrix with a white Gaussian noise (covariance 0.001I). In order to measure the accuracy of separation, we calculate the signal to noise interference ratio (SNIR) [4], as Eq. 7.

$$\mathrm{SNIR}_i = 10\log\left(\frac{(s_i(t))^2}{(s_i(t) - \tilde{s}_i(t))^2}\right) \tag{7}$$

Where $\tilde{s}_i(t)$ is i-th estimated signal. The larger the value SNIR_i (dB) indicate the lower interference between signal and noise in i-th signal. In Continuous, simulation is done for the two scenarios. For each scenario, mixing matrix and noise are the same. Noise free source signals and noisy mixed signals are shown in Fig. 2 and Fig. 3, respectively.

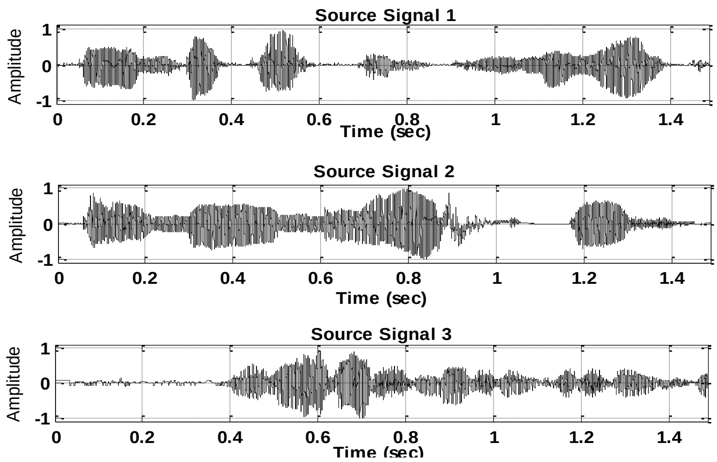

Fig 2: Noise free source signals

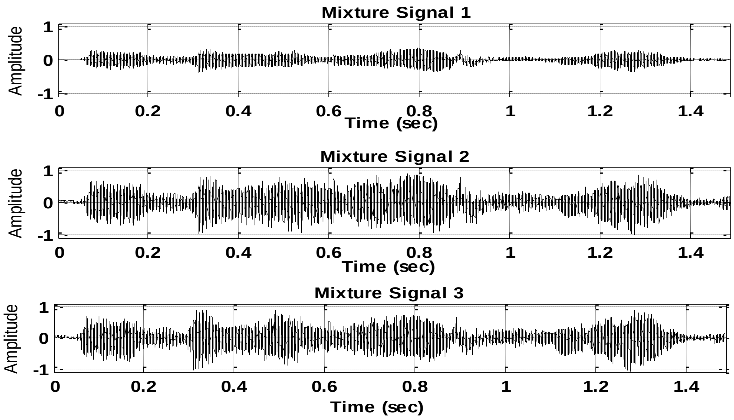

Fig 3: Noisy mixed signals

Estimated signals in Fig. 4 are obtained by proposed algorithm in the former scenario using nonlinear autocorrelation G(x) $=x^2$ with $\tau = 9$ and wavelet 'Db4' at decomposition level 3 with soft thresholding for denoising.

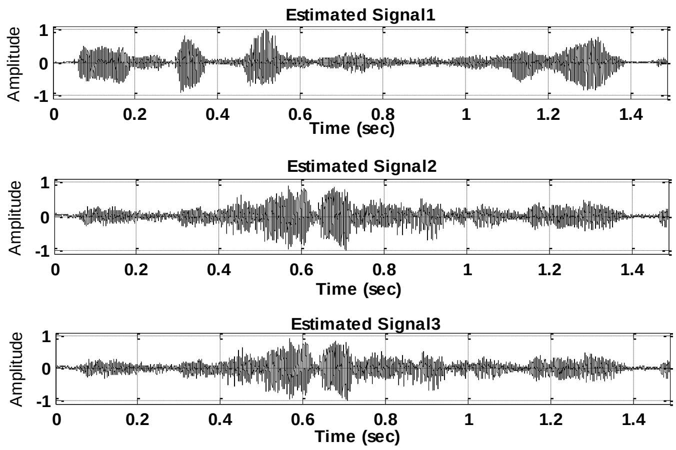

Fig 4: Estimated signals in former scenario using wavelet 'Db4'at level=3 with τ=9

Estimated signals in Fig. 5 are obtained by proposed algorithm in the latter scenario using nonlinear autocorrelation G(x) $=x^2$ with $\tau = 9$ and wavelet packet transform 'Db4' at decomposition level 3.

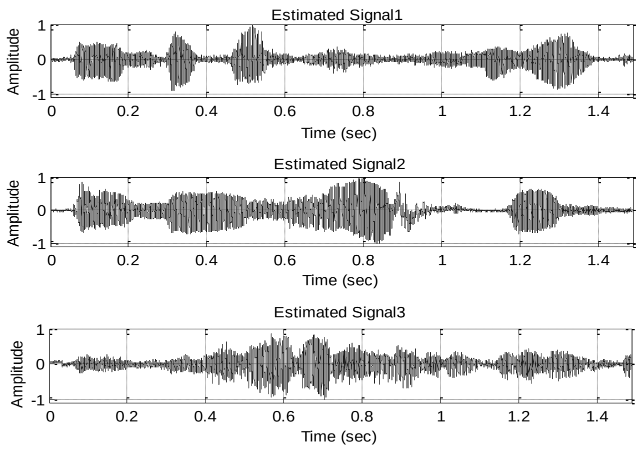

Fig 5: Estimated signals in latter scenario using wavelet 'Db4'at level=3 with τ=9

The mean values of SNIR are obtained over 30 independent trials by the two algorithms, which are shown in Fig. 6 for each signal, and the results are summarized in Table 1.

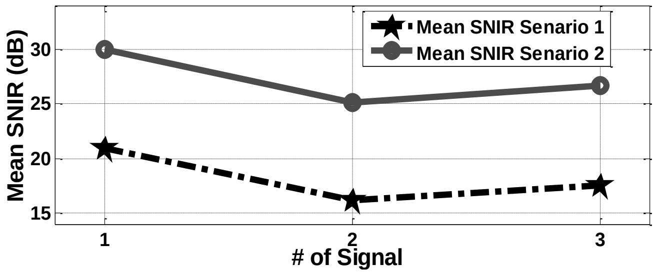

Fig 6: Mean values of SNIR in the two scenarios

$SNIR_i$	$SNIR_1$ (dB)	$SNIR_2$ (dB)	$SNIR_3$ (dB)
Scenario 1	20.9685	16.1688	17.5504
Scenario 2	29.9967	25.1176	26.6690

Table 1. Mean value of $SNIR_i$ for the two scenarios over 30 iteration of algorithm.

The left column of Table 1 shows the scenario number and the next columns show the corresponding $SNIR_i$ (dB) for the i-th estimated signal. We can see that the SNIR value in the second scenario is approximately 9 (dB) better than the first scenario.

5. Conclusion

In this paper, we introduce the two algorithms for noisy blind separation of speech signals. In the first scenario, without the use of (using the) wavelet transform we separate the whitend noisy mixed signals, and then we use wavelet transform to reduce the noise. In the second scenario, we obtain the wavelet packet transform of the noisy mixed signal and by considering the "qausi-whitening" in the preprocessing, and then we apply the BSS to the mixing signal according to these packet signals. We use the LMS algorithm to maximize the objective function. According to the SNIR ratio in the simulation, it was found that the source signal estimates approximately 9 (dB) were better in the second scenario, and the wavelet was a useful tool for noise reduction in noisy blind source separation.

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