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Single Channel Source Separation Using Non-Gaussian NMF and Modified Hilbert Spectrum

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Abstract. **In this paper, a new and powerful method for Blind Source Separation (BSS) for single channel mixtures is presented. This method is based on non-Gaussian nonnegative matrix factorization (NG-NMF) in which modified Hilbert spectrum is employed. In the proposed algorithm, the Adaptive EEMD (AEEMD) is introduced to transfer the signal to the Enhancement Intrinsic Mode Functions (EIMF). The Hilbert spectrums of EIMFs are used as artificial observations.**

In order to make estimated spectrum of EIMF of sources using NMF, the maximization of Non-Gaussianity is used. Then, spectra of estimated oscillation modes are transferred to the time domain by the inverse Hilbert spectrum (IHS). In order to cluster of these oscillation modes, *k*-means clustering algorithm based on KLD (Kullback Leibler Divergence) is used. The simulation results indicate that the proposed algorithm performs the separation of speech and interfering sounds. from a single-channel mixture, successfully.

Keywords: *Blind Source Separation (BSS); Non-Gaussian Nonnegative Matrix Factorization (NG-NMF); Adaptive Ensemble Empirical Mode Decomposition (AEEMD); modified Hilbert spectrum (HS).*

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1. Introduction

Blind source separation methods are divided into two different categories: (i) single–channel source separation which is recorded only by one sensor and (ii) multi-channel source separation which is recorded by several sensors in various positions. Methods based on Single-Channel Blind Source Separation (SCBSS) are more practical than multi-channel methods in the real word applications. In some applications, we have to perform source superstation only one observation due to some constraints for instance show-through or bleed-through. However, SCBSS is one of the challenging issues in the signal-processing field because of finding two or some source signals from only one mixture. It can include widespread applications in audio processing [1], wireless communications, biomedical signal processing[2], [3], radar signal processing, and image processing [4] and so on [5].

Different methods are available to separating the signals from a single mixture. In general, SCSS can be divided into two main groups of non-blind and blind methods. The method which is based on additional information and priori distribution of sources are called non-blind single channel source separation. However, another group that is not based on additional information of sources, and it only relies on partial assumptions is so-called to blind single channel source separation (SCBSS).

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The conventional methods of SCBSS are Singular Spectrum Analysis (SSA) [6], Hilbert Huang spectrum based methods [7], [8] and Nonnegative Matrix Factorization (NMF) based methods [9].
These methods are used in the time, frequency or time-frequency domain. In this method, basic assumptions are considered in order to separation of mixture of sources.

In the SSA based methods, time series of the single-channel signal is converted to the trajectory matrix. Then using the Singular Value Decomposition (SVD) method, trajectory matrix is divided into some sub-group matrixes. In the last stage, these matrixes are returned into the vectors with special assumption. Problems of this method, existence of parameters that are selected regulatory and there are restrictions on the type of source signals, such as the stationary and independence of sources [6].

Hilbert Huang spectrum directly [7] or indirectly [8] is used to separate sources. This method is based on the use of Empirical Mode Decomposition (EMD). EMD decomposes the signal into oscillation modes called Instantaneous Mode Function (IMF). Each IMF satisfies two conditions, the number of zero crossing points has to be equal to the number of extrema point and the mean value of upper envelop and lower envelop is close to zero at any point. Using transfer of IMFs into the time-frequency domain, the Hilbert Huang spectrum is obtained.

However, EMD method is very sensitive to noise and type of interpolation function. Therefore, Different interpolation functions give different results. This method requires to signals that has the oscillation mode and the amplitude of signals should not change at any moment strongly. Furthermore, this method has mode mixing problem in the signals with intermittency frequency [7].

To solve these problems, the method based on adding several Gaussian noises to the signal and decomposes the signal to the oscillating mode and the averaging of IMF are presented. This method called Ensemble Empirical Mode Decomposition (EEMD) that is improved version of EMD method [10].
However, to calculate the number of added noise and its amplitude are not introduced any solution. Time consumed of EEMD is much longer than the EMD. So that implementation of it as a decomposition algorithm is not impossible.

Among non-blind and blind methods, NMF algorithm is the simplest method to separate two or more sources that Paatero introduces it in 1994 [11]. The most important issue in relation to NMF is the calculation of non-negative matrixes W and H, which are the factorizations of the matrix or signal X. Unknown matrices W and H have to be calculated so that the costs function of the distance X, and WH is minimized. How to minimize the cost function is the main discussion in scientific literature and is still one of the open issues in this field.

However, the total effort that can be done in this field has been classified as follow:
A group of algorithms tries to change or improve the cost function. After introducing the standard NMF algorithm by Lee and Seung [12], many scientific papers are published in the analysis area, development and applications of NMF algorithms in various fields of science, engineering and biomedicine. This group of NMF algorithms is presented by several authors with different mathematical formulas for the time, frequency and time - frequency domain.
Another group of algorithms is based to search of appropriate methods to initialize matrixes W and H to speed up to convergence of cost function [13].

However, any of these NMF methods is not presented the uniqueness W and H which be the same latent source in mixture.

In order to find a solution to the mentioned problems in the deferent SCBSS methods, we proposed the algorithm that is based on a modified Hilbert spectrum and non-Gaussian NMF. The key component of the proposed algorithm is to decompose the non-stationary signals into the total of pseudo-stationary signals in time–frequency domain by modified Hilbert's spectrum and maximize the non-Gaussianity of the obtained spectrum in NMF method.

Because of Fourier-based time-frequency, representation includes a remarkable amount of cross-spectral terms due to the harmonic assumption and the window overlapping between successive time frames. However, the Hilbert spectrum does not include a noticeable amount of cross spectral energy, and it can represent the instantaneous spectra of any time series without employing any window. Therefore, our method is based on changing non-stationary single-channel signal into pseudo-stationary multichannel signals, using Hilbert spectrum.

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The EMD based methods [7], [8] has several disadvantages, including dependency of interpolation type on sifting process, mode mixing, not specified the number of IMFs functions, sensitivity to Non-uniform noise, not unique oscillation modes arising from a signal.

In the proposed algorithm, Adaptive EEMD (AEEMD) is introduced to transfer the signal to the Enhancement Intrinsic Mode Functions (EIMF). These EIMFs have the highest correlation to observation and the lowest correlation to each other. In fact, using these EIMFs, instead of the simple IMFs, decreases the error detection of original sources in BSS applications. In contrast to EMD [7], AEEMD has fewer numbers of spurts; and has lower sensitivity to type of interpolation function, and it properly solves the problem of mode mixing in signals with intermittence frequency. In AEEMD, an adaptive process is also selected in order to decrease the time computation of the algorithm EEMD [10].

In this paper, a novel framework for separation of sources from modified Hilbert spectrum based on Non-Gaussian Nonnegative Matrix Factorization (NG-NMF) is proposed. In the proposed separation method, the NG-NMF relies on maximization of non-Gaussianity of each factors W and H.
Contrary to conventional methods based on NMF such as NMF2D [14], SNMF2D [15], and so on, that only under certain conditions such as different frequency of sources or sparseness are efficient; our proposed technique separates speech sources and interfering sounds from them mixture only using of independency of EIMFs Hilbert spectrum.

The rest of paper is organized as follows: In section II, a brief background on Hilbert spectrum and NMF methods are presented. In section III the main idea of our SCBSS algorithm is described. In section IV the results of a computer simulation and comparison are shown. Section V and VI are the conclusion and the references, respectively.

2. Background

Since concepts of Hilbert spectrum and Nonnegative Matrix Factorization (NMF) are the bases of our proposed algorithm, brief descriptions of them are presented in subsections A and B, respectively.

2.1. Hilbert spectrum

Hilbert Spectrum (HS) represents the distribution of the signal energy as a function of time and frequency [3], [5]. To construct HS, all Intrinsic Mode Functions (IMF) are calculated using EMD method. The relationship between IMFs and original signal is as Eq. (1).

$$x(t) = \sum_{i=1}^{M} C_i(t) + r_N(t) \tag{1}$$

Where M is number of oscillation modes, C_i is i^{th} IMF and r_N is last remaining that is a tone signal.
Instantaneous Frequency (IF) represents the frequency of a signal at any time instance and is defined as the rate of phase changes at that instant, the instantaneous phase is stated in Eq.(2).

$$\theta_i(t) = \arctan\left(\frac{\hbar[c_i(t)]}{c_i(t)}\right) \ , \ i = 1, \dots, M \tag{2}$$

Where $\hbar[.]$ indicates Hilbert transform of signals. The amplitude of IMFs in the each time is defined as Eq. (3).

$$a_i(t) = [{c_i}^2(t) + (\hbar[c_i(t)])^2]^{\frac{1}{2}} \quad , \ i = 1, \dots, M \tag{3}$$

Instantaneous frequency of a signal is computed as Eq. (4).

$$\omega = \frac{d\tilde{\theta}(t)}{dt} \tag{4}$$

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In which $\tilde{\theta}$ is the unwrapped of instantaneous phase.

After calculating the instantaneous frequency and amplitude of IMFs, the Hilbert spectrum of signal in each time ($t = 1, \dots, N$) and frequency bin ($l = 1, \dots, B$) is obtained as Eq. (5).

$$X(l,t) = \sum_{m=1}^{M} a_m(t)\gamma_m^l(t) \ , \tag{5}$$

The coefficient γ_m^l is equal to 1 if m^{th} IMF is within the l^{th} band, otherwise it is 0. Therefore, the Hilbert spectrum is defined as the weighted sum of the amplitudes of all oscillation modes.

2.1. Nonnegative matrix factorization

Nonnegative Matrix Factorization (NMF) is a method which is used for decompose a nonnegative matrix *X* into two nonnegative factors *W* and *H* [8].

$$X_+ \approx W_+ H_+ \tag{6}$$

Where $X = [x_{bn}]$ is the $B \times N$ spectrum matrix, $W_+ = [w_{lp}] \epsilon \mathbb{R}^{B\times P}$ and $H_+ = [h_{pt}] \epsilon \mathbb{R}^{P\times N}$ are base matrix and gain matrix respectively. P parameter is chosen so that the following inequality is kept:

$$(B + N) \times P < B \times N \tag{7}$$

In the blind speech separation, X can represent the time-frequency of observation signal x. Therefore, the number of rows and columns of the matrix *X* is equal to number of frequency bins and the length of time-domain signal *x*, respectively. In the NMF algorithm, we're interested to estimate two factors *W* and *H* so that its product has a minimum distance from the *X* matrix. There are conventional cost functions to minimize this distance. It is based on Euclidean distance or least squares, Eq. (8).

$$J_{Ls} = D_{LS}(X; W_+H_+) = \frac{1}{2}\|X - W_+H_+\|_2^2 \tag{8}$$

where $\|X - W_+H_+\|_2^2$ is the Euclidean distance between *X* and *WH* product. Since any matrices, *W* and *H* can be existed to minimize the cost function. So, several constraints should be introduced into cost function based on source characters. Constraints are introduced so that the matrices *W* and *H* are uniquely determined. The cost function is developed by the constraints as follows:

$$J = D(X; W_+H_+) = D_{LS}(X; W_+H_+) + \alpha F(X; W_+H_+) \tag{9}$$

where α is the regularization parameter and *F* is the added constraint function.
In this paper, we introduce a constraint into NMF based on independence of spectrum EIMFs of sources signals through minimizing the Gaussianity each of factors.

3. Proposed separation method

Blind source separation algorithm that is presented in this paper is based on the separation of two or more source signals from a single mixture of them, such as extraction of independent speeches in the single acoustic channel in that human listeners show a remarkable ability to separation an acoustic mixture and attend to a target sound, even with one ear as Figure 1.

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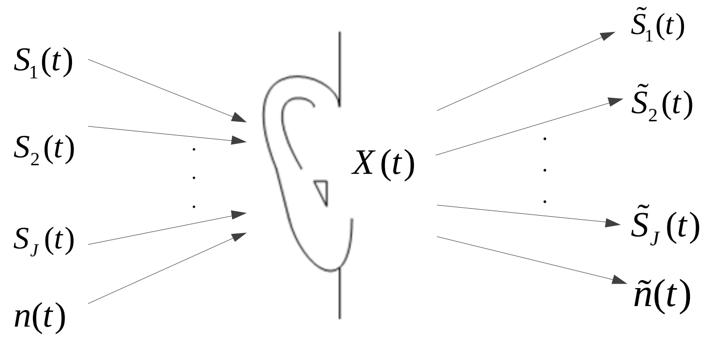

Figure 1. Hearing system with single channel source separation capability

Since source separation presented in this paper is performed by only one mixture of sources, this model, called "single-channel source separation", is stated in Eq. (10).

$$x(t) = \sum_{j=1}^{J} a_j s_j(t) + n(t) \quad for \quad t = 0,1,\dots,T. \tag{10}$$

in which J is the number of sources that are latent in observation, T is the length of observation signal or any of the source signals, n is the additive Gaussian noise signal and a_i is the coefficient of i^{th} source in the mixture. The main technique of our proposed separation algorithm is decomposition of the single observation into its oscillation modes called EIMFs using Adaptive EEMD (AEEMD) and then, Hilbert spectra of oscillation modes were factorized into the independent frequency and time components using Non-Gaussian NMF (NG-NMF). Product of each frequency component in its time component gives the estimation of EMIF spectrum. Estimated EIMFs spectra are returned into the time domain using Inverse Hilbert Spectrum (IHS). These independent estimated EIMFs are classified into some groups according to the number of sources using KLD clustering. Signals of any groups add together, and these added signals are an estimation of latent sources.

Four benefits are obtained from using the EIMFs spectra instead of the observation spectrum, as follows:

- Factorizing of EIMFs spectra to the independent frequency and time components has less complexity than the observation spectrum.
- Clustering of EIMFs frequency and time components is simpler than the observation spectrum.
- Each oscillation mode has the property of pseudo-stationary.
- Eventually, Hilbert spectra of EIMFs are the linear summation of corresponding EIMFs of sources.

The proposed method consists of three steps, as follow:

Step 1: Dividing the observation mixture into some segment with shorter length, called windowing.

Step 2: Decomposing each segmented signal to oscillation modes (EIMFs) using the AEEMD.

Step 3: Transforming EIMFs into time-frequency domain using Hilbert Spectrum (HS).

Step 4: Obtaining estimated oscillation modes spectrum for any sources using NG-NMF.

Step 5: Reconstructing estimated source using transforming estimated EIMFs spectrum into the time domain, and then clustering them into some groups according to the number of sources using KLD clustering.

The core procedure of the SCBSS proposed method is shown in Figure 2. In the following subsections, these steps are described in details.

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3.1. Windowing

In this step, called windowing, the time-series of observation signal is divided into some segment with a shorter length than T. It is an important process because it decreases the complexity of computations and increases the stationary of observation signals.

This process is available in both fixed and variable length [6], [8]. Usually, a window with variable length is used to create stationary signals [6], since, in our algorithm; signals are converted into pseudo-stationary oscillation modes, we use a fixed window to segment the observation of $x(t)$. The windowed observation of $x(t)$, called $x^i(t)$, is stated in Eq. (11).

$$x^i(t) = [x(i \times L - L + 1), \dots, x(i \times L)] \quad for \quad i = 1, \dots, D \tag{11}$$

where i is the index sample, and L is the length of the window.

3.2. Modified Hilbert spectrum

As mentioned in the background to obtain the Hilbert spectrum, first oscillation modes of signal has to be obtained using EMD. In comparison with other signal analysis methods, EMD method is only based on their signal and don't need to signal parameters such as the window or the base signal. EMD acts as a dyadic filter bank with automatic band pass for a white noise. Therefore, the uniform Gaussian white noise can be separated from the original signal. However, when noise is non-uniformly combined to the signal or when the IMFs have the mode mixing problem, then the property of dyadic filter of EMD is failed. This problem not only can cause serious aliasing, but also causes unclear physical interpretations. Furthermore, EMD is very sensitive to type of interpolation function. Therefore, different interpolation functions give different results.

In order to overcome these problems, a noise-assistant data analysis (NADA) method called Ensemble Empirical Mode Decomposition (EEMD) was proposed [10]. EEMD adds white noise with the arbitrary amplitude to the signal, several times, and then decompose noised signals into oscillation modes. In this method, the ensemble term indicates adding noise more than once. However, before EEMD is used, the amplitude of added noises and the number of ensemble noises are two parameters to be adjusted. In [10], the authors assume that the amplitude of the added white noise a is fixed to 0.2 times of maximum amplitude of the signal.

They also consider that the number of ensemble noises N is greater or equal 1000 [10].

With increasing N, execution time of EEMD algorithm will increase linearly, so that makes it almost impossible to decompose

signals. On the other hand, in order to remove mode mixing problem, when the data is dominated by high-frequency signals, the noise amplitude hast to be smaller than 0.2; and when the data is dominated by low-frequency signals, the noise amplitude has to be bigger than 0.2.

In this paper a novel method is presented to decompose observation signal into their sub-signal. The proposed method is called to Adaptive EEMD (AEEMD). In AEEMD, an adaptive process is selected in order to decrease the time computation of the algorithm and sensitivity to noise and interpolation function.

In EEMD [10], the relationship between the number of ensembles (N), added noise amplitude (a), and the standard deviation of error (δ) is stated in Eq. (11).

$$\delta = \frac{a}{\sqrt{N}}. \tag{12}$$

The aim is to decrease the standard deviation of error (δ), by either increasing N or decreasing a. Increasing the number of ensemble N increases the computation time of the algorithm. On the other hand, the amplitude of the added noise (a) cannot be decreased from a threshold value. If a goes under this threshold value, the extrema cannot be detected and the mode mixing problem not be solved.

In order to find optimum values for N and, first initial values for N and a are considered. Then, a primary value for standard deviation of error is calculated, Eq. (20). The observation signal is

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decomposed into oscillation modes using EEMD with noise amplitude a and the number of ensemble noise N. The standard deviation of IMFs is then calculated using Eq. (12).

$$\delta = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{N}\sum_{j=1}^{N}\frac{1}{L}\sum_{k=1}^{L}\left|c_i(t_k) - c_{ij}(t_k)\right|\right]. \tag{13}$$

where $c_{ij}(.)$ is the i^{th} IMF using EEMD after j steps of noise addition, $c_i(.)$ is the mean corresponding to i^{th} IMF, L is the length of data, and n is the number of IMFs using Eq. (13).

$$n = \lfloor log_2^N \rfloor - 1 \quad . \tag{14}$$

If the standard deviation obtained from Eq. (14) is smaller than the primary standard deviation of error, then the amplitude of noise reduces the error. The amplitude of noise is updated using Eq. (12), and the pervious procedures are repeated several times to obtain a that gives the standard deviation of error bigger than before steps. This shows that the amplitude of noise cannot be smaller than this value.

Therefore, if the difference of standard deviation obtained in the earlier stages is smaller than the threshold value (in this paper is 0.0005), the algorithm is stopped and the optimum amplitude of added noises a corresponding to ensemble number N is found. Otherwise ensemble number N is updated by $N = 2N$ and search for finding the optimum amplitude would continue. Therefore, repeating Eq. (12) and Eq. (13) form a recursive loop to converge the optimal values of N and a, as Fig. (2).

The number of ensemble noises of AEEMD is lower than this number in EEMD method; and accuracy of our algorithm is higher than EMD. We call the oscillation modes obtained from propose the method AEEMD to Enhancement IMF (EIMF). After applying the Hilbert transform and calculating the instantaneous amplitude and frequency of the oscillating modes using Eq. (3) and (4), Hilbert spectrum of m^{th}EIMF is obtained as Eq. (15).

$$X_m(l,t) = a_m(t)_+ \gamma_m^l(t)_+ \qquad l = 1,\ldots,L \quad \text{and} \quad m = 1,\ldots,n \tag{15}$$

where the coefficient γ_m^l is equal to 1 if m^{th} EIMF is within the l^{th} band, otherwise it is 0. Therefore, the Hilbert spectrum of m^{th} EIMF is defined as the nonnegative weighted sum of the amplitudes of all oscillation modes.

3.3. Non-Gaussian NMF

Now we assume the products of first and second column of the matrix W in the first and second row of the matrix H gives first and second source in Hilbert spectrum of i^{th} EIMF, respectably, as Eq. (16).

$$\boldsymbol{X} = \boldsymbol{WH} = \boldsymbol{W}(:,\boldsymbol{1})\boldsymbol{H}(\boldsymbol{1},:) + \boldsymbol{W}(:,\boldsymbol{2})\boldsymbol{H}(\boldsymbol{2},:) = \boldsymbol{W_1H_1} + \boldsymbol{W_2H_2} \tag{16}$$

In according to the central limit theorem that the sum of two independent sources is more Gaussian than either of the sources, it is assumed that each of the matrices $\boldsymbol{W_1H_1}$ and $\boldsymbol{W_2H_2}$ are more non-Gaussian than matrix $\boldsymbol{X}$.

Therefore, using maximization of non-gaussianity matrices W_1H_1 and W_2H_2, correct estimation of the EIMFs spectrum are obtained. To use non-gaussianity in NMF, we must have a quantitative measure of non-gaussianity of a random matrix W_1H_1 and W_2H_2. In this paper, criteria kurtosis to measurement of non-Gaussianity is used as stated in Eq. (17).

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$$\boldsymbol{Kurt(x) = E\{x^4\} - 3(E\{x^2\})^2} \tag{17}$$

Therefore, the cost function is introduced in the equation (9) becomes as Eq. (18).

$$J = \frac{1}{2}\|X - WH\|_F^2 + \frac{\alpha kurt(W_1H_1) + \beta kurt(W_2H_2)}{kurt(W_1H_1) \times kurt(W_2H_2)} \tag{18}$$

Where α and β parameters control the non-Gaussianity of matrices W_1H_1 and W_2H_2. Differentiating J with respect to a given element W_1 give

$$\frac{\partial J}{\partial W_{t,1}} = \frac{\partial}{\partial W_{t,1}}\left(\frac{1}{2}\sum_{i,j}\left(X_{i,j} - W_{i,1}H_{1,j} + W_{i,2}H_{2,j}\right)^2 + \frac{\alpha\left(\frac{1}{BN}\sum_{i,j}(W_{i,1}H_{1,j})^2\right)^2}{\frac{1}{BN}\sum_{i,j}(W_{i,1}H_{1,j})^4}\right) \tag{19}$$

After simplifying the equation (19), its matrix notation can be written as:

$$\frac{\partial J}{\partial W_1} = -(X - W_1H_1 + W_2H_2)H_1^T + \alpha\frac{4m_2(W_1H_1)mean(H_1^2)W_1 - 4m_2^2(W_1H_1)mean(H_1^4)W_1^3}{m_4^2(W_1H_1)} \tag{20}$$

where $(.)^T$ stands here as transpose operator and m_i is the i^{th} moment. The recursive multiplicative update step for gradient descent is given by

$$W_1 \leftarrow W_1 - \eta_W\frac{\partial J}{\partial W_1} \tag{21}$$

$$H_1 \leftarrow H_1 - \eta_H\frac{\partial J}{\partial H_1}$$

where η is positive learning rate that it is chosen so that the first and third term in Eq. (21) is removed as Eq. (22).

$$\eta_W = W_1./((X - W_1H_1 + W_2H_2)H_1^T - 4\alpha\frac{m_2(W_1H_1)mean(H_1^2)W_1}{m_4^2(W_1H_1)} + 4\alpha\frac{m_2^2(W_1H_1)mean(H_1^4)W_1^3}{m_4^2(W_1H_1)}) \tag{22}$$

$$W_1 \leftarrow W_1.*[XH_1^T]./[(X - W_1H_1 + W_2H_2)H_1^T - 4\alpha\frac{m_2(W_1H_1)mean(H_1^2)W_1}{m_4^2(W_1H_1)} + 4\alpha\frac{m_2^2(W_1H_1)mean(H_1^4)W_1^3}{m_4^2(W_1H_1)}] \tag{23}$$

$$H_1 \leftarrow H_1.*[W_1^TX]./W_1^T[(X - W_1H_1 + W_2H_2) - 4\alpha\frac{m_2(W_1H_1)mean(W_1^2)H_1}{m_4^2(W_1H_1)} + 4\alpha\frac{m_2^2(W_1H_1)mean(W_1^4)H_1^3}{m_4^2(W_1H_1)}] \tag{24}$$

Where $.*$ and $./$ are element-wise multiplication and divide, respectively. Similarly, the updates for W_2 and H_2 can be obtained.

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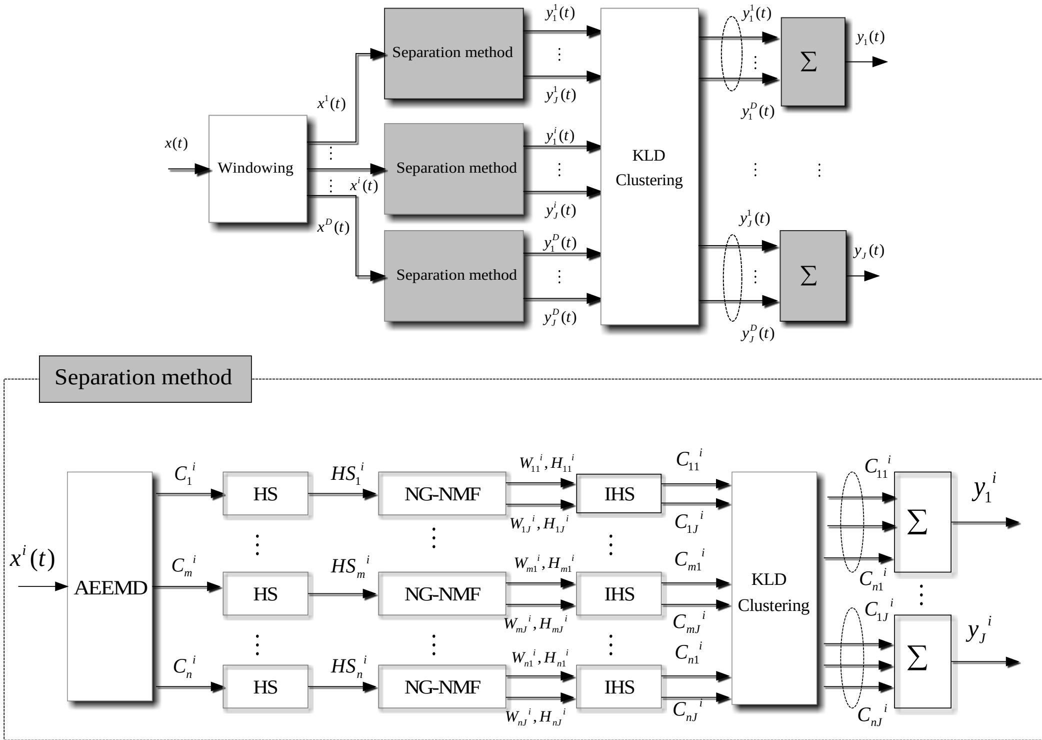

Figure 2. Block diagram of proposed SCBSS algorithm

(1) *Initialize* $\boldsymbol{m}$=*1and ensemble number* $\boldsymbol{N}$ *=2*
(2) *Assume* $\boldsymbol{a_1} = \boldsymbol{max}(\boldsymbol{x}(\boldsymbol{t}))$ *and the standard deviation of error* $\boldsymbol{\delta_1} = \frac{\boldsymbol{a_1}}{\sqrt{\boldsymbol{N}}}$.
(3) *Decompose the signal with EEMD and obtain the matrix of IMFs.*
(4) *Increment* $\boldsymbol{m}$ *and Calculate*
$\boldsymbol{\delta_m} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{N}\sum_{j=1}^{N}\frac{1}{L}\sum_{k=1}^{L}\left|\boldsymbol{c_i}(\boldsymbol{t_k}) - \boldsymbol{c_{ij}}(\boldsymbol{t_k})\right|\right]$.
(5) *If* $\boldsymbol{\delta_m} < \mathbf{0.00001} + \boldsymbol{\delta_{m-1}}$
then set $\boldsymbol{a_m} = \boldsymbol{\delta_m}\sqrt{\boldsymbol{N}}$ *and go to step 3,*
else if $\Delta\boldsymbol{\delta} < 0.00004$
then $\boldsymbol{N}$ *=2*$\boldsymbol{N}$ *and go to step 3.*
else optimum values of $\boldsymbol{N}$ *and* $\boldsymbol{a}$ *are found.*

Figure 3. Proposed adaptive EEMD

4. Simulation result

In this section, computer simulations are used to verify the accuracy of the proposed BSS method and to compare it to other BSS algorithms. The criterion that is used for these comparisons is the Output Signal to Noise Ratio (OSNR) of the first and second independent components, IC1 and IC2.
The OSNR of the separated sources is depicted in Eq. (25).

$$OSNR = 10 \times \log \frac{\sum_t \left|s_j^2\right|}{\sum_t \left|s_j - \tilde{s}_j\right|^2} \quad , \quad j = 1,\dots,m \qquad (25)$$

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where *m* is the number of sources, s_j is the j^{th} source, and $\tilde{s}_j$ is a estimation of the s_j source.
In these simulations, all algorithms are tested using a single-channel signal that includes two speech signals, as is shown in the Figure 4. Table 1 shows a comparison between the proposed BSS method and BSS methods based on SSA and EMD in noisy environments, respectively. Tabel 1 affirms that the OSNR of IC2 of the SSA-based method is lower than 11 dB; and the IC1 and IC2 of the EMD based method is not separated from its mixture, in the noisy environment, successfully. That means that EMD method is sensitive to noise and the separated signals using SSA method are mixed together yet. However, the proposed BSS method in this paper is powerful in distinguishing between sources and noise, with OSNR above 14 dB for IC1 and above 16 dB for IC2. Figure 5 shows that two hidden sources in the single mixture Figure 4.c are obtained after applying our proposed SCBSS.

In the future works, we will like to improve the proposed method by adding the better constraints on Gaussian-NMF and increase speed up our algorithm by its implementation on FPGA prototype.

Table 1. Comparison between performance of the proposed method and SSA and EMD based methods in noisy environment in term of OSNR applying the proposed BSS method

Method	OSNR of IC1(dB)	OSNR of IC2(dB)
EMD-based method with noise[8]	11.831	14.239
SSA-based method with noise[6]	11.626	10.89
Proposed method with noise	14.709	16.392

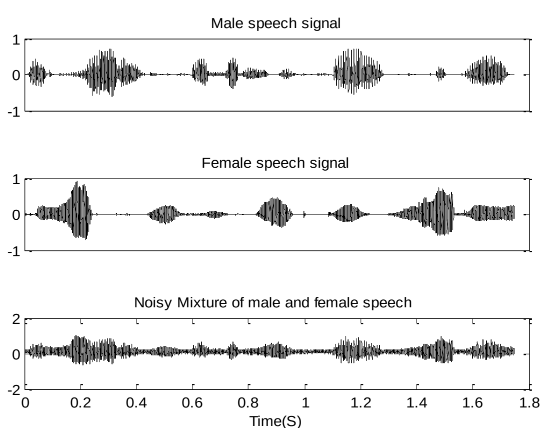

Figure 4. Waveform of two real speech signal (a) Male speech signal (b) Female speech signal (c) Mixture of two above signals.

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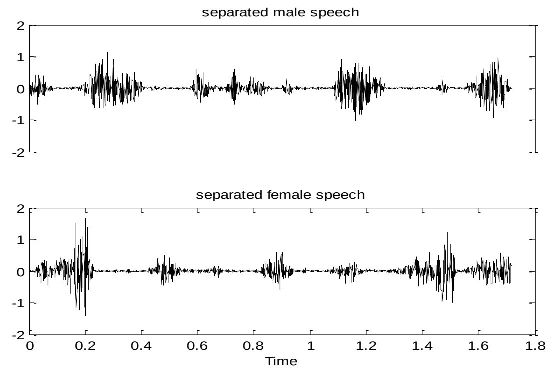

Figure 5. Two Independent components of Figure 2.c after applying the proposed SCBSS method

5. Conclusion

In this paper, we proposed a new nonnegative matrix factorization based on maximization of non-Gaussianity sources using modified Hilbert spectrum. In this paper, a fast and accurate single-channel source separation algorithm was presented. This algorithm, which was based on the adaptive EEMD and NG-NMF, was able not only to separate independent sources but also to separate the noise from the sources. Computer simulations showed that the proposed algorithm improved the performance of the BSS system in a noisy environment, compare to the SSA and EMD methods.

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