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Subband-based Single-channel Source Separation of Instantaneous Audio Mixtures

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Abstract: In this paper, a new algorithm is developed to separate the audio sources from a single instantaneous mixture. The algorithm is based on subband decomposition and uses a hybrid system of Empirical Mode Decomposition (EMD) and Principle Component Analysis (PCA) to construct artificial observations from the single mixture. In the separation stage of algorithm, we use Independent Component Analysis (ICA) to find independent components. At first the observed mixture is divided into a finite number of subbands through filtering with a parallel bank of FIR band-pass filters. Then EMD is employed to extract Intrinsic Mode Functions (IMFs) in each subband. By applying PCA to the extracted components, we find uncorrelated components which are the artificial observations. Then we obtain independent components by applying Independent Component Analysis (ICA) to the uncorrelated components. Finally, we carry out subband synthesis process to reconstruct fullband separated signals. The experimental results substantiate that the proposed method truly performs the task of source separation from a single instantaneous mixture.

Key words: Blind source separation • independent component analysis • empirical mode decomposition • principle component analysis • single-channel audio source separation • subband decomposition

INTRODUCTION

The problem of Blind Source Separation (BSS) includes finding independent source signals from their observed mixtures without prior knowledge about the actual mixing channels. The source separation problem is of interest in various applications [1, 2]. In this paper, we consider the separation of mixed audio signals. Audio source separation has many potential applications such as music transcription, speaker separation in video conferencing and robust audio indexing in multimedia analysis. Recording done with multiple microphones enables techniques which use the spatial location of sources in the separation process [3, 4] so that it often makes the separation task easier. However, often only a single channel recording is available and methods based on single-channel audio source separation are more practical in the real world applications. There are some existing algorithms of single-mixture audio source separation [5, 6]. In [7] an independent subspace analysis (ISA) method has been introduced to separate the component sources from their single mixture. In [8] the ISA method has been employed to separate the drum tracks from polyphonic music. The basic consideration of the ISA method is to decompose the Time-frequency (TF) space of a mixed signal as a sum of independent source subspaces. The TF representation is obtained by applying Short-time Fourier Transform (STFT).

In this paper, we consider the BSS of a single instantaneous mixture of audio signals. We propose a new BSS algorithm that employs subband processing named subband BSS. By using this algorithm, the observed mixture is converted into subband domain with a filter bank so that we can choose a moderate number of subbands and maintain a sufficient number of samples in each subband. The proposed subband-based single-channel algorithm employs a hybrid system of Empirical Mode Decomposition (EMD) [9], Principle Component Analysis (PCA) [10] to construct artificial observations from the mixture. In separation stage, Independent Component Analysis (ICA) is used to find independent components. For this purpose, we use the fixed-point algorithm (FastICA algorithm) [11, 12] because it provides fast convergence and acceptable separation. Generally, ICA algorithms suffer scaling and permutation ambiguities. To eliminate the scaling ambiguity, we propose a new method which is based on solving overdetermined equations. To solve permutation ambiguity, we use a K-means clustering algorithm which is based on Kullback-Leibler Divergence (KLD).

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We have simulated the proposed algorithm to separate the sources from a single mixture of two audio signals. In order to demonstrate the proficiency of our algorithm, the separation performance of both our algorithm and ISA method is compared.

The organization of this paper is as follows. The basics of utilized ICA and EMD algorithms are described in Section II and Section III, respectively. Section IV describes the KLD-based K-means clustering algorithm. Section V describes the proposed signal separation algorithm. Section VI presents the experimental results. Finally Section VII concludes this paper.

INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis (ICA) is a statistical model where the observed data is expressed as a linear combination of underlying latent variables. The latent variables are assumed to be non-Gaussian and mutually independent. The task is to find out both the latent variables and the mixing process. The basic ICA model is $x(t) = A\, s(t)$ where $x(t) = [x_1(t),\ldots,x_m(t)]^T$ is the vector of observed random variables, $s(t) = [s_1(t),\ldots,s_n(t)]^T$ is the vector of statistically independent variables called the independent components and A is an unknown constant mixing matrix. m and n are the number of observed mixtures and original sources respectively and $(\cdot)^T$ denotes transpose operation. In this paper, we choose the fixed-point algorithm given by [11, 12] since it is a computationally efficient and robust fixed type algorithm for ICA BSS. It is also named FastICA algorithm. The independent components in the ICA model are found by searching a matrix W such that $y(t) = W\, x(t)$ where $W = [w_1,\ldots,w_n]^T$ and w_i $(i = 1,2,\ldots,n)$ are m-dimensional weight vectors. The fixed point algorithm searches for the extrema of the cost function

$$\mathbf{J}_G(\mathbf{w}) = E\{G(\mathbf{w}^T\mathbf{x}(t))\}$$

where $G: \Re^+ \cup \{0\} \rightarrow \Re$ is a smooth even function and

$$E\{(\mathbf{w}^T\mathbf{x}(t))^2\} = \|\mathbf{w}\|^2 = 1$$

The algorithm requires a pre-whitening of the data. Whitening can be accomplished by PCA. The stabilized fixed-point algorithm for one unit is [11]:

$$\mathbf{w}^+ = \frac{\mathbf{w} - \mu\,[E\{\mathbf{x}(t)g(\mathbf{w}^T\mathbf{x}(t))\} - \beta\mathbf{w}]}{[E\{g(\mathbf{w}^T\mathbf{x}(t))\} - \beta]} \qquad (1)$$
$$\mathbf{w}_{new} = \mathbf{w}^+ / \|\mathbf{w}^+\|$$

where $\beta = E\{w^T x(t) g(w^T x(t))\}$, μ is a step size parameter that may change with the iteration count and $g(\cdot)$ is the derivative of $G(\cdot)$ and $g'(\cdot)$ is the derivative of $g(\cdot)$

The one-unit algorithm can be extended to the estimation of the whole ICA transformation $y(t) = W\, x(t)$ [12].

EMPIRICAL MODE DECOMPOSITION

The empirical mode decomposition is a signal processing technique to decompose any non-stationary and nonlinear signal into oscillating components with some basic properties. The key benefit of using EMD is that it is automatic and fully data adaptive.

EMD decomposes a time series x(t) into a sum of band-limited functions $c_b(t)$ by empirically identifying the physical time scales intrinsic to the data. Each extracted mode $c_b(t)$ named Intrinsic Mode Function (IMF) contains two basic conditions. First, in the whole data set, the number of extrema (maxima and minima) and the number of zero crossings must be the same or differ at most by one. Second, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The first condition is similar to the narrow-band requirement for a stationary Gaussian process and the second condition is a local requirement induced from the global one and is necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by asymmetric waveforms. There are several approaches for computing EMD. The following algorithm is employed here to decompose signal x(t) into a set of IMF components.

- Identification of all maxima and minima of the time series x(t)
- Generate the upper and lower envelopes u(t) and *l*(t) respectively, by connecting the maxima and minima separately with cubic spline interpolation.
- Determine the local mean as $\mu_1(t) = [u(t)+l(t)]/2$
- An IMF should have zero local mean thus we subtract $\mu_1(t)$ from the original signal x(t) as $e_1(t) = x(t) - \mu_1(t)$.
- Check whether $e_1(t)$ is an IMF or not by checking the two basic conditions as described above.
- Repeat steps 1 to 5 and stop when an IMF $e_1(t)$ is obtained.

Once the first IMF is obtained, define $c_1(t) = e_1(t)$ which is the smallest temporal scale in x(t) To find the rest of the IMFs, generate the residue $r_1(t)$ of the data by subtracting $c_1(t)$ from the signal x(t) as

$r_1(t) = x(t) - c_1(t)$. The sifting process will be continued until the final residue is a constant, a monotonic function, or a function with only one maximum and one minimum from which no more IMFs can be obtained. The subsequent IMFs and the residues are computed as:

$$r_1(t) - c_2(t) = r_2(t) \ldots r_{B-1}(t) - c_B(t) = r_B(t) \quad (2)$$

where $r_B(t)$ is the final residue. At the end of the decomposition, the signal x(t) is represented as:

$$x(t) = \sum_{b=1}^{B} c_b(t) + r_B(t) \quad (3)$$

where B is the number of IMFs and $r_B(t)$ is the final residue.

The IMFs are the fundamentals for representing the time series data. Being data adaptive, the fundamentals usually offer a physically meaningful representation of the underlying processes. There is no need for considering the signal as a stack of harmonics and, therefore, EMD is ideal for analyzing non-stationary and nonlinear data [13]. Moreover, EMD uses only a single mixture to extract IMFs.

KLD-BASED K-MEANS CLUSTERING

In this section a K-means clustering algorithm based on Kullback-Leibler divergence introduced in [14] is used in our paper for the grouping process. Symmetric KLD measures the relative entropy between two probability mass functions p(z) and q(z) over a random variable Z as Here:

$$KLD(p,q) = \frac{1}{2}\left[\sum_{z\in Z} p(z)\log\frac{p(z)}{q(z)} + \sum_{z\in Z} q(z)\log\frac{q(z)}{p(z)}\right] \quad (4)$$

KLD is used to measure the information theoretic distance between two basis vectors during K-means clustering whereas traditional K-means clustering uses the Euclidean distance.

By using the KLD-based K-means clustering algorithm, vectors are automatically grouped into clusters corresponding to the given number of sources according to the entropy contained by individual vectors. The KLD-based K-means clustering algorithm is summarized as:

- Initialize P cluster center weights $w_1, w_2, \ldots, w_p$ and repeat steps 2 to 4 until convergence is reached. For iteration t:
- Select a normalized basis function ν (sequentially from reduced set of basis functions)
- (a) Calculate the distances d_j of ν from w_j by $d_j = KLD(v, w_j), j = 1,2,\ldots,P$.

  (b) Identify the center i closest to ν so that $i = \arg\min\{d_j\}, j = 1,2,\ldots,P$.
- (a) Update the weight of the i^{th} center by $w_i(t+1) = w_i(t) + \eta(t)(v - w_i(t))$.

  (b) Update the learning rate factor η by:

  $$\eta(t+1) = \frac{\eta(t)}{1 + 0.0005t^{0.02}}.$$

  (c) Calculate the change c of weights by:

  $$c = \frac{\|\bar{w}(t+1) - \bar{w}(t)\|_2}{\|\bar{w}(t+1)\|_2}$$
- Check, if c<ε then stop, else repeat. The term ε represents error threshold (of the order 10^{-6} in this method).

PROPOSED SEPARATION MODEL

In this section we propose a new algorithm for separating instantaneous audio mixtures which are recorded by one microphone. Our single-channel BSS model is shown in Fig. 1.

At first, the observed mixture x(t) is divided into D segments with short length, in comparison to the whole length of the signal, by windowing. The windowing process is necessary since it considerably reduces the running time of the algorithm and improves the separation performance when the data is non-stationary. Then, the algorithm is applied to the windowed signal $x^{(i)}(t)$ in the i_{th} (i = 1,2,…,D) segment to derive separated signals in each segment.

Subband analysis stage: The observed mixture $x^{(i)}(t)$ is divided into a finite number of K subbands through filtering it with a parallel bank of FIR band-pass filters. To execute BSS on real-valued signals, we use the subband analysis filter bank as the cosine modulated version of a prototype filter $h_0(n)$ of length N and cutoff frequency $\omega_c = \pi/K$ [15]:

$$h_k(n) = h_0(n)\cos[(k - \frac{1}{2})\frac{n\pi}{K}],\ k = 1,2,\ldots,K \quad (5)$$

$$h_0(n) = \mathrm{sinc}(\frac{2n\pi}{N})w(n) \quad (6)$$

As shown in Fig. 2, $h_0(n)$ is a truncated sinc(·) function weighted by a Hamming window with $w(n) = 0.54 - 0.46\cos(2n\pi/N)$ where n = 1,2,…,N. The

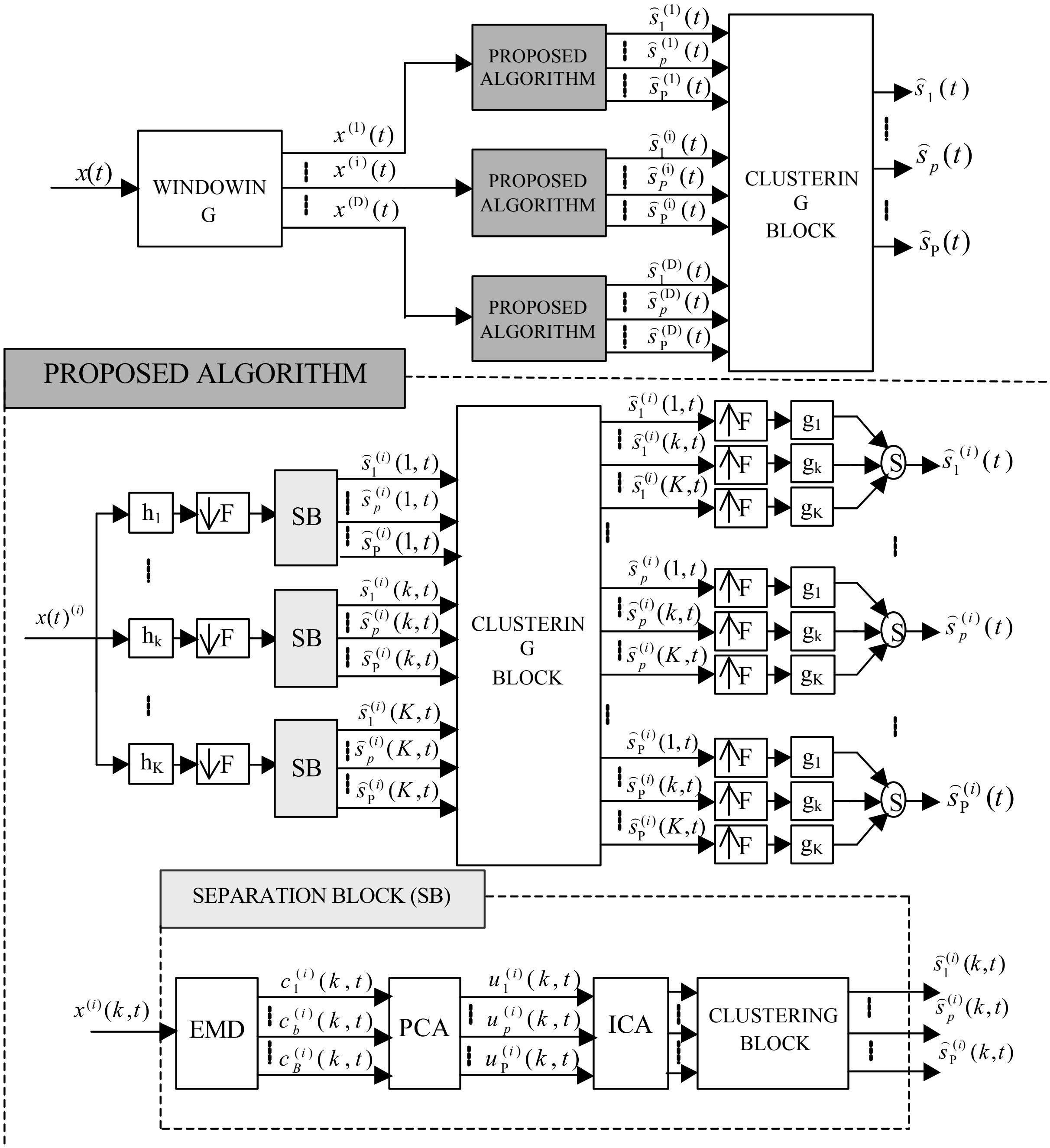

Fig. 1: The proposed single-channel subband-based BSS algorithm. SB denotes Separation Block. D, B, P and K indicate the number of segments, IMFs, original sources and subbands, respectively, where i = 1,2,…,D, b = 1,2,…,B, p = 1,…,P, k = 1,2,….,K. F indicates down-sampling rate

prototype filter $h_0(n)$ is used to derive the analysis and the corresponding synthesis filter banks depicted in Fig. 1. The effective bandwidth of the decomposed signal in each subband is reduced by a factor of 1/K compared to the wider bandwidth of the original fullband signal. Then, we employ decimation at the down-sampling rate F (F<K) to reduce the aliasing problem. Finally, the observed mixture $x^{(i)}(t)$ is decomposed to K real-valued subband signals:

$$x^{(i)}(k,t)=\sum_{n=1}^{N} h_k(n)x^{(i)}(t-n) \qquad (7)$$

where $x^{(i)}(k,t)$ is down-sampled and band-limited signal in the k_{th} subband (k = 1,2,…,K) and t = l.F denotes the

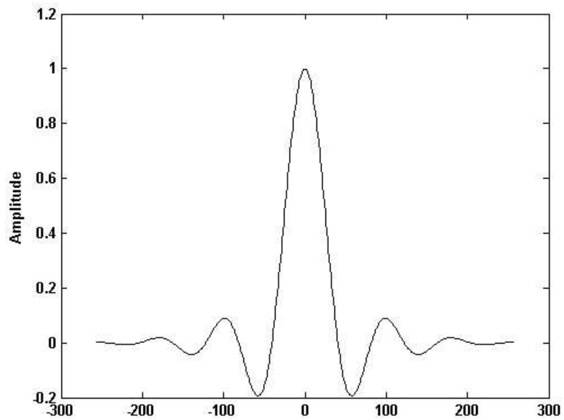

Fig. 2: Impulse response of the low-pass real-valued prototype FIR filter $h_0(n)$ with length N = 512

time index at the reduced sampling rate for some integer *l*.

Separation stage: In this stage, subband decomposition combined with a hybrid system of EMD and PCA constitutes a single-channel separation model that employs ICA in the separation process to find independent components. The process is shown in Fig.. 1.

Step 1: The EMD algorithm is applied to the down-sampled and band-limited signal $x^{(i)}(k,t)$ in each subband to extract IMFs $c_b{}^{(i)}(k,t)$ where b = 1,2,…,B and B is the number of IMFs. The dimensionality of $c_b{}^{(i)}(k,t)$ is $1\times L$ where L is the length of data segment. Thus, an observation matrix $Y^{(i)}_{L\times B}(k,t)$ is formed in each subband for k = 1,2,…,K:

$$Y^{(i)}_{L\times B}(k,t) = [(c_1^{(i)}(k,t))^T,(c_2^{(i)}(k,t))^T,\ldots,(c_B^{(i)}(k,t))^T] \quad (8)$$

Step 2: In order to find the uncorrelated basis components which are our artificial observations, PCA algorithm is used. PCA is implemented by employing SVD. The SVD of $Y^{(i)}_{L\times B}(k,t)$ is a factorization of the form

$$\mathbf{Y}^{(i)}_{L\times B}(k,t) = \mathbf{U}^{(i)}_{L\times L}(k,t)\mathbf{D}^{(i)}_{L\times B}(k,t)\mathbf{V}^{(i)\,T}_{B\times B}(k,t)$$

where $U^{(i)}(k,t)$ and $V^{(i)}(k,t)$ are orthogonal matrices with orthogonal columns and $D^{(i)}(k,t)$ is a matrix of B singular values $\sigma_b = \sigma_{b\times b}$, where $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_B \geq 0$ Matrix $U^{(i)}(k,t)$ is referred to as a row basis representing the principal components of $\mathbf{Y}^{(i)}_{L\times B}(k,t)$. The singular values represent the standard deviations proportional to the amount of information contained in the corresponding principal components. A reduced set of P basis vectors are selected from $U^{(i)}(k,t)$ (i.e. $\mathbf{U}^{(i)}_{L\times P}(k,t) = [u^{(i)}_{L\times 1}(k,t),\ldots,u^{(i)}_{L\times P}(k,t)]$) by using the first P singular values. We set P equal to the number of original sources.

Step 3: After finding the uncorrelated basis vectors in each subband, FastICA algorithm (introduced in Sec. II) is applied to each uncorrelated components $\mathbf{U}^{(i)}_{T\times P}(k,\omega,)$ to obtain independent basis vectors in each subband i.e.

$$\hat{\mathbf{s}}^{(i)}(k,t) = [\hat{s}^{(i)}_{1\times L}(k,t),\hat{s}^{(i)}_{2\times L}(k,t),\ldots,\hat{s}^{(i)}_{P\times L}(k,t)]^T\,)$$

Subband synthesis stage: Generally, ICA has two ambiguities [12]. First, the variances of the independent components can not be determined (i.e. scaling ambiguity) and second, they can appear at the output of the source-estimating network in any order (i.e. permutation ambiguity). To eliminate scaling ambiguity we multiply the separated output signals $\hat{\mathbf{s}}^{(i)}_{p\times T}(k,t)$ by scaling coefficients to ensure equality between separated and original signals in each segment. In order to obtain these coefficients, we need to solve an over-determined linear system of equations in the simple case of an instantaneous mixture such as our case Q.c = b In this equation c is an P-by-1 vector indicating the unknown coefficients, b is a L-by-1 vector, where L is the length of data, consisting of the windowed signal $x^{(i)}(k,t)$ and Q is a L-by-P matrix composed of P separated signals where L>P (i.e. an over determined system). The least square solution to this matrix equation is vector c that minimizes the 2-norm of the residual b-Qc over all vectors c A least square solution to Q.c = b can be found easily as $c = Q^{+}b$ where $(\cdot)^{+}$ denotes pseudo-inverse operation and c is the unique solution of minimal 2-norm. The pseudo-inverse Q^{+} of Q can be written explicitly in terms of the SVD. The SVD of Q is given by $Q = U\Sigma V^T$ where U is L-by-L unitary matrix, V is an P-by-P unitary matrix and Σ a real L-by-P diagonal matrix with (i,i) interior σ_i. The singular values σ_i satisfy $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_{\min(L,P)} \geq 0$. Therefore, if the SVD of Q is given by $Q = U\Sigma V^T$ then $Q^{+} = U\Sigma^{+}V^T$ where Σ^{+} is P-by-L diagonal with (i,i) entry $1/\sigma_i$ if $\sigma_i > 0$ and otherwise 0 After finding c coefficients and applying them to the appropriate separated output signals $\hat{\mathbf{s}}^{(i)}_{P\times T}(k,t)$ we can eliminate the scaling ambiguity from the separated signals in each segment.

Solving the permutation ambiguity is necessary since due to the permutation ambiguity of the ICA algorithm, the order of separated signals in each subband is not constant. For this purpose and obtaining fullband separated signals in each segment, we need to apply KLD-based K-means clustering algorithm (Sec. IV) to all separated signals to group them into P clusters (P is equal to the number of original sources) so that each cluster contains separated subband signals which are related to their corresponding original source.

To reconstruct the fullband separated signals in each segment, we perform the following steps: all of the separated subband signals in each cluster are first up-sampled by the interpolation factor F next filtered by the synthesis filters

$$g_k(n) = g_0(n)\cos[(k-\frac{1}{2})\frac{n\pi}{K}]$$

where the baseband synthesis filter $g_0(n)$ is actually a time reversed copy of the analysis prototype filter $h_0(n)$ (6) equal to $g_0(n) = h_0(N\text{-}n\text{-}1)$ with n = 1,2,…, N and k = 1,2,…,K. The subband synthesis stage is indicated in Fig. 1. Finally, each fullband separated signal in the subband synthesis stage output is given by:

$$\hat{s}_j^{(i)}(t) = \sum_{k=1}^{K}\sum_{n=1}^{N} g_k(n)\hat{s}^{(i)}(k,t)(t-n) \quad (9)$$

for j = 1,2,…,P where P is equal to the number of original sources and *t* denotes the time index at the restored sampling rate, such that t = *l*/F.

To achieve the full-length separated signals, we should appropriately join the fullband separated signals in each segment to those in other segments. The problem is that the order of separated signals in the segments is not the same. Therefore, we should use the KLD-based K-means clustering again to group separated signals appropriately. At last, to reconstruct the full-length separated signals, we join grouped signals in each cluster. The full-length separated signals are denoted by $\hat{\mathbf{S}} = [\hat{s}_1, \hat{s}_2, \ldots, \hat{s}_P]^T$.

EXPERIMENTAL RESULTS

In this section we examine the separation performance of the proposed algorithm for separating audio signals from a single instantaneous mixture. Four mixtures are considered in the experiments. One of the two signals of mixtures denoted by m1, m2, m3 and m4, is male speech and the others are rock music, jazz music, flute sound and female speech, respectively. All of the mixtures have been recorded at a sampling rate of 8 kHz and 16-bit amplitude resolution. The length of these mixtures is 5.85 seconds.

Table 1: Used parameters in the simulation setup

Symbol	Definition	Value
D	Number of segments	4
N	Length of prototype filter	512
K	Number of subbands	32
F	Down-sampling rate	1

How to measure the distortion between original source and the estimated one has no completely trivial solution. It depends on the mixing system and the separation process as well as the field of application. It is still hard to evaluate the separation algorithm because of the lack of appropriate performance measures even in the very simple case of linear instantaneous mixtures [16]. In this paper, in order to measure the distortion between the original sources and the estimated sources, we use the improvement of signal-to-noise ratio (ISNR) as the quantitative measure of separation performance [16]. The ISNR is the difference between input and output SNRs. The input SNR (SNR_I) is defined as:

$$SNR_I = 10\log\frac{\sum_t |s_j(t)|^2}{\sum_t |x(t)-s_j(t)|^2} \quad (10)$$

where x(t) is the mixed signal and $s_j(t)$ is the original signal of the j_{th} source. If $u_j(t)$ is the separated signal (estimated source signal) corresponding to j_{th} source, the output SNR (SNR_O) is defined as:

$$SNR_O = 10\log\frac{\sum_t |s_j(t)|^2}{\sum_t |s_j(t)-u_j(t)|^2} \quad (11)$$

Then we employed ISNR (dB) = SNR_O - SNR_I as the performance measure. The ISNR represents the degree of suppression of the interfering signals to improve the quality of the target one. Recently, it is widely used to measure the separation quality between the mixed and demixed signal [16]. The higher value of ISNR indicates better separation performance.

Table 1 indicates parameters used in the simulation setup of the proposed algorithm which yield the best result in our experiments. The results of applying the algorithm to the mixtures (m1-m4) are shown in Table 2 in terms of ISNR. In order to demonstrate the competence of the proposed algorithm, the separation performance of our algorithm and ISA method is also compared in this Table.

Figure 3 presents the first eight subband signals after applying subband decomposition to the first segment of the observed mixture m4. Figure 4

Table 2: Separation results in terms of ISNR

Mixture	Method	ISNR of Sig1 (dB)	ISNR of Sig2 (dB)
m1 (male speech & rock music)	The proposed algorithm	9.81	10.84
	ISA method	6.94	7.89
m2 (male speech & jazz music)	The proposed algorithm	8.92	9.54
	ISA method	5.77	6.48
m3 (male speech & flute sound)	The proposed algorithm	10.01	11.13
	ISA method	7.04	8.78
m4 (male & female speech)	The proposed algorithm	7.97	8.75
	ISA method	4.46	5.14

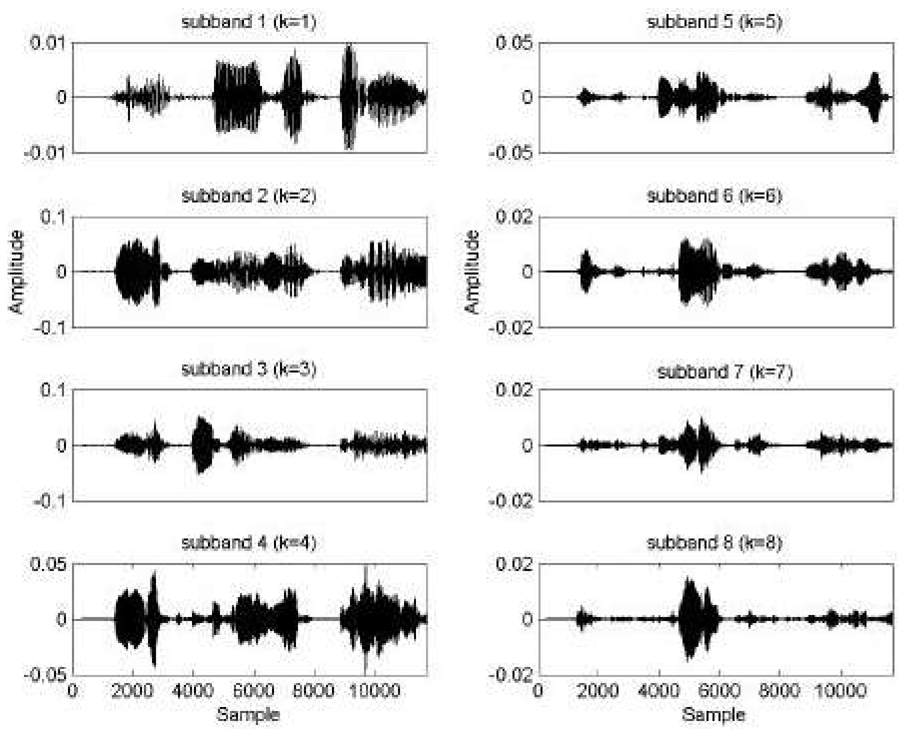

Fig. 3: The first eight subband signals after applying subband decomposition to the first segment of the mixture m4

illustrates extracted IMF components after applying EMD algorithm to the decomposed signal at the first subband. Finally, the separated signals after applying the proposed algorithm to m4 are shown in Fig. 5.

CONCLUSION

In this paper, we proposed a new subband-based BSS algorithm to separate audio signals from a single instantaneous mixture. The use of subband BSS enabled us to maintain a sufficient number of samples to estimate the statistics in each subband. The proposed separation algorithm included a hybrid system of EMD, PCA to construct artificial observations from the single mixture. We used FastICA in the separation process to find independent components. Since the ICA algorithms suffer from scaling ambiguity, a new method for removing the ICA scaling ambiguity was proposed. Moreover, a K-means clustering algorithm based on Kulback-Leibler divergence was used to group the independent basis vectors, suffering from permutation ambiguity of ICA algorithms, into the number of component sources inside the mixture. It is noticeable that the proposed algorithm did not require any training data. A quantitative separation performance was presented in the experimental results in terms of the ISNR by which we compared the separation efficiency of our algorithm to that of the ISA method.

Extending the proposed separation model for separating convolutive mixtures and improving the

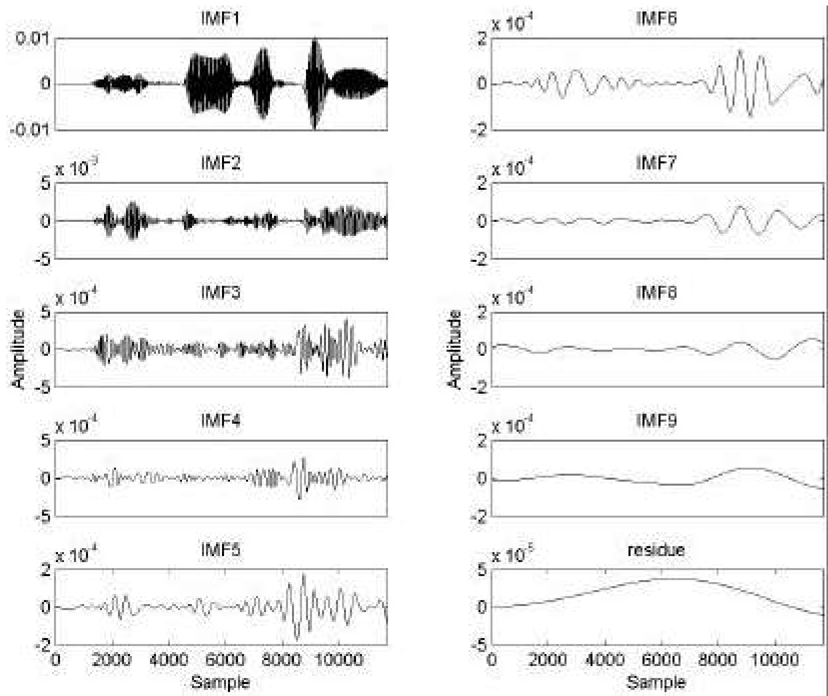

Fig. 4: Extracted IMF components and the residue after applying EMD algorithm to the decomposed signal at the first subband

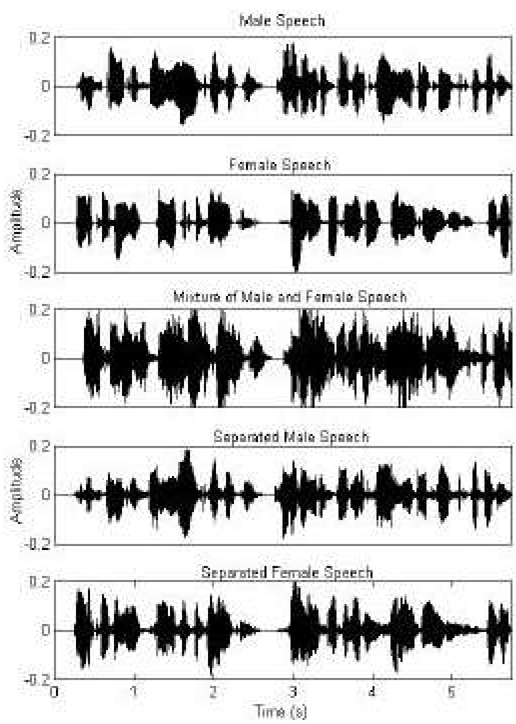

Fig. 5: Waveforms of original sources, the recorded mixture m4 and separated signals; 1) original male speech and female speech (upper two), 2) the mixture m4 (middle one), 3) separated male speech and female speech after applying the proposed algorithm (lower two)

robustness of the proposed algorithm are concerns for our future work.

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