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THE SUBBAND-BASED INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT

Independent Component Analysis (ICA) is a powerful statistical signal analysis tool, which can separate signals from mixtures without any prior knowledge. However, the performance of many current ICA algorithms degrades seriously in the presence of strong noise. Inspired by the psychoacoustic discovery that humans perceive and process the acoustic signals in different frequency bands independently, we propose a new algorithm that integrates ICA with time-frequency analysis to separate mixed signals. Wavelet decomposition and best basis selection in wavelet/DCT packet can be incorporated into this algorithm. The new algorithm is able to accomplish the separation task successfully in the presence of strong noise. Experimental results on acoustic signals demonstrate its effectiveness.

1. INTRODUCTION

Independent Component Analysis (ICA) can recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved source signals and noise. In contrast to Principal Component Analysis that decorrelates signals based on covariance matrix, ICA uses higher order statistics of the signals to find the independent components. ICA has many applications in speech enhancement and recognition, telecommunication, biomedical signal analysis, and image denoising and recognition [2] [4] [6] [14][15] [10]. However, the performance of many current ICA algorithms degrades seriously in the presence of strong noise. Inspired by the psychoacoustic discoveries connecting auditory perception and wavelet theory, a new ICA algorithm, the subband-based ICA algorithm, is proposed to separate independent signals. Experimental results fully demonstrate its robustness to noise.

2. SYSTEM MODEL AND LEARNING RULE

While some nonlinear ICA algorithms have been proposed[7][11], most of the contributions to the ICA literature are based on the linear input mixture model, which is defined as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{b}(t),$$

where $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_n]^T$ is an unknown source signal vector at discrete time t, $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^T$ is the observation signal vector, $\mathbf{A}$ is a full rank $n \times n$ mixing matrix, and $\mathbf{b}(t)$ is noise. The components of the vector $\mathbf{s}(t)$, i.e., $s_1(t), s_2(t), \ldots, s_n(t)$ come from n independent sources. Unlike factor analysis addressed by EM algorithm[5], which assumes the $\mathbf{b}(t)$ is normally distributed with a diagonal covariance matrix and $\mathbf{s}(t)$ is also normally distributed, ICA algorithms are derived on the assumption of noise free measurements. In practice, many ICA algorithms do not work well in noisy mixture.

Given the mixture model, the aim of ICA is to recover the original source signal $\mathbf{s}(t)$. To this end, the following simple separation model is used, corresponding to the above linear mixture model:

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t),$$

where $\mathbf{y}(t) = [y_1(t), y_2(t), \ldots, y_n(t)]^T$ is an estimate of $\mathbf{s}(t)$ and $\mathbf{W}$ is the unmixing matrix, i.e., an estimate of the inverse of $\mathbf{A}$.

To obtain the learning rule for the demixing matrix $\mathbf{W}$, we use natural gradient[1] to minimize the Kullback-Leibler divergence between the source signal vector $\mathbf{s}$ and its estimate $\mathbf{y}$, i.e.,

$$D(f_{\mathbf{y}} \parallel f_{\mathbf{s}}) = \int f_{\mathbf{y}}(t) log \frac{f_{\mathbf{s}}(t)}{f_{\mathbf{y}}(t)} d\mathbf{y}$$

where $f_{\mathbf{y}}$ and $f_{\mathbf{s}}$ are the probability density functions (pdfs) of $\mathbf{y}$ and $\mathbf{s}$. The pdfs are approximated by the truncation of the Gram-Charlier expansion. Then the following learning rule (and its nonholonomic version [3]) is obtained:

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \eta(n)[\mathbf{I} - \mathbf{g}(\mathbf{y}(n))\mathbf{y}^T(n)]\mathbf{W}(n), \quad (1)$$

Where $\mathbf{I}$ is the identity matrix, $\eta(n)$ is the learning rate, and the $\mathbf{g}(\mathbf{y}) = (g(y_1), \cdots, g(y_n))^T$ is a nonlinear function[22],

$$\begin{aligned} g(z) &= \frac{1}{2}z^5 + \frac{2}{3}z^7 + \frac{15}{2}z^9 + \frac{2}{15}z^{11} - \\ &- \frac{112}{3}z^{13} + 128z^{15} - \frac{512}{3}z^{17}. (2) \end{aligned}$$

3. THE SUBBAND-BASED ICA

Many psychoacoustic experiments have shown that humans perceive and process the acoustic signals on different frequency bands independently [19][20]. Inspired by these discoveries, we propose a new algorithm, namely, the subband-based ICA, that integrates ICA with time-frequency analysis to separate mixed signals. The subband-based ICA and the early auditory models are compared in figure 1. The new algorithm can accomplish the separation task successfully in the presence of strong noise.

The outline of the algorithm is described in the following:

1. First, each component, $x_j(t)$, where $1 \leq j \leq m$, of the observation $\mathbf{x}(t)$ is decomposed into subband signals.

   Though digital filter banks have been built to mimic the subbanding function of cochlea[21] for the simplicity and the linearity required by ICA the orthogonal Daubechies wavelet packet decomposition[23] is used instead of the cochlear filter bank as in the following:

   $$x_j^k(n) = < x_j^{n,N}, e_k^N >, \quad (3)$$

   where $x_j^{n,N} = (x_j(n), x_j(n-1), \cdots, x_j(n-N+1))$ and $e_k^N = (e_k(1), e_k(2), \cdots, e_k(N))$ is a vector of coefficients determined by the k^{th} band Daubechies wavelet filter and N is a window size.

2. The averaged powers of the decomposed signals in every band are computed and sorted by a fast sorting algorithm, for example, heap sorting.

3. Then the learning rule (1) is applied only on some of the bands which have the strongest powers, for example, in the top one fourth of all the signal bands, for the following reasons:

   - If noise is broad-band, the signal to noise ratio (SNR) will be larger on those bands which have strongest power.
   - If noise is limited to some narrow bands, then many signal bands will be noiseless, which means good separation results can be obtained in those noiseless bands.

   We denote the demixing matrix obtained on the k^{th} selected band as:

   $$\mathbf{W}^k = \begin{pmatrix} \mathbf{W}_1^k \\ \vdots \\ \mathbf{W}_n^k \end{pmatrix}$$

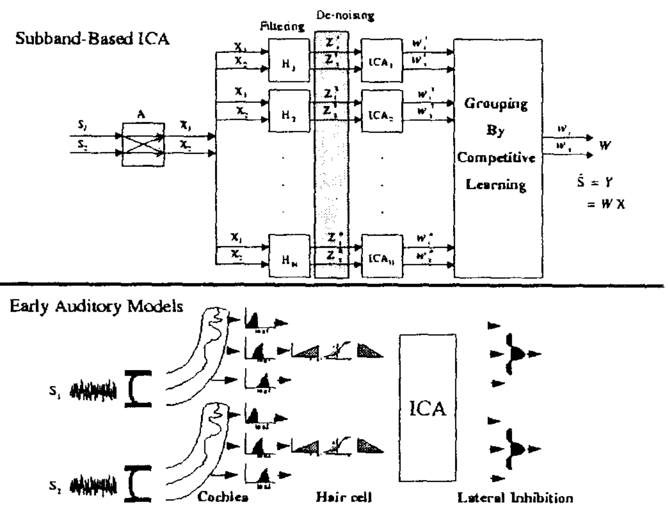

Figure 1: The Subband-based ICA and Early Auditory Models

where the row $\mathbf{W}_j^k, 1 \leq j \leq n$ is used to get to the j^{th} component, $y_j^k(t)$, of the estimated source signal $\mathbf{y}(t)$ on the k^{th} band.

4. Noise is reduced using a soft thresholding algorithm[24] applied to the subband decomposed signals.

5. To recover the estimated source signal $\mathbf{y}(t)$, we have two methods:

   a First recover the overall unmixing matrix $\mathbf{W}$ from the unmixing matrices associated to different subbands, and then recover $\mathbf{y}(t)$ from $\mathbf{Wx}(t)$. Competitive learning[22] is applied to cluster the rows of the unmixing matrices obtained on different subbands. The overall unmixing matrix $\mathbf{W}$ consists of n clustered rows.

   b Recover $\mathbf{y}(t)$ directly from the $y_j^k(t), 1 \leq j \leq n$ by wavelet packet reconstruction algorithm.

Depending on the practical situation, we can choose (a) or (b) to get the better result.

4. ADAPTIVE BASIS SELECTION IN WAVELET/DCT PACKET

The subband-based ICA enhances the separation capability by decomposition of the signal into different frequency bands. But the problem of designing the filter bank remains. For example, it will be good if we do not split the signal into two bands at the frequency where the energy of the signal concentrates because otherwise we might segment one or several continuous signal streams in time-frequency plane into two different bands, which could affect the performance of ICA in each band. So, depending on different signal properties, we can design different filterbank to improve the performance of the subband-based ICA.

To address this problem, we incorporate the adaptive basis selection algorithm, proposed by Coifman, et al., into the subbband-based ICA algorithm.

Similar to the procedure we described in section 3, we have the following steps:

1. First we choose Shannon entropy as the cost function and apply adaptive basis selection algorithm in Wavelet or DCT packet (See the details in [25]) on the summation of the different mixed signals to get the best bases.

2. Then we project each mixed signal onto the best bases.

3. The learning rule (1) is applied only on some of the projected signals which have the strongest normalized power. The power is normalized in frequency domain. Noise is reduced by thresholding method if necessary.

4. Competitive learning is used to group the rows of the demixing matrices obtained on different bases and get the overall demixing matrix W.

Best basis selection algorithm actually accomplishes the task of adaptively selecting filter bank based on the properties of the signals, which makes the subband-based ICA more robust against noise.

5. EXPERIMENTAL RESULTS

Before describing our experimental results, we introduce the performance index E, which is defined as in [1]:

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

where $\mathbf{P} = \{p_{ij}\} = \mathbf{WA}$. The smaller the index is, the better $\mathbf{P}$ approximates a permutation matrix which has only one nonzero element in each row and each column, and the better the separation is.

First, we separated two mixtures of two speech signals, randomly selected from TIMIT speech library and added strong white noise. These speech signals were sampled at 8K Hz. The average SNR of the mixtures was 0.51 dB. From the mixtures it was hard to understand any word of the speech sentences. Then the subband-based ICA was applied to separate the mixture signals. The performance index E of this separation was 0.08 and the SNR increased to 5.64 dB. The separated speech signals were understandable though still noisy.

Second, we tested our algorithm on two mixtures of strong white noise and the test data used in ICA 1999 conference, i.e., street.wav and beet.wav[27]. The power of the noise was the same as the average mixed signal power, i.e., the average SNR is 0.0 dB. Despite the low SNR, the subband-based ICA based on adaptive basis selection is successful in separation. For the purposes of comparison, we also tested the Fast ICA algorithm [12] and the Extended Infomax algorithm [6] on those noisy mixtures. The codes for Fast ICA and the Extended Infomax were downloaded from [13] and [9] repectively. For the Extended Infomax we modified the learning rate trying to get the best performance for our test data. The separation results are shown in table 1

Approaches	Index E	Average SNR of the separated signals
Subband based ICA	0.051	4.31 dB
Fast ICA	0.124	-1.63 dB
Extended Infomax	0.118	-1.38 dB

Table 1: The Simulation Results of different ICA algorithms. The average SNR of the mixed signal is 0.0 dB

From the above table, we can see that the subband-based ICA is robust against noise. The waveforms in the separation of the subband-based ICA are shown in figure 2.

6. CONCLUSION

Inspired our understanding of the subbanding strategies used in early auditory system, we present the the subband-based ICA, a new powerful algorithm to separate mixed signals. First, by performing parallel separation on several

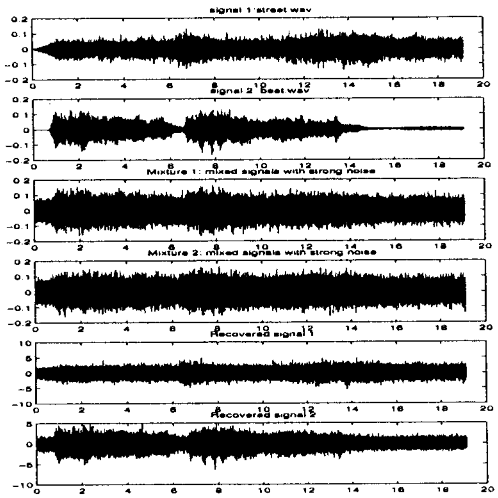

Figure 2: The Separation in the presence of strong white noise

frequency bands, the subband-based ICA is robust against noise. Even in the presence of strong white noise it can successfully separate signals as demonstrated in our experiments. By incorporating the best basis selection algorithm it can be adaptive to the properties of the signal and noise, which makes it robust for different kinds of signals. When the mixed noise is only located in some narrow frequency bands, the subband-based ICA can achieve very accurate separation results. But we do not show this point in last section because of the page limitations.

The subband-based ICA can also be used as a fast algorithm because it reduces the computational complexity by performing separation in the down sampled signals in several frequency bands in parallel.

Furthermore, we can generalize the subband-based ICA by replacing the subband decomposition with any appropriate projection. For example, nonlinear projection can be used under some criterion, e.g., maximum likelihood, to derive a nonlinear ICA.

Our future work will include separating real world signals such as reverberating speech signals in a room with noise. We aim to apply the subband-based ICA to address this problem. Also, we aim to use some signal cues and prior knowledge to do separation when the number of sensors is less than the number of sources. Some work has been initiated in this direction.

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