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Letters

A filter bank approach to independent component analysis and its application to adaptive noise cancelling

Hyung-Min Park[a,*], Sang-Hoon Oh[b], Soo-Young Lee[a,c]

[a]*Department of Electrical Engineering and Computer Science, Korea Advanced Institute of Science and Technology, Daejon, 305-701, South Korea*

[b]*Department of Information Communication Engineering, Mokwon University, Daejeon, 302-729, South Korea*

[c]*Department of BioSystems, and Brain Science Research Center, Korea Advanced Institute of Science and Technology, Daejeon, 305-701, South Korea*

Abstract

We present a filter bank (FB) approach to perform independent component analysis for adaptive noise cancelling. This approach is based on FBs, and its decimation provides much less computational complexity and faster convergence speed than the time-domain approach. In addition, the approach does not have a performance limitation unlike the frequency-domain approach. One can select the number of filters in the FB regardless of reverberation and implement the method to fit for parallel processing. We verify the effectiveness of the FB approach through simulations on adaptive noise cancelling.

Keywords: Independent component analysis; Filter bank; Adaptive noise cancelling

1. Introduction

Independent component analysis (ICA) is a linear transform of multivariate data to make the resulting random variables as statistically independent as possible [2,3]. Most of ICA algorithms for convolved mixtures can be categorized into the time-domain and the frequency-domain approaches [2,5,6]. The time-domain approach requires intensive computations for long reverberative mixtures and shows slow convergence

* Corresponding author. Tel.: +82-42-869-5431; Fax: +82-42-869-8490.
E-mail address: hmpark@kaist.ac.kr (H.-M. Park).

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especially for colored input signals [7]. The computational load can be reduced by the frequency-domain approach, in which multiplication at each frequency bin replaces convolution operation in the time domain. However, the performance of the frequency-domain approach is limited. A long frame size is required to cover a long reverberation, whereas the number of learning data in each frequency bin decreases as the frame size increases [1]. In this letter, we propose a filter bank (FB) approach to overcome these disadvantages of the time-domain and the frequency-domain ICA approaches, and apply it to adaptive noise cancelling.

2. A FB approach to ICA

Fig. 1 shows a 2×2 network for the oversampled FB approach to ICA. Input signals which are mixtures of unknown independent components are split into subband signals by analysis filters $H_k(z), k = 0, 1, \ldots, K-1$. Then, each subband signal is subsampled by factor M. In each subband, these subsampled signals are independently processed by a usual ICA algorithm. Finally, independent components are expanded by M and reconstructed through synthesis filters $F_k(z), k = 0, 1, \ldots, K-1$ after fixing permutation and scale. Due to band-limited characteristics of the oversampled FB, signals in each subband may be subsampled without aliasing error for computational efficiency.

Since critically sampled FBs require additional cross adaptive filters or spectral gaps, we adopt oversampled FBs in which aliasing is negligible by using filters with high stopband attenuation [7]. To implement uniform complex-valued oversampled FBs, we obtain analysis filters $h_k(n)$ from a real-valued low-pass prototype filter $q(n)$ by a generalized discrete Fourier transform (GDFT)

$$h_k(n) = \mathrm{e}^{\mathrm{j}(2\pi/K)(k+1/2)(n-(L_q-1)/2)}\, q(n),$$
$$k = 0, 1, \ldots, K-1, \quad n = 0, 1, \ldots, L_q - 1, \tag{1}$$

where L_q is the length of $q(n)$. The prototype filter can be designed by iterative least-squares algorithm with a cost function which considers reconstructiveness and stopband attenuation [7].

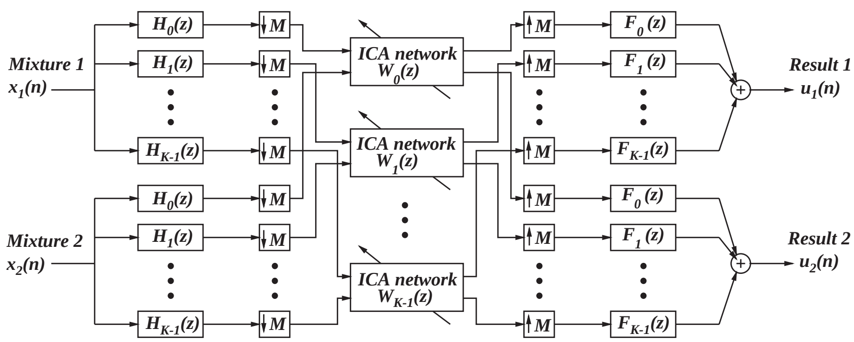

Fig. 1. A 2×2 network for the oversampled FB approach to ICA.

When we perform ICA in the oversampled FBs, adaptive filter coefficients in each subband can be adjusted without any information of the other subbands due to negligible aliasing of the FBs. Thus, the approach is appropriate to parallel processing. Filter coefficient normalization and envelope correlation method may be incorporated to fix scale and permutation problems, respectively [5].

The ICA algorithm in each subband is basically the same as the time-domain approach. As an ICA network in each subband, a feedforward architecture may be considered as

$$u_i(n) = \sum_{j=1}^{N} \sum_{k=0}^{K-1} w_{ij}(k) x_j(n-k), \tag{2}$$

where adaptive filters $w_{ij}(k)$ supposedly make outputs $u_i(n)$ reproduce the original independent components. With complex-valued data, entropy maximization algorithm provides learning rules of the adaptive filter coefficients as

$$\begin{aligned} &\Delta \mathbf{W}(0) \propto [\mathbf{W}^{\mathrm{H}}(0)]^{-1} - \varphi(\mathbf{u}(n))\mathbf{x}^{\mathrm{H}}(n), \\ &\Delta w_{ij}(k) \propto -\varphi(u_i(n)) x_j^*(n-k), \quad k \neq 0, \quad \varphi(u_i(n)) = -\frac{\partial p(u_i(n))/\partial u_i(n)}{p(u_i(n))}, \end{aligned} \tag{3}$$

where $\mathbf{W}(0)$ is a matrix composed of zero-delay weights, and $\mathbf{u}(n)$ and $\mathbf{x}(n)$ denote a set of estimated independent components and the observation vector, respectively. H denotes Hermitian transposition. $\varphi(\cdot)$ is called as a score function, and $p(u_i)$ denotes the probability density function of u_i. Since ICA in each subband is based on the time-domain approach, the FB approach does not have the problems of the frequency-domain approach due to block processing. In addition, it improves the convergence speed because input signals are more whitened by decimation than the time-domain approach. Since the unmixing filter length becomes reduced by a factor $1/M$ for decimated input signals with a decimation factor M and the input signals are processed at the subsampled rate in each subband, computational complexity is considerably reduced for a long adaptive filter length. With a K-channel oversampled FB, the number of multiplications for the FB approach is approximately $2K/M^2$ times as large as that for the time domain approach. Furthermore, the approach is able to choose the number of subbands regardless of reverberation.

3. Adaptive noise cancelling based on the FB approach

Adaptive noise cancelling is an approach to reduce noise based on reference signals [4]. In conventional adaptive noise cancelling systems, the primary input signal is a combined signal and noise $c(n) = s(n) + r_0(n)$, and the reference signal is a noise signal $r_1(n)$ through another channel from the same noise source. Although the most popular algorithm for noise cancellation is least-mean-squares algorithm, the performance can be improved by ICA, which adapts as [4]

$$\Delta w(k) \propto \varphi(u(n)) r_1(n-k), \text{ where } u(n) = c(n) - \sum_{k=1}^{K} w(k) r_1(n-k). \tag{4}$$

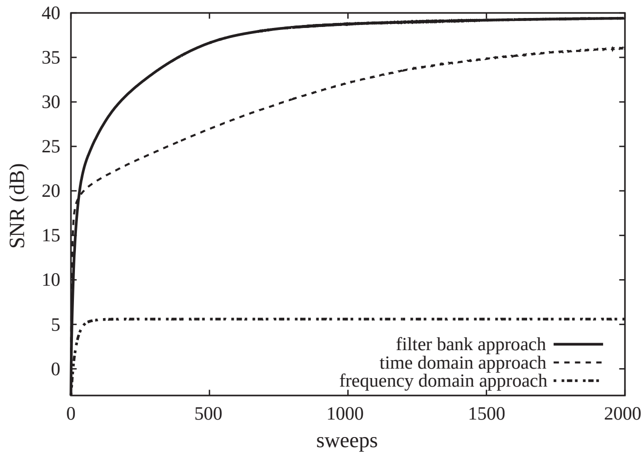

Fig. 2. Learning curves of the three different approaches to adaptive noise cancelling.

The FB approach to ICA can be applied to the adaptive noise cancelling system. In this case, noise components in the primary input signal are cancelled using the reference input signal, and the desired signal is observed in the output without distortion. Therefore, it does not have the permutation and scaling problem which ICA generally has.

4. Experimental results

We have performed experiments on the adaptive noise cancelling with the proposed FB approach. Two real-recorded speech data were used as the signal and the noise sources. Each signal had 10 s length at 16 kHz sampling rate. Since speech signal approximately follows Laplacian distribution, $\mathrm{sgn}(\cdot)$ was used as the score function. Experimental results were compared in terms of signal-to-noise ratio (SNR), which we define as the power of components caused by the signal source versus that caused by the noise source at the output $u(n)$,

$$\mathrm{SNR} = \frac{\langle (s(n))^2 \rangle}{\langle (r_0(n) - \sum_{k=1}^{K} w(k) r_1(n-k))^2 \rangle}. \tag{5}$$

The mixing filters from the signal source to the primary input and from the noise source to the reference input were simple linear scales. The scale values were chosen to obtain desired initial SNRs. For the mixing filter from the noise source to the primary input, we have used a measured filter in a normal office room as shown in [4].

Fig. 2 shows a learning curve of the proposed FB approach. We have used an 192-tap eight-channel oversampled FB with alias-free decimation factor $M = 6$. These parameters are chosen after simulations with various parameter values. The adaptive filter length was $\lceil 1024/M \rceil$ in each subband. For comparison, we have also applied the time-domain approach (corresponding to the method in [4]) and the frequency-domain approach. 1024 adaptive filter coefficients were used for the time-domain approach. In the frequency-domain approach, the frame size was 8192, and the frame shift was a half of the frame size. SNRs of the frequency-domain approach are much lower than those of the others and the FB approach has much faster convergence speed than the time-domain approach, as we insisted on the advantages of the FB approach. Experiments for a car and a music noise showed the same tendency.

5. Conclusions

In this letter, we proposed a uniform oversampled FB approach to perform ICA for adaptive noise cancelling. The approach provides a much better performance than the frequency-domain approach and faster convergence speed than the time-domain approach with much less computational complexity.

Acknowledgements

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