Post-Processing with Frequency Domain Wiener Filter for Blind Source Separation

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(Received March 6 2006; Accepted March 30 2006)

Abstract

In this paper, a novel post processing using Wiener filtering technique is proposed to p rm further interference reduction in FDICA. Using the proposed method, the target signal components are remained with little attenuation while the interference components are drastically suppressed. The results of experiments show that the proposed method achieves a reduction of the residual crosstalk. Compared to the NLMS method, the proposed method has slightly better separation performance in SIR, and even requires much less computational complexity.

Keywords: *Blind source separation (BSS), Independent component analysis (ICA), Frequency domain wiener filter, Post-processing, Interference-to-signal ratio (SIR)*

I. Introduction

Blind source separation (BSS) is an emerging technique, which enables the extraction of target signals from observed mixtures without information of sources and mixing system. The goal of BSS is to "demix"" a vector of signals after they have passed through a matrix multiplication and transform operation. Promising applications can already be found in many fields such as speech recognition [1], in biomedical signals like ECG, EEG [2], and in communication systems [3].

To achieve BSS, attention has been focused on independent component analysis (ICA) [4]. ICA is a signal processing technique that is still receiving an increasing attention [5-6]. It uses an adaptive gradient algorithm to maximize the information content of the output of non-linear "logistic"" function. It is somewhat akin to "principle" component analysis" but seeks to decompose a signal into statistically independent rather than just uncorrelated components. ICA exploits the non-Gaussianity of the mixed data and assumes statistically independence of the source signals to perform separation. Similar methods for ICA have been developed from a number of different view points: minimizing Kullback-Leibler (KL) divergence [7], "infomax" [8], or Maximum Likelihood (ML) estimation [9].

ICA in the frequency domain (FDICA) is one of the most important and practical method for BSS. A convolutive mixture in the time domain is converted into multiple instantaneous mixtures in the frequency domain, and a complex-valued ICA algorithm can be applied for each frequency bin, [10]. Recently, noisy convolutive source separation method is studied which is a hard problem in the frequency domain BSS [11]. Araki et al., pointed out there is a trade-off in the implementation of FDICA for convolutive mixtures [12]. According to that study, FDICA requires proper frame size of the FFT. The degradation of conventional ICA is mainly caused by the crosstalk components derived from the reverberation of the interference signal. To address this problem, several studies are explored ; such as by using time delayed and attenuation parameters [13], by using of the NLMS filters to estimate the residual crosstalk components in each of the FDICA outputs [14], hereinafter referred to as 'NLMS post-processing', and by employing an adaptive noise canceller (ANC) [15].

This paper proposes a post-processing method by using the Wiener filter in the frequency domain. In the time-frequency

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domain, often called the spectrogram domain, the speech has a sparsely distributed characteristics [16]. Therefore, the target signal components and interference signal components are well distinguished in that domain. By the proposed post-processing, the straight components are remained with little loss, while the interference signal components are drastically reduced by endowing small weight. In addition, the proposed algorithm needs not the processing of spectral subtraction as in NLMS post-processing, i.e., there is no concerning about the distortion of the target signals caused by over subtraction. As the proposed one has its weight between '0' and '1', the system has a stable performance without worry about the divergence of the filter coefficients [17].

The separation performance of the proposed method is shown by experimental results of both the artificial convolutive and real-world recorded speech signals. We compare the separative performances of the proposed method with that of the NLMS post-processing. Also, the computational complexity of proposed method is compared to that of NLMS post-processing. The proposed method has slightly better performances than NLMS post-processing in the separative performance, and has considerable reduction of the computational complexity.

The rest of the paper is organized as follows. First, in Section II, the straight and crosstalk components in FDICA are examined. In the Section III, we describe the Wiener filter in the frequency domain, and then propose a post-processing method using Wiener filtering technique to reduce the residual crosstalk of FDICA. In the Section IV, the results of experiments show the separation performance of FDICA is improved by the proposed post-processing. Furthermore, we compare the separation performance and computational complexity between the proposed method and the NLMS post-processing. Finally, a conclusion is made in Section V.

II. BSS in the frequency domain

Suppose that the number of microphone is K, and the number of multiple sound sources is N. When the multiple sound sources are linearly mixed, the observed signals are expressed as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t), \tag{1}$$

where $\mathbf{s}(t) = [s_1(t), \dots, s_N(t)]^T$ is the source signal vector, and $\mathbf{x}(t) = [x_1(t), \dots, x_K(t)]^T$ is the observed signal vector. Both vectors are sampled at time t. Matrix $\mathbf{A}$ is the transfer function between the sources and the array sensors. In the following, this matrix is referred to as the "array matrix"" or "mixing matrix."" This full rank matrix is given as

$$\mathbf{A} = \begin{bmatrix} \sum_{n=0}^{L-1} a_{11}(n)z^{-n} & \cdots & \sum_{n=0}^{L-1} a_{1N}(n)z^{-n} \\ \vdots & \ddots & \vdots \\ \sum_{n=0}^{L-1} a_{M1}(n)z^{-n} & \cdots & \sum_{n=0}^{L-1} a_{MN}(n)z^{-n} \end{bmatrix}, \tag{2}$$

where z^{-1} is used as the unit-delay operator, i.e., $z^{-n}\cdot x(t) = x(t-n)$. And $\sum_{n=0}^{L-1} a_{ij}(n)z^{-n}$ denotes the L-tap FIR impulse response between the i -th microphone and the j-th sound source.

Using a short-time discrete-time Fourier transform (DFT), the separating process can be formulated, in each frequency bin ω and with τ frame index, as;

$$\mathbf{Y}(\omega,\tau) = \mathbf{W}(\omega)\mathbf{A}(\omega)\mathbf{S}(\omega,\tau) = \mathbf{W}(\omega)\mathbf{X}(\omega,\tau), \tag{3}$$

where $\mathbf{X}(\omega,\tau) = \mathbf{A}(\omega)\mathbf{S}(\omega,\tau)$,

where $\mathbf{Y}(\omega,\tau)$ is the estimated signal vector, $\mathbf{W}(\omega)$ represents the separating matrix $\mathbf{X}(\omega,\tau)$ is the observed signal vector, $\mathbf{A}(\omega)$ is the mixing matrix, and $\mathbf{S}(\omega,\tau)$ is source signal vector in the frequency domain. For notational simplicity, ω or τ may be annihilated if not confused. Given $\mathbf{X}$, $\mathbf{W}$ is determined so that all elements of $\mathbf{Y}$ become mutually independent using the natural gradient approach [18] as following iterative equation:

$$\mathbf{W}_{i+1} = \mathbf{W}_i + \eta \cdot \Delta\mathbf{W}_i \tag{4}$$

where $\Delta\mathbf{W}_i = [\mathbf{I} - \langle \Phi(\mathbf{Y})\mathbf{Y}^H \rangle]\mathbf{W}_i$,

$$\Phi(\mathbf{Y}) = \tanh[re(\mathbf{Y})] + j\tanh[im(\mathbf{Y})],$$

where $\langle\cdot\rangle$ denotes the averaging operator, subscript i expresses the i-th step in iterations, and η is the step size parameter. The nonlinear function $\Phi(\mathbf{Y})$ is applied separated in the real $re(\mathbf{Y})$ and imaginary $im(\mathbf{Y})$ parts, respectively.

When the concatenation of a mixing system and a separating system is denoted as $\mathbf{G}$, i.e., $\mathbf{G} = \mathbf{W}\mathbf{A}$, each of the separated signals $Y_i(\omega,\tau)$ obtained by BSS can be described as follows:

$$Y_i(\omega,\tau) = \sum_{j=1}^{N} G_{ij}(\omega) S_j(\omega,\tau). \tag{5}$$

Let decompose $Y_i(\omega,\tau)$ into the sum of straight component $Y_i^{(s)}(\omega,\tau)$ from the signal $S_i(\omega,\tau)$ and crosstalk component $Y_i^{(c)}(\omega,\tau)$ from signals $S_j(\omega,\tau)(j \neq i)$. Then

$$Y_i(\omega,\tau) = Y_i^{(s)}(\omega,\tau) + Y_i^{(c)}(\omega,\tau), \tag{6}$$

$$Y_i^{(s)}(\omega,\tau) = \sum_i G_{ii}(\omega) S_i(\omega,\tau), \tag{7}$$

$$Y_i^{(c)}(\omega,\tau) = \sum_{j \neq i} G_{ij}(\omega) S_j(\omega,\tau). \tag{8}$$

The direct sound of the interference signals can be almost completely removed by FDICA, but the residual crosstalk components are still remained by the reverberation [19].

III. Proposed Post-Processing with Frequency Domain Wiener Filter

This chapter describes Wiener filter in the frequency domain, then proposes a post-processing of FDICA using the Wiener filtering technique. To compare the performances, the NLMS post-processing method [14] is shortly described.

There are a number of tasks in numerical processing that are routinely handled with Fourier techniques. In the frequency domain, the Wiener filter output $Y(\omega)$ is the product of the input signal $C(\omega)$, and the filter frequency response $\Phi\omega)$

$$Y(\omega) = \Phi\omega)\ C(\omega). \tag{9}$$

The estimation error signal $e(\omega)$ is defined as the difference between the desired signal $U(\omega)$ and the filter output $Y(\omega)$ as

$$e(\omega) = U(\omega) - Y(\omega) = U(\omega) - \Phi(\omega)C(\omega), \tag{10}$$

and the mean squared error at a frequency ω is given by

$$E\left[|e(\omega)|^2\right] = E\left[(U(\omega) - \Phi(\omega)C(\omega))^*(U(\omega) - \Phi(\omega)C(\omega))\right], \tag{11}$$

where E[·] is the expectation function, and the symbol * denotes the complex conjugate. To obtain the least squared error filter, set the complex derivative of equation (11) with respect to filter $\Phi(\omega)$ to zero

$$\frac{\partial E\left[|e(\omega)|^2)\right]}{\partial \Phi(\omega)} = 2\Phi(\omega)P_{YY}(\omega) - 2P_{CY}(\omega) = 0, \tag{12}$$

where $P_{YY}(\omega) = E[Y(\omega)Y^*(\omega)]$ is the power spectrum of $Y(\omega)$, and $P_{CY}(\omega) = E[C(\omega)Y^*(\omega)]$ is the cross power spectrum of $C(\omega)$ and $Y(\omega)$. From equation (12) the least mean squared error Wiener filter in the frequency domain is given as

$$\Phi(\omega) = \frac{P_{CY}(\omega)}{P_{YY}(\omega)}. \tag{13}$$

One of applications of Wiener filter is for removal of noise from a "corrupted" signal. The particular situation we consider is this: there is some underlying, target signal $c(t)$ that we want to obtain. The measured signal $y(t)$ may contain an additional component of noise $n(t)$,

$$y(t) = c(t) + n(t). \tag{14}$$

Assuming the signal and the noise are uncorrelated, it follows that the power spectrum of the noisy signal is the sum of the power spectra of the target and the noise signal, resulting in,

$$R_{YY}(\omega) = R_{CC}(\omega) + R_{NN}(\omega), \tag{15}$$

and

$$R_{CY}(\omega) = R_{CC}(\omega), \tag{16}$$

where $R_{YY}(\omega), R_{CC}(\omega)$ and $R_{NN}(\omega)$ are the power spectra of the noisy signal, the target signal and noise signals, respectively. $R_{CY}(\omega)$ denotes the cross power spectrum of the target signal and noisy signal which has the same result of the power spectrum of the target signal as (16). The corresponding Wiener filter is

$$\Phi(\omega) = \frac{P_{CY}(\omega)}{P_{YY}(\omega)} = \frac{R_{CC}(\omega)}{R_{CC}(\omega) + R_{NN}(\omega)}. \tag{17}$$

From equation (17) the following interpretation of the Wiener filter frequency response, $\Phi(\omega)$, in terms of the signal to noise ratio can be deduced. For additive noise, the Wiener filter frequency response is a real positive number in the range $0 < \Phi(\omega) < 1$. Now consider the two limiting cases of a noise-free signal, i.e., SNR=∞, and an extremely noisy signal SNR=0. At very high SNR, $\Phi(\omega) \approx 1$, and the filter applies little or no attenuation to the noise-free signal component. On the other extreme high noise case, with SNR=0, $\Phi(\omega) \approx 0$. Therefore, for additive noise, the Wiener filter attenuates each frequency component in proportional to an estimate of the signal to noise ratio.

By equation (6), the output signal of FDICA can be decomposed into the sum of the straight component and crosstalk component which are assumed to be mutually independent. In addition, it can be assumed that the straight components have stronger energy than the crosstalk components after applying FDICA, i.e., the each output signal $Y_i(\omega)$ can be assumed to be target component in itself, and the output signals of the other channels can be assumed to be interference components $Y_j(\omega), (j \neq i)$. Therefore, we propose the Wiener filtering technique in equation (17), as the post-processor of FDICA. Regarding the proposed post-processing method of FDICA, the residual crosstalk components are attenuated as proportional to the power spectral ratio of the straight components and crosstalk components spectra. The magnitude spectrum is used for obtaining the weight in the proposed method, and combined with the phase spectrum then transformed into the time domain to restore the signal.

For the signal $Y_1(\omega)$, the following weight is adopted as (18).

$$\Phi_1(\omega) = \frac{E[|Y_1(\omega)|^2]}{E[|Y_1(\omega)|^2] + E[|Y_2(\omega)|^2]}, \tag{18}$$

Symmetrically, for the other signal $Y_2(\omega)$,

$$\Phi_2(\omega) = \frac{E[|Y_2(\omega)|^2]}{E[|Y_1(\omega)|^2] + E[|Y_2(\omega)|^2]}. \tag{19}$$

Observing equation (18), if the components of $Y_1(\omega)$ are dominant and the components of $Y_2(\omega)$ are weak, the target components can be preserved with little attenuation. If the components of $Y_1(\omega)$ are weak and the components of $Y_2(\omega)$ are dominant, the residual crosstalk components are drastically attenuated by the weight in (18). Conversely, it is vise-versa concerning the other signal $Y_2(\omega)$in equation (19). It is worthy of note that the proposed post-processing is available since the speech signal is usually sparsely distributed in the spectral domain [16].

The power spectra, $E[|Y_i(\omega)|^2], (i=1,2)$, in equations (18) and (19), are estimated by a recursive first order lowpass filter as given by

$$|\hat{Y}_i(\omega)_{k+1}|^2 = p|\hat{Y}_i(\omega)_k|^2 + (1-p)|Y(\omega)_{k+1}|^2, \tag{20}$$

where $|\hat{Y}_i(\omega)|^2$ is an estimated power spectra, the k denotes a frame index, and the forgetting factor, p, controls the smoothness of the estimated power spectra. The estimated power spectrum by the lowpass filter is only used for updating weights, and then the weights are applied to each magnitude spectrum.

Fig. 1. represents the block diagram of the proposed method of 2-input 2-output BSS system. In [14], the NLMS adaptive filter is used to estimate the residual crosstalk components then spectral subtraction (SS) is applied to remove the crosstalk.

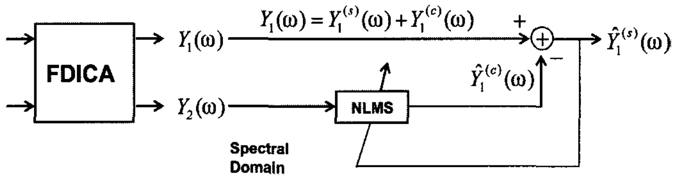

Fig. 1. Block diagram of FDICA postprocessing using Wiener filter.

Fig. 2 shows the block diagram of NLMS method in which $Y_1(\omega)$ is assumed as a target signal. This method is similar to the study of BSS+GSC (generalized sidelobe canceller) algorithm [20], but the ideas are different and independently progressed.

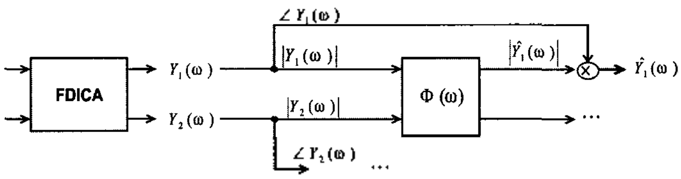

Fig. 2. Postprocessing with NLMS adaptive filter and spectral subtraction to for estimating $Y_1^{(s)}(f)$.

Accordingly, for the narrow band signal in each frequency bin, the crosstalk components in $Y_i(\omega)$ can be approximated by the output of the filter whose input is the straight components of the signal $Y_j(\omega)$.

The Wiener filtering technique can be considered as a subset of the LMS class algorithm, however, two post-processing algorithms are apparently different. While the NLMS post-processing is based on an adaptive updating algorithm, the proposed Wiener filtering technique is based on the weighting method by the ratio of the power spectrum of the target-interference components.

IV. Computer Simulations

4.1. Simulation conditions

To examine the performances of the proposed method, the separation was performed by the Amari's FDICA algorithm [18]. Six sentences spoken by three males and three females were used as source signals. Each speech signal is recorded with an 8 second length at a 16 kHz sampling rate. The frame length for a short time DFT is 1,024-tap as recommended in [12], the frame shift is 64 tap, the window function is a Hamming window, the number of epochs in FDICA is 30, and the step-size is set to be 1×10^{-4}, as had the best separation performance in our experiment. For NLMS post-processing, the filter length of NLMS was set as a 16-tap. The smoothing coefficient p in (20) is 0.998.

The energy decay curve $r(t)$ of an impulse response $h(t)$ is defined as follows:

$$r^2(t) = \int_t^{\infty} h^2(t)dt. \tag{21}$$

The reverberation time T_R is defined as the time for an energy attenuation of -60dB.

The target component is assumed as a signal, and the difference between the output signal and target signal as a noise. The signal-to-interference ratio (SIR) in the time domain is defined as follows:

$$SIR = 10\log\frac{\sum_t |y_{ii}(t)|^2}{\sum_t \left|\left(\sum_{i\neq j} y_{ij}(t)\right)\right|^2} - 10\log\frac{\sum_t |x_{ii}(t)|^2}{\sum_t \left|\left(\sum_{i\neq j} x_{ij}(t)\right)\right|^2}(dB) \tag{22}$$

The averaged SIR of two channels is used as a performance evaluation of BSS in which the crosstalk components are assumed as noise.

To examine the effectiveness of the proposed method, two dry speech signals are convolved with impulse responses measured in a room. The layout of a room used to measure the speeches is shown in Fig. 3. Two reverberant times ($R_T = 512-\text{tap} \approx 128\,\text{msec}$ and $R_T = 1{,}024-\text{tap} \approx 256\,\text{msec}$) of impulse responses are used in experiment. For each reverberant time, we measured SIR's with nine combinations among the source signals. This experiment is made for noiseless condition.

Next, to be realistic condition, speech signals are recorded in the same room. We used "RT Pro Dynamic Signal Analysis" as a recording system made by "Co. Dactron". To be proper tuning for the loudness of speech, the recording system is set as 0.3V maximum range. We measured SIR's with twelve combinations among the source signals.

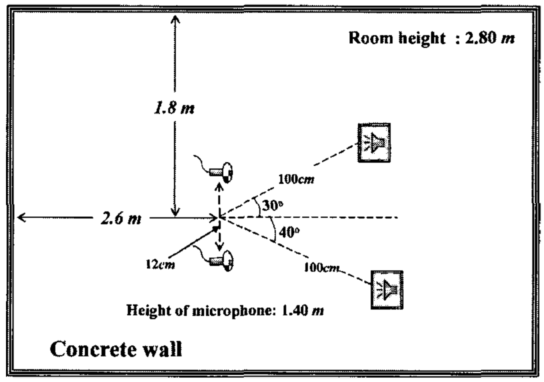

Fig. 3. Layout of a room used in experiments.

4.2. Simulation results

The results of SIR evaluation for 512-tap reverberant time are shown in Fig. 4. Both methods achieve a superior performance to conventional FDICA by about 3~4 dB. The average SIR of the proposed method is slightly improved by about1~2dB compared to the output of FDICA. Fig. 5 shows results of SIR evaluation in 1,024-tap. Similarly, the proposed one has slightly higher gain about 1~2 dB to NLMS method.

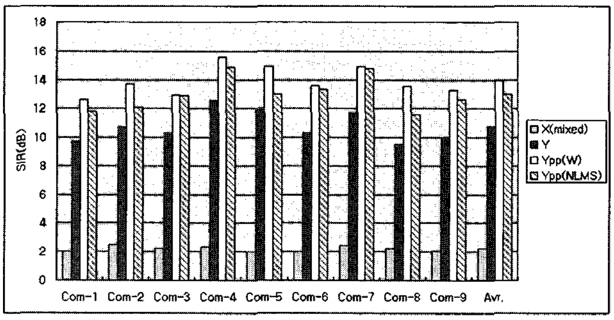

Fig. 4. Comparison of SIR for FDICA and two postprocessing methods.($R_T = 128m\text{sec}$)
X : observed signal,
Y : conventional FDICA, Ypp(W) : proposed method,
Ypp(NLMS) : NLMS post-processing.

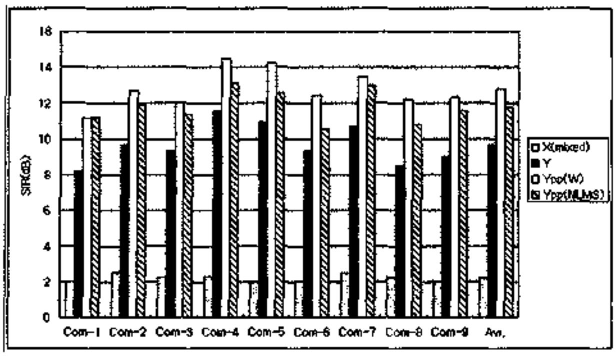

Fig. 5. Comparison of SIR for ICA and two postprocessing methods. ($R_T = 256msec$)
X : observed signal,
Y : conventional FDICA, Ypp(W) : proposed method,
Ypp(NLMS) : NLMS post-processing.

Next, the experiments are performed with speech signals recorded in a real environment. Before viewing the results of SIR evaluation, let investigate one example of narrow power spectrum of input and output signals of the proposed post-processor. Fig. 6 (a) and (b) shows two input signals, Fig. 6 (c) and (d) are the output signals of the post-processor. The circles in the Fig. show the reduction of the interference components to each other. The components, which are assumed as the part of target signal, are alive, while the components, which are assumed as interference signal, are attenuated.

The results of SIR comparison are shown in Fig. 7. The separation performances are degraded than those of experiments with artificially convolved signals without noise, since the

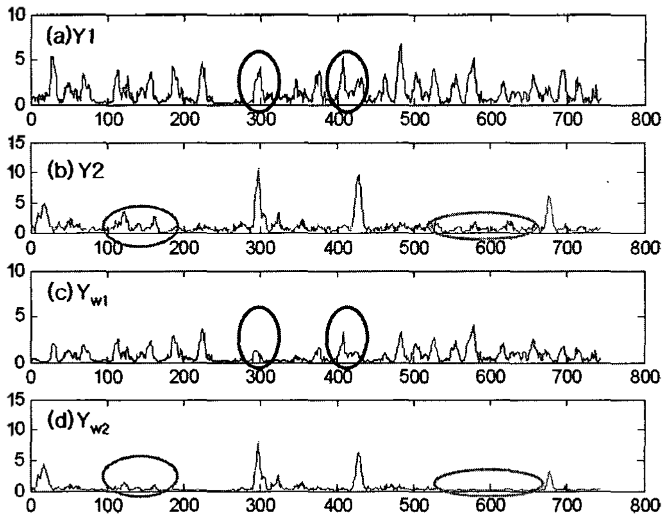

Fig. 6. Example of output signal power spectra of FDICA and the proposed method respectively (144-th bin among 1,024 frequency bins), where the circles mean the reduction of the cross-talk components from (a)/(b) to (c)/(d).
(a) output 1 of FDICA (b) output 2 of FDICA (c) output 1 of Wiener filter (d) output 2 of Wiener filter.

experiments with real-recorded signals are performed in noisy condition. The SIR of the proposed method is improved by about 3~4dB compared to the output of FDICA. The proposed Wiener method have an improvement in SIR about 1~2dB compared to NLMS post-processing.

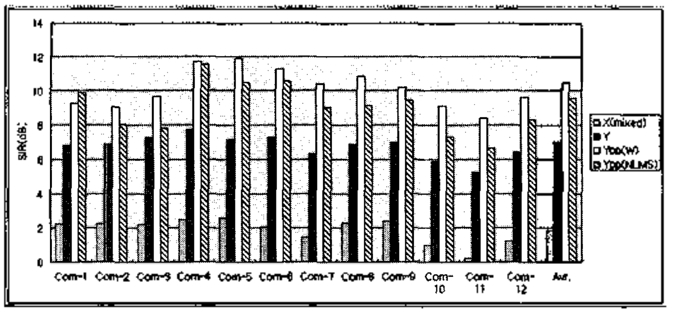

Fig. 7. Comparison of SIR with real recorded signals.
X : observed signal,
Y : conventional FDICA, Ypp(W) : proposed method,
Ypp(NLMS) : NLMS post-processing.

We also compare the complexity of calculations between the NLMS post-processing method and the proposed method. Table 1 represents the results of complexity of multiplications and additions at each iteration. While the quantities of addition operations are invariant, the proposed method has much less burdensome in multiplication operations. In our experiment, L=16, so that the proposed method achieves a drastic reduction of multiplications.

Table 1. Comparison of calculation complexity.
L : filter length of NLMS

	Multiplication	Addition
NLMS	3L+2	2
Wiener Filter	4	2

V. Conclusion

In this paper, the frequency domain ICA of convolved mixtures is examined, and proposed a post-processing method using Wiener filtering technique. The proposed post-processing method reduces the residual crosstalk components of the output of FDICA. In the time-frequency domain, the speech has the sparse characteristics so it is possible to improve the independency of the output of the FDICA by the proposed method. The results of experiments showed that the proposed method can slightly improve the separation performance compared to the NLMS post-processing even with much less calculation burden.

References

1. T.W.Lee, A.J.Bell and, R.Orglmeister, "Blind source separation of real world signals," Neural Networks, International Conference on **4**, 2129-2134, 1997.
2. S. Makeig, T. Jung, A.J. Bell, D. Ggahremani and, T. J. Seijnowski, "Blind separation of auditory event-related brain response into independent components," Proceedings on National Academic Science. USA, 10979-10984, 1997.
3. T. Ristaniemi and, J. Joutsensalo, "On the performance of blind source separation in CDMA downlink," Proc. Int. Workshop on Independent Analysis and Signal Separation (ICA ' 99), 437-441, Aussois, France, 1999.
4. A. Hyvarinen, J. Karhnen, and E. Oja, Independent Component Analysis, John Wiley & Sons, 2001.
5. K. Zhang, L. Chan, "Dimension reduction as a deflation method in ICA," IEEE Signal proc. Letters, **13** (1) 2006.
6. Q. Lv and X. Zhang, "A unified method for blind separation of sparse sources with unknown source number," IEEE Signal proc. Letters, **13** (1) 2006.
7. J. F. Cordoso, "Blind source separation: statistical principles," Proc. IEEE, **9** 2009-2025, 1998.
8. A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," Neural Computation, **7** (6) 1129-1159, 1995.
9. T. W. Lee, M. Girolami, A. J. Bell, and T. J. Sejonwski, "A unifying information-theoretic framework for independent component analysis," Computers and Mathematics with Applications, **31** (11) 1-12, 2000.
10. P. Smaragdis, "Blind separation of convolved mixtures in the frequency domain," Nerucomputing, **22** 21-34, 1998.
11. I. Jang, K. Kang, S. Kim and S. Choi, "F-SEONS: A second-order frequency-domain algorithm for noisy convolutive source separation," Proc. IEEE Int' l Symposium on Circuit and Systems (ISCAS), 3595-3598, Kobe, Japan, 23-26, 2005.
12. S. Araki, S. Makino, T. Nishikawa and H. and Saruwatari, "Fundamental limitation of frequency domain blind separation for convolutive of speech," Proc. ICASSP 2001, 2737-2740, 2001.
13. R. Mukai, S. Araki, H. Sawada and S. Makino, "Removal of residual crosstalk components in blind source separation using time-delayed spectral subtraction," Proc. ICASSP 2002, 1789-1792, 2002.
14. R. Mukai, S. Araki, H. Sawada and S. Makino, "Removal of residual crosstalk components in blind source separation using LMS filters," Proc. NNSP 2002, 435-444, 2002.
15. S.Y. Low, S.Nordholm, and R. Togneri, "Convolutive blind signal separation with post-processing," IEEE Trans. On speech and audio processing, **12** (5) 2004.
16. S. Araki, S. Makino, H. Sawada and R. Mukai, "Underdetermined blind separation of convolutive mixtures of speech with directivity pattern based mask and ICA," Proc. ICA 2004 (Fifth International Conference on Independent Component Analysis and Blind Signal Separation), 898-905, 2004.
17. S. Haykin, Adaptive Filter Theory, Chap. 2, Third Edition, Prentice Hall Inc., NJ 1996.
18. S. I. Amari, A. Cichocki and H. H. Yang, "A new learning algorithm for blind signal separation," Advances in neural information Processing systems 8. MIT Press, Cambridge, MA.
19. R. Mukai, S. Araki, and S. Makino, "Separation and dereverberation performance of frequency domain blind source separation," Proc. ICA 2001, (Second International Conference on Independent Component Analysis and Blind Signal Separation), 230-235, 2001.
20. C. Fancourt, and L. Parra, "The generalized sidelobe decorrelator," IEEE Workshop on the Applications of Signal Processing to Audio and Acoustics, 167-170, 21-24 2001.

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