Analysis of Signal Separation and Signal Distortion in Feedforward and Feedback Blind Source Separation Based on Source Spectra

フィードフォワード形およびフィードバック形ブラインド信号源分離における信号分離および信号歪の解析

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あらまし　ブラインド信号源分離では (BSS) は出力を独立にするように学習が行なわれる．したがって，信号歪みが生じる可能性がある．フィードフォワード形ブラインド信号源分離 (FF-BSS) は分離回路における自由度が高く，出力信号を互いに独立にする学習が信号歪みを生じる可能性がある．信号を無歪みで出力するためにはなんらかの制約が必要になる．そこで信号歪みの基準を観測信号と考え，完全分離の条件と無歪の条件から導かれた制約を学習の際に加味する信号歪み抑制学習法をこれまでに提案している [11]．これにより信号源を s_i，観測信号を x_i，出力信号を y_i とするとき，信号を分離するとともに y_i を x_i における s_i 成分のみに近づけることができる．一方，フィードバック形ブラインド信号源分離 (FB-BSS) は信号分離と信号歪み抑制を同時に満たす．本稿では信号歪み抑制学習法を他の方式とさまざまな信号を使って比較することによりその特性を解析する．

キーワード　ブラインド信号源分離　信号歪み　フィードフォワード　収束性　信号歪み抑制

Analysis of Signal Separation and Signal Distortion in Feedforward and Feedback Blind Source Separation Based on Source Spectra

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Abstract　Source separation and signal distortion in three kinds of blind soure separation (BSS) systems with convolutive mixture are analyzed. They consist of two feedforward BSS system, one trained in the time domain and the other trained in the frequency domain, and a feedback BSS system, trained in the time domain. An evaluation measure of the signal distortion has been investigated and conditions for source separation and distortion free have been derived. Based on these conditions, source separation and signal distortion have been analyzed. The feedforward BSS systems have some degree of freedom and the output spectrum can be changed. The feedforward BSS system, trained in the frequency domain, has a weighting effect, which can suppress signal distortion. However, this weighting effect is only effective only when the source spectra are similar to each other. Since, the feedforward BSS system, trained in the time domain, does not have any constraints on signal distortion free, its output signals can be easily distorted. A new learning algorithm with a distortion free constraint has been proposed. On the other hand, the feedback BSS system can satisfy both source separation and distortion free conditions simultaneously. Performed simulation results support our theoretical analysis.

Key words　Blind source separation, Signal distortion, Feedforward, Convergence property, Controlling signal distortion

1. Introduction

Since, in many applications mixing processes are convolutive mixtures, several methods in the time domain and the frequency domain have been proposed. Two kinds of network structures have been proposed, i.e. that is feedforward (FF) and feedback (FB) structures. Separation performance is highly dependent on the signal sources and the transfer functions in the mixture [7], [9].

BSS learning algorithms make the output signals to be statistically independent. This direction cannot always guarantee distortion free separation. Some signal distortion may be caused. A regularization method has been proposed, in which the distance between the observed signals and the separated signals is added to the cost function [4]. However, since the observations include many kinds of signal sources, it is difficult to suppress signal distortion. Furthermore, even though signal distortion in the BSS systems is an important problem, it has not been addressed well up to now [10].

Therefore, we have discussed an evaluation measure of signal distortion and derived conditions for source separation and signal distortion free. Based on these conditions, convergence properties have been analyzed. Furthermore, new learning algorithm for the FF-BSS system, trained in the time domain, has been proposed.

In this paper, we analyze the performance of the new learning algorithm by some computer simulations. Simulation results support our theoretical analysis.

2. FF-BSS system for Convolutive Mixture

2.1 Network Structure and Equations

For simplicity, 2 signal sources and 2 sensors are used. A block diagram is shown in Fig.1. The observations and the

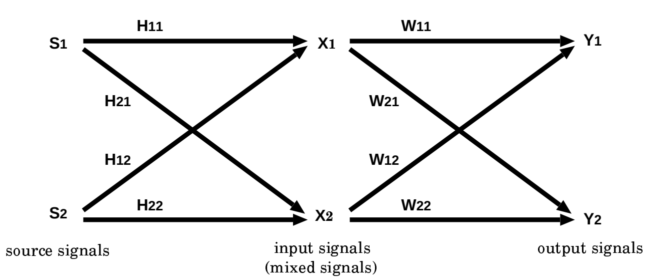

図 1 FF-BSS system with 2 signal sources and 2 sensors.

output signals are given by:

$$x_j(n) = \sum_{i=1}^{2}\sum_{l=0}^{K_h-1} h_{ji}(l)s_i(n-l), j=1,2 \tag{1}$$

$$y_k(n) = \sum_{j=1}^{2}\sum_{l=0}^{K_w-1} w_{kj}(l)x_j(n-l), k=1,2 \tag{2}$$

2.2 Learning Algorithm in Time Domain

The learning algorithm is derived following the natural gradient algorithm using the mutual information as a cost function [3].

$$w_{kj}(n+1,l) = w_{kj}(n,l) + \eta\{w_{kj}(n,l) - \sum_{p=1}^{2}\sum_{q=0}^{K_w-1} \varphi(y_k(n))y_p(n-l+q)w_{pj}(n,q)\} \tag{3}$$

$$\varphi(y_k(n)) = \frac{1-e^{-y_k(n)}}{1+e^{-y_k(n)}} \tag{4}$$

η is the learning rate.

2.3 Learning Algorithm in Frequency Domain

Filter coefficients in the separation block are trained according [3], [5], [6], [8]

$$\begin{aligned}\boldsymbol{W}(r+1,m) &= \boldsymbol{W}(r,m) + \eta[diag(\langle\Phi(\boldsymbol{Y}(r,m))\boldsymbol{Y}^H(r,m)\rangle \\ &\quad -\langle\Phi(\boldsymbol{Y}(r,m))\boldsymbol{Y}^H(r,m)\rangle]\boldsymbol{W}(r,m)\end{aligned} \tag{5}$$

$$\Phi(\boldsymbol{Y}(r,m)) = \frac{1}{1+e^{-\boldsymbol{Y}^R(r,m)}} + \frac{j}{1+e^{-\boldsymbol{Y}^I(r,m)}} \tag{6}$$

r is the block number used in FFT, and m indicates the frequency point in each block. $<>$ is an averaging operation. $\boldsymbol{W}(r,m)$ is a weight matrix of the r-th block FFT and the m-th frequency point. Its (k,j) element is $W_{kj}(r,m)$, which is the connection from the j-th observation to the k-th output. $\boldsymbol{Y}(r,m)$ is the output vector of the r-th block FFT and the m-th frequency point. Its k-th element is $Y_k(r,m)$, which is the k-th output. $\boldsymbol{Y}^R(r,m)$ and $\boldsymbol{Y}^I(r,m)$ indicate the real part and the imaginary part.

3. FB-BSS System for Convolutive Mixture

3.1 Network Structure and Equations

Figure 2 shows an FB-BSS system proposed by Jutten et all [1]. The mixing stage has a convolutive structure. C_{ij} consists of an FIR filter.

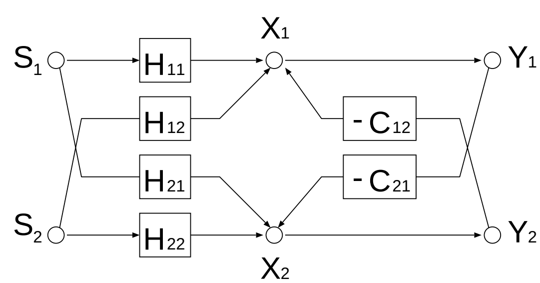

図 2 FB-BSS system with 2 signal sources and 2 sensors.

The observations and the output signals are expressed as follows:

$$x_j(n) = \sum_{i=1}^{N}\sum_{m=0}^{M_{ji}-1} h_{ji}(m)s_i(n-m) \tag{7}$$

$$y_k(n) = x_k(n) - \sum_{\substack{k=1\\ \neq j}}^{N}\sum_{l=0}^{L_{jk}-1} c_{jk}(l)y_k(n-l) \tag{8}$$

3.2 Learning Algorithm

In the FB-BSS system, the learning algorithm in the time domain is used [2]. The following learning algorithm has been derived by assuming several conditions [7], [9]. The signal sources $S_1(z)$ and $S_2(z)$ are located close to the sensors of $X_1(z)$ and $X_2(z)$, respectively. Therefore, the time delays of $H_{ji}(z), i \neq j$ are slightly longer than those of $H_{ii}(z)$. Furthermore, the amplitude responses of $H_{ji}(z), i \neq j$ are smaller than those of $H_{ii}(z)$. These conditions are practically acceptable.

$$\begin{aligned} c_{jk}(n+1,l) &= c_{jk}(n,l) \\ &+ \eta f(y_j(n))g(y_k(n-l)) \end{aligned} \tag{9}$$

$f(y_j(n))$ and $g(y_k(n-l))$ are odd functions.

4. Criterion of Signal Distortion

In this paper, the signal distortion is evaluated as a distance from the observed signal sources [2], [10], [11]. However, in this case, several criteria can be taken into consideration. The signal sources included in the observations $x_j(n)$ are given by $H_{ii}(z)S_i(z)$ and $H_{ji}(z)S_i(z), i \neq j$. Here, the following measures are considered.

$$\begin{aligned} \sigma_{d1a} &= \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega})S_i(e^{j\omega}) \\ &- Y_k(e^{j\omega})|^2 d\omega \end{aligned} \tag{10}$$

$$\begin{aligned} \sigma_{d1b} &= \frac{1}{2\pi}\int_{-\pi}^{\pi} (|H_{ji}(e^{j\omega})S_i(e^{j\omega})| \\ &- |Y_k(e^{j\omega})|)^2 d\omega \end{aligned} \tag{11}$$

$$\sigma_1 = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega})S_i(e^{j\omega})|^2 d\omega \tag{12}$$

$$SD_{1x} = 10\log_{10}\frac{\sigma_{d1x}}{\sigma_1}, x=a,b \tag{13}$$

$$\sigma_{d2a} = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega}) - A_{ki}(e^{j\omega})|^2 d\omega \tag{14}$$

$$\sigma_{d2b} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|H_{ji}(e^{j\omega})| - |A_{ki}(e^{j\omega})|)^2 d\omega \tag{15}$$

$$\sigma_2 = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega})|^2 d\omega \tag{16}$$

$$SD_{2x} = 10\log_{10}\frac{\sigma_{d2x}}{\sigma_2}, x=a,b \tag{17}$$

5. Source Separation and Signal Distortion in FF-BSS System

5.1 Learning in Frequency Domain

For simplicity, a FF-BSS system with 2-sources and 2-sensors, shown in Fig.1, is used. Furthermore, $S_i(z)$ is assumed to be separated at the output $Y_i(z)$. This does not lose generality. Taking the signal distortion criterion into account, the condition on distortion-free source separation can be expressed as follows:

$$W_{11}(z)H_{11}(z) + W_{12}(z)H_{21}(z) = H_{11}(z) \tag{18}$$

$$W_{11}(z)H_{12}(z) + W_{12}(z)H_{22}(z) = 0 \tag{19}$$

$$W_{21}(z)H_{11}(z) + W_{22}(z)H_{21}(z) = 0 \tag{20}$$

$$W_{21}(z)H_{12}(z) + W_{22}(z)H_{22}(z) = H_{22}(z) \tag{21}$$

The above equations imply two conditions. First, complete source separation, that is the non-diagonal elements are all zero, as shown in Eqs.(19) and (20). Secondly, signal distortion free, that is the diagonal elements are $H_{ii}(z)$ as shown in Eqs.(18) and (21). These equations are further investgated.

From the relations of Eqs.(19) and (20), $H_{ji}(z)$ are expressed as follows:

$$H_{12}(z) = -\frac{W_{12}(z)}{W_{11}(z)}H_{22}(z) \tag{22}$$

$$H_{21}(z) = -\frac{W_{21}(z)}{W_{22}(z)}H_{11}(z) \tag{23}$$

By substituting the above equations into the relations of Eqs.(18) and (21), $H_{ji}(z)$ can be removed, and the following equations consisting only of $W_{kj}(z)$ can be obtained.

$$W_{11}(z)W_{22}(z) - W_{12}(z)W_{21}(z) = W_{22}(z) \tag{24}$$

$$W_{11}(z)W_{22}(z) - W_{12}(z)W_{21}(z) = W_{11}(z) \tag{25}$$

From these equations, $W_{11}(z) = W_{22}(z)$ is derived. Therefore, the above equations result in

$$\begin{aligned} &W_{jj}^2(z) - W_{jj}(z) - W_{jk}(z)W_{kj}(z) = 0 \\ &j=1,2, k=1,2, j \neq k \end{aligned} \tag{26}$$

This 2nd-order equation expresses the condition on complete source separation without signal distortion. This constraint can be included in the learning processes of the FF-BSS system in the time domain as well as in the frequency domain.

5.2 Learning Algorithm with Constraint in Time Domain

The conventional learning algorithm given by Eqs.(3),(4) does not satisfy the condition given by Eq.(26). Usually, only Eqs.(19) and (20) are approximately satisfied. Equations (18) and (21) are not guaranteed. Therefore, in general, signal distortion cannot be suppressed.

The constraint given by Eq.(26) is taken into account in the learning process. This constraint is used in the learning process as follows: Given $W_{12}(z)$ and $W_{21}(z)$, the coefficients of $W_{jj}(z)$ are obtained so as to approximate the relation of Eq.(26).

The condition for the distortion free source separation is derived based on the complete separation and signal distortion free. However, the learning of the separation block starts from an initial guess. Therefore, in the early stage of the learning process, the signal sources are not well separated. Taking these situations into account, the constraint of Eq.(26) is gradually imposed as the learning process makes progress. The following learning algorithm has been proposed.

$$\begin{aligned} &w_{kj}(n+1,l) = w_{kj}(n) + \eta\{w_{kj}(n) \\ &- \sum_{o=0}^{K_w-1}\sum_{p=1}^{2}\phi(y_k(n))y_p(n-o+p)w_{kp}(n,o)\} \end{aligned} \tag{27}$$

$$\begin{aligned} &w_{jj}(n+1,l) = (1-\alpha)w_{jj}(n+1,l) \\ &\qquad +\alpha\tilde{w}_{jj}(n+1) \end{aligned} \tag{28}$$

$\tilde{w}_{jj}(n+1)$ is determined so as to approximate the relation of Eq.(26). α is usually set to a small positive number.

5.3 Conventional Learning Algorithm for Reducing Distortion in Time Domain

A learning algorithm for reducing distortion has been proposed. The distance between the observed signals and the separated signals is added to the cost function [4].

$$\boldsymbol{y}(n+1,l) = \boldsymbol{y}(n,l) - \alpha \sum_{m=0}^{K_w-1} [diag(\langle \Phi(\boldsymbol{y}(n))\boldsymbol{y}^T(n-l+m)\rangle - \langle \Phi(\boldsymbol{y}(n))\boldsymbol{y}^T(n-l+m)\rangle + \beta(\boldsymbol{y}(n)-\boldsymbol{x}(n))\boldsymbol{y}^T(n-l+m)]\boldsymbol{w}(n,l) \quad (29)$$

$$\varphi(\boldsymbol{y}(n)) = \frac{1-e^{-\boldsymbol{y}(n)}}{1+e^{-\boldsymbol{y}(n)}} \quad (30)$$

This algorithm is effective if the spectra of sources are similar to each other, because the spectra of observed signals are similar to the criteria. However, if the spectra of sources are not similar to each other such as in music, it can be expected that this method is not effective.

5.4 Signal Distortion in FF-BSS System Trained in Frequency Domain

In the frequency domain, there is some weighting effect. From Eq.(5), the correction of the weights is highly dependent on $\boldsymbol{Y}$, that is the frequency response of the outputs. If the initial guess of $\boldsymbol{W}(r,m)$ is set to the identity matrix, that is $\boldsymbol{W}(0,m) = \boldsymbol{I}$, then $\boldsymbol{Y}(0,m) = \boldsymbol{X}(0,m)$, where $\boldsymbol{X}(r,m) = \boldsymbol{HS}(r,m)$. Therefore, the correction of $\boldsymbol{W}(r,m)$ is proportional to $\boldsymbol{HS}(r,m)$. If the signal sources are all speech, their spectra are similar to each other. In this case, the spectra of X_i, which are composite signals of the signal sources, are also similar to those of speech. This means the correction of $\boldsymbol{W}(r,m)$ is weighted by the spectra of the observed signal sources. Furthermore, as the learning makes progress the weighting effects still maintain, because Y_k, which is modified through the mixing and separation processes gradually approaches to the S_i. As discussed in Sec.4., the signal distortion is evaluated based on the distance from $H_{ji}S_i$. Therefore, when the signal source spectra are similar to each other, the above weighting can suppress signal distortion. If the signal sources exist in different frequency, e.g. as is in music, their spectra are not similar and it can be expected that masking will cause signal distortion.

6. Source Separation and Signal Distortion in FB-BSS System

There are two cases, in which possible solutions for perfect separation exist, as shown below:

$$(1)\quad C_{21}(z) = \frac{H_{21}(z)}{H_{11}(z)} \qquad C_{12}(z) = \frac{H_{12}(z)}{H_{22}(z)} \quad (31)$$

$$(2)\quad C_{21}(z) = \frac{H_{22}(z)}{H_{12}(z)} \qquad C_{12}(z) = \frac{H_{11}(z)}{H_{21}(z)} \quad (32)$$

It is assumed that the delay times of $H_{11}(z)$ and $H_{22}(z)$ are shorter than that of $H_{21}(z)$ and $H_{12}(z)$. This means that in Fig.2, the sensor of X_1 is located close to S_1, and the sensor of X_2 close to S_2. From this assumption, the solutions in case (1) become causal systems. On the other hand, the solutions in case (2) are noncausal.

When $C_{ij}(z)$ satisfy the separation conditions Eqs.(31), the output signals can be given by:

$$Y_1(z) = H_{11}(z)S_1(z) \qquad Y_2(z) = H_{22}(z)S_2(z) \quad (33)$$

They are exactly the same as the criteria of the signal distortion discussed in Sec.4. Therefore, the FB-BSS system has a unique solution, which satisfies both source separation as well as the signal distortion free simultaneously. Thus, in the FB-BSS system, if complete signal separation is achieved, signal distortion free is also automatically satisfied.

7. Simulation and Discussion

7.1 Simulation Conditions

The transfer functions of the cross paths are related to the direct paths as $H_{jk}(z) = 0.9z^{-1}H_{kk}(z)$.Speeches and colored signals, created by 2nd-order AR models, are used as sources. FFT size is 256 points in the frequency domain training. FIR filters with 256 taps are used in the FF-BSS system, trained in the time domain and in the FB-BSS system. The initial guess of the separation block are $W_{11}(z) = W_{22}(z) = 1$ and $W_{ij}(z) = 0, i \neq j$, in the FF-BSS system, and $C_{12}(z) = C_{21}(z) = 1$ in the FB-BSS system.

Source separation is evaluated by the following two signal-to-interference ratios SIR_1 and SIR_2. $A_{ki}(z)$ is a transfer function from the i-th source to the k-th output. In this case, $S_1(z)$ and $S_2(z)$ are assumed to be separated in $Y_1(z)$ and $Y_2(z)$, respectively. However, it does not lose generarity.

$$\sigma_{s1} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|A_{11}(e^{j\omega})|^2 + |A_{22}(e^{j\omega})|^2)d\omega \quad (34)$$

$$\sigma_{i1} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|A_{12}(e^{j\omega})|^2 + |A_{21}(e^{j\omega})|^2)d\omega \quad (35)$$

$$SIR_1 = 10\log_{10}\frac{\sigma_{s1}}{\sigma_{i1}} \quad (36)$$

$$\sigma_{s2} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|A_{11}(e^{j\omega})S_1(e^{j\omega})|^2 + |A_{22}(e^{j\omega})S_2(e^{j\omega})|^2)d\omega \quad (37)$$

$$\sigma_{i2} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|A_{12}(e^{j\omega})S_2(e^{j\omega})|^2 + |A_{21}(e^{j\omega})S_1(e^{j\omega})|^2)d\omega \quad (38)$$

$$SIR_2 = 10\log_{10}\frac{\sigma_{s2}}{\sigma_{i2}} \quad (39)$$

7.2 Speech Signals

7.2.1 Source Separation and Signal Distortion

Evaluation measures are summarized in Table 1. Regarding SIR_1 and SIR_2, the FB-BSS system was the best performance. The signal distortion in the FF-BSS system in time can be drastically improved by applying the distortion constraint free. Also with respect to the evaluation of the signal distortion, the FB-BSS system has the best performance.

表 1 Comparison of five different BSS systems for speech signals. FF-BSS time(1), time(2) and freq. are trained following Eqs.(3)-(4), Eqs.(27)-(28) and Eqs.(5)-(6), respectively.

Methods	SIR_1	SIR_2	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS time(1)	5.56	12.2	0.34	-2.70	0.57	-3.82
FF-BSS time(2)	4.33	8.29	-7.05	-10.4	-15.4	-19.9
FF-BSS time with [4]	6.38	10.9	-10.3	-13.8	-14.5	-16.9
FF-BSS freq.	4.87	7.02	-3.15	-8.22	-9.20	-11.3
FB-BSS	9.24	14.1	-11.3	-14.6	-14.7	-17.3

7.2.2 Signal Spectra

The criteria for the signal distortion, that is the amplitude response of $H_{11}(z)S_1(z)$ and $H_{22}(z)S_2(z)$ are shown in Fig.3.

The spectra of the output signals are shown in Figs.4, 5, 6, 7 and 8.

In the FF-BSS system, trained in the time domain, the spectra are not similar to the criteria shown in Fig.3. Since, the FF-BSS system has a degree of freedom, the output spectra can be changed in a way to make the output signals to be more statistically independent. On the other hand, as shown in Fig.5 and 6, the spectra of the FF-BSS system, trained with the distortion free constraint, and that of the FF-BSS system using [4] are drastically improved compared to the previous one, and are similar to the criteria.

The results of the FF-BSS system, trained in the frequency domain, and FB-BSS support the discussion of Sec.5. 4 and 6., respectively.

7. 3 Colored Signals with Different Frequency Bands

表 2 Comparison of four different BSS systems for colored signals.

Methods	SIR_1	SIR_2	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS time(1)	7.07	9.49	-0.08	-2.76	-0.69	-4.99
FF-BSS time(2)	4.07	8.05	-7.54	-10.1	-10.4	-13.2
FF-BSS time with [4]	2.20	4.49	-5.43	-7.80	-13.7	-16.5
FF-BSS freq.	2.62	5.12	-6.28	-8.74	-8.23	-10.1
FB-BSS	7.19	16.5	-12.4	-15.0	-10.4	-13.6

As discussed in Sec.5. 4, there exist a weighting effect in the FF-BSS system trained in the frequency domain. This weighting effect suppresses the signal distortion when the spectra of the sources are similar to each other, and as a result, the spectra of the observed signals are also similar to those of the souces. However, it can be expected that the weighting effect is not effective and signal distortion will occur for the sources, which have a different envelop of the spectrum. In order to confirm this point, another result is shown. Figs.9 and 10 show the spectra of the observed signals and the spectra of $H_{ii}(z)S_i(z)$, respectively. They are not similar to each other, because the frequency bands, where the spectra are dominant, are different.

The spectra of the output signals are shown in Figs.11, 12, 14 and 15. The outputs of the FF-BSS system trained in the frequency domain are not similar to the criteria (Fig.10), but are similar to the observed signals. This result supports our theoretical analysis. The FF-BSS system using [4] has good evaluations of signal distortion, but bad separation performances. It can be expected that this is caused by the weighting effect. Since $Y_i(z)$ becomes similar to $X_i(z)$, $A_{ii}(z)$ becomes similar to $H_{ii}(z)$. $S_j(z)$ in $X_i(z)$ $(i \neq j)$ remain in $Y_i(z)$ at the same time. Therefore the FF-BSS system using [4] has not good separation performances. The other methods obtained similar results as in the simulations for speech signals.

8. Conclusions

In this paper, source separation and signal distortion in the FF-BSS system and the FB-BSS system have been analyzed. A new distortion free constraint has been proposed for the FF-BSS system trained in the time domain. The FF-BSS, trained in the frequency domain, having the weighting effect, which can suppress signal distortion when the spectra of the sources are similar to each other. However, if the spectra

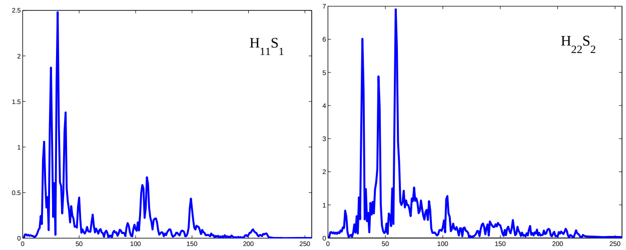

図 3 Spectrum of $H_{11}(z)S_1(z)$ and $H_{22}(z)S_2(z)$ for speech signals.

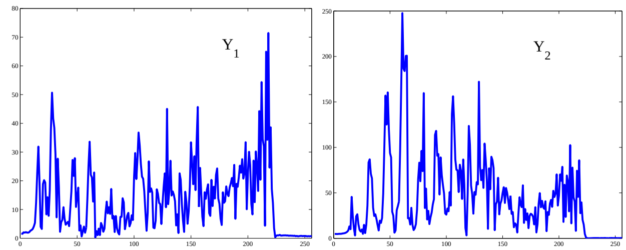

図 4 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in time domain for speech signals

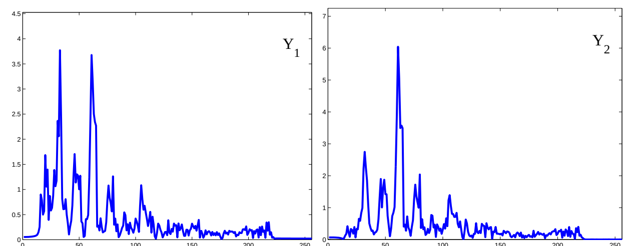

図 5 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in time domain with constraints for speech signals.

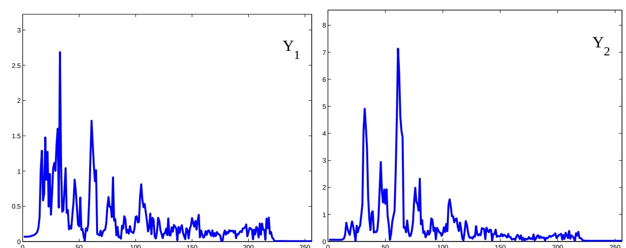

図 6 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in [4] for speech signals.

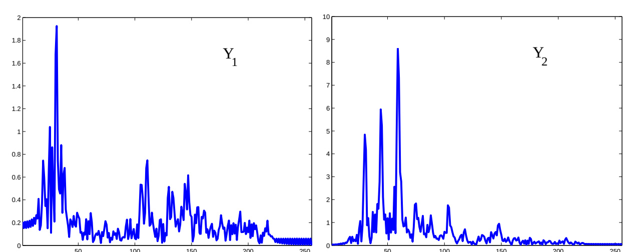

図 7 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in frequency domain for speech signals.

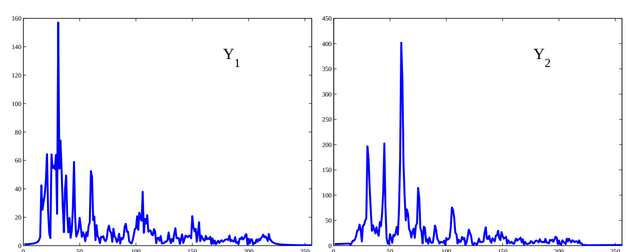

図 8 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FB-BSS system trained in time domain for speech signals.

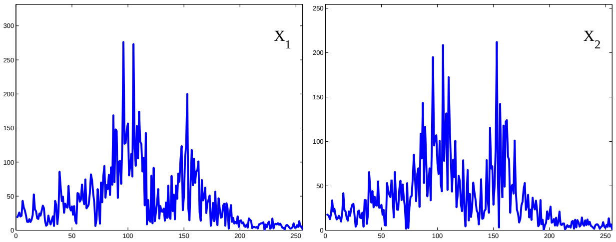

図 9 Spectrum of observed signals for colored signals.

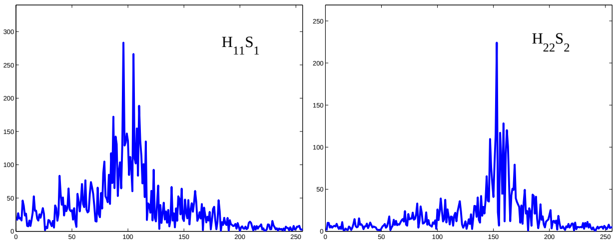

図 10 Spectrum of $H_{11}(z)S_1(z)$ and $H_{22}(z)S_2(z)$ for colored signals.

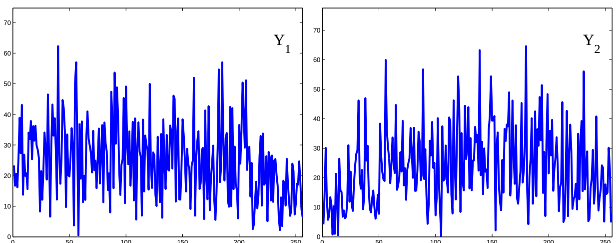

図 11 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in time domain for colored signals.

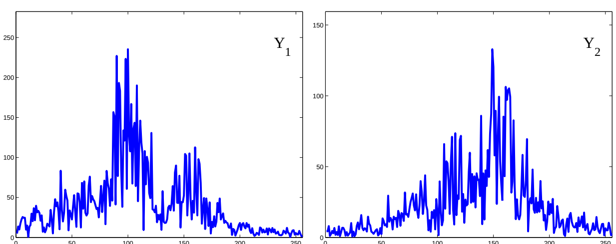

図 12 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in time domain for colored signals.

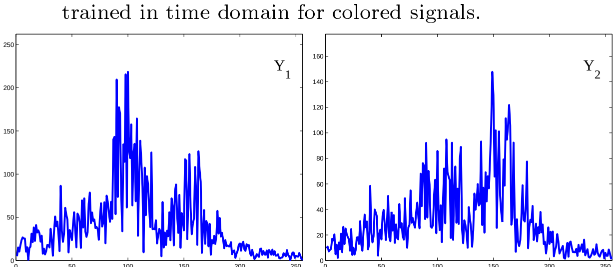

図 13 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in [4] for colored signals.

of the sources differ from each other, the weighting effect is not effective, and signal distortion occurs. Forthermore the FF-BSS system using [4] doesn't get good separation performances because of the weighting effect. The FB-BSS system, trained in the time domain, has a unique solution, which satisfies both the source separation as well as the distortion free conditions simultaneously. The simulation results support our theoretical analysis.

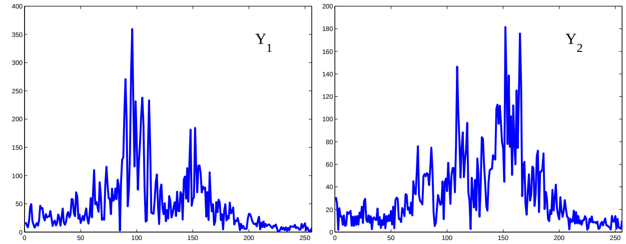

図 14 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS trained in frequency domain with constraints for colored signals.

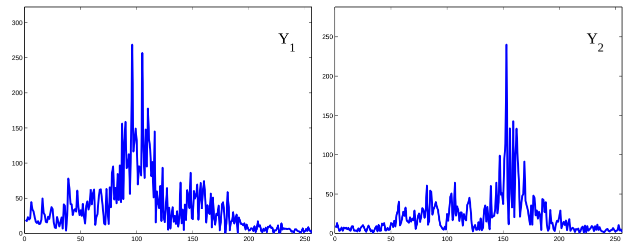

図 15 Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FB-BSS trained in time domain for colored signals.

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