Analysis of A Learning Algorithm with Distortion Free Constraint for Convolutive Blind Source Separation in Time Domain
時間領域畳み込み形ブラインド信号源分離における信号歪み抑制学習法の性能解析

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ABSTRACT

In Blind Source Separation (BSS), a separation block is trained so as to make the output signals to be statistically independent. In this case, the independency is able to be increased by changing frequency response of the output signals, resulting in signal distortion. Especially, a feed-forward BSS (FF-BSS) has some degree of freedom in the separation block, and the signal distortion will be caused. The signal distortion is evaluated as difference between the output signal and the signal source in the measured signal. Some equations are derived from the conditions of complete separation and signal distortion free. They are used as the distortion free constraint in the conventional learning process [11]. On the other hand, a feedback BSS (FB-BSS) has a solution, which can satisfy both complete separation and distortion free. In this paper, the learning algorithm with the distortion free constraint is applied to the FF-BSS in time domain. Many kinds of signal sources are used in simulation in order to compare the proposed method and the conventional, in which difference between the output signals and the measured signals is included in the cost function [4]. Furthermore, the FB-BSS is also evaluated.

あらまし

ブラインド信号源分離では (BSS) は分離回路がその出力信号が統計的に独立になるように学習される．この場合，出力信号の周波数特性が変化することにより，独立性が高まることもあるので，信号歪みが生じる可能性がある．特に，フィードフォワード形 BSS(FF-BSS) は分離回路における自由度が高く，信号歪みを生じる可能性がある．信号歪みの基準を観測信号に含まれる信号源と考え，完全分離の条件と信号無歪の条件から導かれた制約条件を学習に加味する信号歪み抑制学習法を提案した [11]．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 成分に近づけることができる．これに対し，観測信号と出力信号の差を評価関数に追加する従来法では，観測信号に含まれる複数の信号源の影響で信号源分離が充分ではない．一方，フィードバック形 BSS(FB-BSS) では，信号源分離と信号歪み抑制の条件を同時に満たす回が存在する．本稿では信号歪み抑制学習法を時間領域で学習する FF-BSS に適用し，種々の信号源を使って従来方式 [4] と比較することによりその特性を解析する．同時に，FB-BSS の有効性も検証する．

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 proposed network structures are 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 previously proposed regularization method suppresses signal distortion, however, it has difficulties separating the signals. 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 our new learning algorithm in comparison with the previously proposed method, by performing computer simulations. The 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

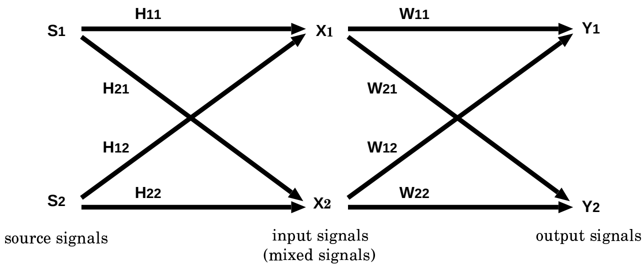

Figure 1: FF-BSS system with 2 signal sources and 2 sensors.

and the output signals are given by:

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

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

2.2 Learning Algorithm

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

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

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

The learning rate is given by η.

3 FB-BSS System for Convolutive Mixture

3.1 Network Structure and Equations

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

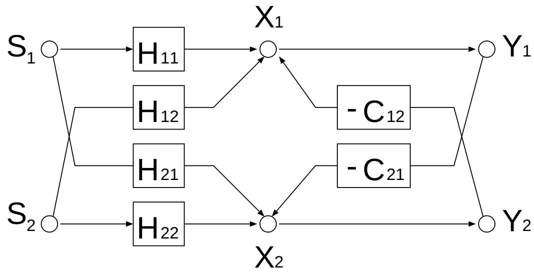

Figure 2: FB-BSS system with 2 signal sources and 2 sensors.

The observations and the output signals are expressed as follows:

$$x_j(n) = \sum_{i=1}^{N}\sum_{m=0}^{M_{ji}-1} h_{ji}(m)s_i(n-m) \quad (5)$$

$$y_k(n) = x_k(n) - \sum_{\substack{k=1 \\ \neq j}}^{N}\sum_{l=0}^{L_{jk}-1} c_{jk}(l)y_k(n-l) \quad (6)$$

3.2 Learning Algorithm

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.

$$\begin{aligned} c_{jk}(n+1,l) &= c_{jk}(n,l) \\ &+ \eta f(y_j(n))g(y_k(n-l)) \end{aligned} \quad (7)$$

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

4 Criterion of Signal Distortion

In this paper, signal distortion is evaluated as the distance to the observed signal sources[2],[10],[11]. By doing so, 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:

$$\begin{aligned} \sigma_{d1a} &= \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega})S_i(e^{j\omega}) \\ &- A_{ki}(e^{j\omega})S_i(e^{j\omega})|^2 d\omega \end{aligned} \quad (8)$$

$$\begin{aligned} \sigma_{d1b} &= \frac{1}{2\pi}\int_{-\pi}^{\pi} (|H_{ji}(e^{j\omega})S_i(e^{j\omega})| \\ &- |A_{ki}(e^{j\omega})S_i(e^{j\omega})|^2 d\omega \end{aligned} \quad (9)$$

$$\sigma_1 = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega})S_i(e^{j\omega})|^2 d\omega \quad (10)$$

$$SD_{1x} = 10\log_{10}\frac{\sigma_{d1x}}{\sigma_1}, x=a,b \quad (11)$$

$$\sigma_{d2a} = \frac{1}{2\pi}\int_{-\pi}^{\pi} |H_{ji}(e^{j\omega}) - A_{ki}(e^{j\omega})|^2 d\omega \quad (12)$$

$$\sigma_{d2b} = \frac{1}{2\pi}\int_{-\pi}^{\pi} (|H_{ji}(e^{j\omega})| - |A_{ki}(e^{j\omega})|)^2 d\omega \quad (13)$$

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

$$SD_{2x} = 10\log_{10}\frac{\sigma_{d2x}}{\sigma_2}, x = a, b \quad (15)$$

5 Source Separation and Signal Distortion in FF-BSS Systems

5.1 Source Separation and Signal Distortion Condition

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:

$$W_{11}(z)H_{11}(z) + W_{12}(z)H_{21}(z) = H_{11}(z) \quad (16)$$
$$W_{11}(z)H_{12}(z) + W_{12}(z)H_{22}(z) = 0 \quad (17)$$
$$W_{21}(z)H_{11}(z) + W_{22}(z)H_{21}(z) = 0 \quad (18)$$
$$W_{21}(z)H_{12}(z) + W_{22}(z)H_{22}(z) = H_{22}(z) \quad (19)$$

The above equations imply two conditions. First, complete source separation, i.e. the non-diagonal elements are all zero, as shown in Eqs.(17) and (18). Secondly, signal distortion free, that is the diagonal elements are equal to $H_{ii}(z)$ as shown in Eqs.(16) and (19). These equations are further investgated.

From the relations of Eqs.(17) and (18), $H_{ji}(z)$ are expressed as follows:

$$H_{12}(z) = -\frac{W_{12}(z)}{W_{11}(z)}H_{22}(z) \quad (20)$$

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

By substituting the above equations into the relations of Eqs.(16) and (19), $H_{ji}(z)$ can be removed, and the following equations consisting only of $W_{kj}(z)$ can be obtained.

$$W_{11}(z)W_{22}(z) - W_{12}(z)W_{21}(z) = W_{22}(z) \quad (22)$$
$$W_{11}(z)W_{22}(z) - W_{12}(z)W_{21}(z) = W_{11}(z) \quad (23)$$

From these equations, it can be concluded that $W_{11}(z) = W_{22}(z)$. Therefore, the above equations result in:

$$W_{jj}^2(z) - W_{jj}(z) - W_{jk}(z)W_{kj}(z) = 0 \quad (24)$$
$$j = 1, 2, k = 1, 2, j \neq k$$

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.(24). Usually, only Eqs.(17) and (18) are approximately satisfied. Equations (16) and (19) are not guaranteed. Therefore, in general, signal distortion cannot be suppressed.

The constraint given by Eq.(24) is taken into account 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.(24).

The condition for the distortion free source separation is derived based on 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 this situation into account, the constraint of Eq.(24) is gradually imposed as the learning process makes progress. The following learning algorithm has been proposed.

$$w_{kj}(n+1, l) = w_{kj}(n) + \eta\{w_{kj}(n) - \sum_{o=0}^{K_w-1}\sum_{p=1}^{2}\phi(y_k(n))y_p(n-o+p)w_{kp}(n,o)\} \quad (25)$$

$$w_{jj}(n+1, l) = (1-\alpha)w_{jj}(n+1, l) + \alpha\tilde{w}_{jj}(n+1) \quad (26)$$

$\tilde{w}_{jj}(n+1)$ is determined so as to approximate the relation of Eq.(24). α is usually set to a small positive number.

5.3 Conventional Learning Algorithm for Reducing Distortion

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], as a penalty.

$$\begin{aligned}\boldsymbol{w}(n+1, l) &= \boldsymbol{w}(n, l) \\ &- \alpha\sum_{m=0}^{K_w-1}[diag(\langle\Phi(\boldsymbol{y}(n))\boldsymbol{y}^T(n-l+m)\rangle \\ &- \langle\Phi(\boldsymbol{y}(n))\boldsymbol{y}^T(n-l+m)\rangle \\ &+ \beta(\boldsymbol{y}(n)-\boldsymbol{x}(n))\boldsymbol{y}^T(n-l+m)]\boldsymbol{w}(n,m)\end{aligned} \quad (27)$$

$$\varphi(\boldsymbol{y}(n)) = \frac{1-e^{-\boldsymbol{y}(n)}}{1+e^{-\boldsymbol{y}(n)}} \quad (28)$$

In this method, the output signals $Y_i(z) = A_{ii}(z)S_i(z) + A_{ij}(z)S_j(z)$ tend to approach to the observed signals $X_i(z) = H_{ii}(z)S_i(z) + H_{ij}(z)S_j(z)$. Therefore, $Y_i(z)$ may include the $S_j(z)$ component. However, since $S_i(z)$ and $S_j(z)$ are statistically independent, $A_{ii}(z)$ is able to approach to $H_{ii}(z)$ and $A_{ij}(z)$ is able to approach to $H_{ij}(z)$. The former guarantees distortion free, but the latter can disturb source separation.

Consequently, this algorithm might achieve a low signal distortion, but perform poor with respect to signal source separation.

6 Source Separation and Signal Distortion in FB-BSS Systems

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

$$(1)\ C_{21}(z) = \frac{H_{21}(z)}{H_{11}(z)} \qquad C_{12}(z) = \frac{H_{12}(z)}{H_{22}(z)} \quad (29)$$

$$(2)\ C_{21}(z) = \frac{H_{22}(z)}{H_{12}(z)} \qquad C_{12}(z) = \frac{H_{11}(z)}{H_{21}(z)} \quad (30)$$

It is assumed that the delay times of $H_{11}(z)$ and $H_{22}(z)$ are shorter than those 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 solution in case (1) become a causal system. On the other hand, the solution in case (2) is noncausal.

When $C_{ij}(z)$ satisfy the separation conditions Eqs. (29), the output signals can be given by:

$$Y_1(z) = H_{11}(z)S_1(z) \qquad Y_2(z) = H_{22}(z)S_2(z) \quad (31)$$

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 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 direct paths are shown in Fig.3. The transfer functions of the cross paths are

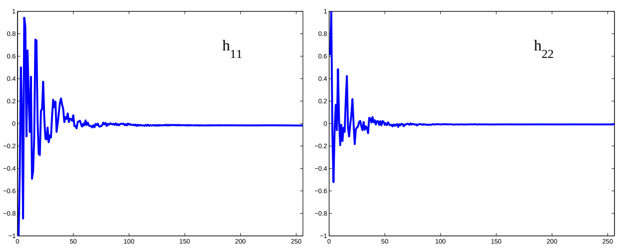

Figure 3: Impulse responses of $H_{11}(z)$ and $H_{22}(z)$.

related to the direct paths as $H_{jk}(z) = 0.9z^{-1}H_{kk}(z)$. White signals, colored signals, created by 2nd-order AR models, and speeches are used as sources. FIR filters with 256 taps are used. 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, this does not lose generarity.

$$\sigma_{s1} = \frac{1}{2\pi}\int_{-\pi}^{\pi}(|A_{11}(e^{j\omega})|^2 + |A_{22}(e^{j\omega})|^2)d\omega \quad (32)$$

$$\sigma_{i1} = \frac{1}{2\pi}\int_{-\pi}^{\pi}(|A_{12}(e^{j\omega})|^2 + |A_{21}(e^{j\omega})|^2)d\omega \quad (33)$$

$$SIR_1 = 10\log_{10}\frac{\sigma_{s1}}{\sigma_{i1}} \quad (34)$$

$$\begin{aligned} \sigma_{s2} &= \frac{1}{2\pi}\int_{-\pi}^{\pi}(|A_{11}(e^{j\omega})S_1(e^{j\omega})|^2 \\ &+ |A_{22}(e^{j\omega})S_2(e^{j\omega})|^2)d\omega \quad (35) \\ \sigma_{i2} &= \frac{1}{2\pi}\int_{-\pi}^{\pi}(|A_{12}(e^{j\omega})S_2(e^{j\omega})|^2 \\ &+ |A_{21}(e^{j\omega})S_1(e^{j\omega})|^2)d\omega \quad (36) \\ SIR_2 &= 10\log_{10}\frac{\sigma_{s2}}{\sigma_{i2}} \quad (37) \end{aligned}$$

7.2 White Signals

The learning curves of SIR_1 are shown in Figs.4.

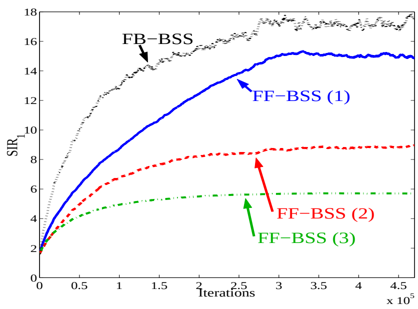

Figure 4: Learning curves of SIR_1 for white signals. FF-BSS(1), (2) and (3) are trained following Eqs.(3)-(4), Eqs.(25)-(26) and Eqs.(27)-(28), respectively.

The convergence speed of the FB-BSS system is faster than those of the FF-BSS systems, and the FB-BSS system is superior to the FF-BSS systems with respect to the separation performance, that is the value of SIR_1. Among the FF-BSS systems, the FF-BSS without distortion free(FF-BSS(1)) obtained the best result. However, this result is caused by signal distortion as will be discussed later. The proposed method(FF-BSS(2)) is better than the conventional method(FF-BSS(3)) regarding separation performance. Moreover, the conventional method has already converged.

The evaluation measures are summarized in Table 1.

Regarding SIR_1 and SIR_2, the FB-BSS system performed best. Regarding SD_{1a}, which is the strictest evaluation, the FB-BSS system is superior to the others. In SD_{1b}, which compares only amplitude responses, the differences become small. However the FB-BSS

Table 1: Comparison of four different BSS systems for white signals. FF-BSS(1), (2) and (3) are trained following Eqs.(3)-(4), Eqs.(25)-(26) and Eqs.(27)-(28), respectively.

Methods	SIR_1	SIR_2	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS(1)	14.8	14.9	-4.72	-8.44	-4.77	-8.54
FF-BSS(2)	8.97	8.93	-14.9	-18.5	-14.9	-18.4
FF-BSS(3)	5.70	5.71	-12.7	-16.6	-12.7	-16.6
FB-BSS	17.5	18.6	-19.1	-22.3	-19.1	-22.1

system is still superior to the others. In SD_{2a} and SD_{2b} evaluations, which compare only transfer functions, almost no differences are observable. Therefore, regarding signal distortion, it can be concluded that the FB-BSS system is the best according to any evaluation measure. The signal distortion in the FF-BSS system with distortion free constraint(FF-BSS(2)) and the conventional FF-BSS for reducing distortion(FF-BSS(3)) can be drastically improved compared to the FF-BSS system without the constraint. However, the conventional FF-BSS for reducing distortion is not good regarding source separation.

As discussed in Sec.5.3, source separation can be disturbed, because $A_{ij}(z)$ might approach $H_{ij}(z)$. This thought is supported by the fact that the performance values displayed in Table 2 for FF-BSS(3) are much lower than the values for the other methods.

Table 2: Evaluations of Signal Distortion of the signal that should be removed for white signals.

Methods	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS(1)	2.45	-1.23	2.42	-1.20
FF-BSS(2)	-3.77	-10.0	-3.78	-9.98
FF-BSS(3)	-10.4	-13.5	-10.3	-13.3
FB-BSS	2.27	-3.79	2.23	-3.59

Regarding SD_{xb},$x = 1, 2$, which compare only amplitude responses, the proposed method (FF-BSS(2)) has much lower values as expected. The cause might be found in the fact that learning algorithm eliminates the signals at the same rate for each frequency, because the frequency band of the white signals are flat.

7.3 Colored Signals

Colored signals, whose frequency bands are not flat, are used as source signals. The evaluation measures are summarized in Table 3 and the evaluations of signal distortion of the signal that should be removed are shown in Table 4.

Similar results as in the simulations using white signals are obtained regarding source separation as well as signal distortion of outputs. Regarding evaluations of signal distortion of the signal that should be removed, the proposed method does not have values as low as the values of the same method in the previous experiment dealing with white signals. However, the conventional method for reducing distortion has still very low performance values similar to the previous experiment.

Table 3: Comparison of four different BSS systems for colored signals.

Methods	SIR_1	SIR_2	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS(1)	7.07	9.49	-0.08	-2.76	-0.69	-4.99
FF-BSS(2)	4.07	8.05	-7.54	-10.1	-10.4	-13.2
FF-BSS(3)	2.20	4.49	-5.43	-7.80	-13.7	-16.5
FB-BSS	7.19	16.5	-12.4	-15.0	-10.4	-13.6

Table 4: Evaluations of Signal Distortion of the signal that should be removed for colored signals.

Methods	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS(1)	1.93	-0.65	1.71	-0.99
FF-BSS(2)	-0.59	-2.61	-2.85	-4.74
FF-BSS(3)	-8.79	-11.1	-9.48	-12.2
FB-BSS	1.02	-1.43	-0.09	-4.08

7.4 Speech Signals

Speech signals, which are non-stationary and correlated to each other are used as sources. The evaluation measures are summarized in Table 5.

Table 5: Comparison of four different BSS systems for speech signals.

Methods	SIR_1	SIR_2	SD_{1a}	SD_{1b}	SD_{2a}	SD_{2b}
FF-BSS(1)	5.56	12.2	0.34	-2.70	0.57	-3.82
FF-BSS(2)	4.33	8.29	-7.05	-10.4	-15.4	-19.9
FF-BSS(3)	6.38	10.9	-10.3	-13.8	-14.5	-16.9
FB-BSS	9.24	14.1	-11.3	-14.6	-14.7	-17.3

The conventional method for reducing distortion has good performance regarding source separation.

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.5. The spectra of the output signals are shown in Figs.6, 7, 8 and 9.

In the FF-BSS system without a distortion free constraint, the spectra are not similar to the criteria shown in Fig.5. 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. This distortion might result in a incorrect view of the source separation performance. On the other hand, as shown in Fig.7 and 8, the spectra of the FF-BSS system with any distortion free constraint are drastically improved compared to the FF-BSS without a distortion free constraint, and are similar to the criteria.

The results of the FB-BSS support the discussion of Sec.6.

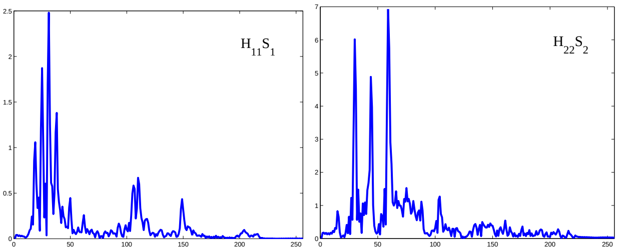

Figure 5: Spectrum of $H_{11}(z)S_1(z)$ and $H_{22}(z)S_2(z)$ for speech signals.

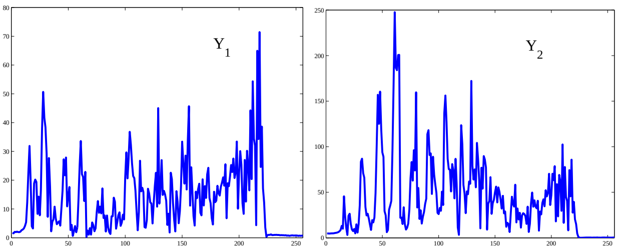

Figure 6: Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS(1) for speech signals

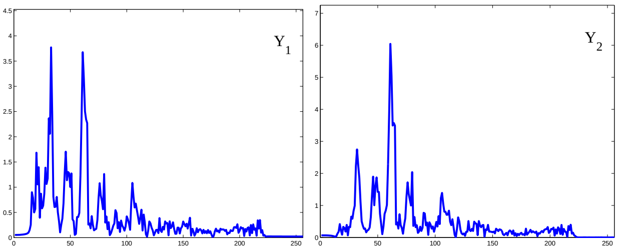

Figure 7: Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FF-BSS(2) for speech signals.

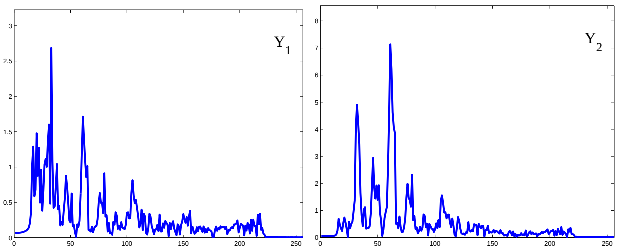

Figure 8: Spectrum of output signals $y_1(n)$ and $y_2(n)$ FF-BSS(3) in for speech signals.

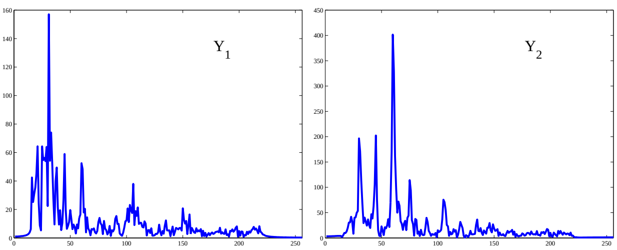

Figure 9: Spectrum of output signals $y_1(n)$ and $y_2(n)$ in FB-BSS system for speech signals.

8 Conclusions

In this paper, source separation and signal distortion in FF-BSS systems and FB-BSS systems have been analyzed. A distortion free constraint has been proposed for the FF-BSS system. Furthermore, the conventional FF-BSS system for reducing distortion has difficulties to obtain good separation performances, because $A_{ij}(z)$ might approach $H_{ij}(z)$. The FB-BSS system has one unique solution, which satisfies source separation as well as the distortion free conditions simultaneously. The simulation results support our theoretical analysis.

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