A SIMPLIFIED FREQUENCY-DOMAIN APPROACH FOR BLIND SEPARATION OF CONVOLUTIVE MIXTURES

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ABSTRACT

In the frequency-domain, a convolutive mixture can be interpreted as several instantaneous mixtures which may be separated using many existing algorithms. The main limitation of this approach is the large number of frequencies that must be considered. In addition, a permutation/amplitude correction must be performed when the sources are recovered in a different order or with different amplitudes in some frequency bins. In this paper we propose a novel approach for solving the convolutive problem using only two frequency bins. The idea deals with finding a 2×2 invertible matrix which relates the signals recovered in these frequency bins and the temporal sources. The existence of this matrix is due to use zero-padding for computing the Fourier transform of the observations. Several simulation results show the good performance of this simplified approach in different applications.

Keywords: Blind source separation, convolutive mixtures, frequency-domain approaches.

1. INTRODUCTION

Blind Source Separation (BSS) consists in recovering statistically independent signals (sources) from the observations recorded by several sensors. This is a fundamental problem in signal processing that arises in a large number of applications such as digital communications and audio processing [7]. Many BSS algorithms have been proposed supposing that the observations are instantaneous mixtures of the sources [2]. Unfortunately, this kind of mixture is seldom found in real world applications and it is more suitable to consider convolutive mixtures of the sources.

During the last years several authors have proposed to separate the convolutive mixtures in the frequency-domain by solving instantaneous mixing problems [4, 5, 9, 10, 11]. The main limitation of this approach is the large number of instantaneous mixtures that must be separated in order to achieve a good performance. In addition, it is not easy to remove the permutation and the amplitude indeterminacies that appear when the sources are recovered in a different order or with different amplitudes in some frequencies.

In this paper, we will propose a frequency-domain separating system which only considers two frequency bins. We will show that the original temporal sources and the signals recovered in these frequencies are related by an invertible matrix when the Fourier transform of the observations is computed using zero-padding. As a consequence, the sources can be recovered multiplying the outputs by the inverse of this matrix. It is apparent that the computational cost of this simplified approach is reduced because only two instantaneous mixtures must be separated and the solution of the permutation/amplitude indeterminacy involves two frequency bins. We will present several simulations results which show the good performance of our approach in different applications. First, we will consider the cocktail-party problem where voice signals must be recovered from the observations recorded by several microphones [10, 11]. In the second experiment, we will consider an industrial application where several motors must be monitored [5, 6].

This paper is structured as follows. Section 2 presents the signals model. Section 3 presents the simplified frequency-domain approach. In Section 4 we apply the proposed solution to the cocktail-party problem. In Section 5 we test the performance of our system for machine monitoring. Finally, Section 6 is devoted to the conclusions.

2. SIGNALS MODEL

We will consider the following model. Let $\mathbf{s}(n) = [s_1(n), ..., s_N(n)]^T$ be the vector of N sources whose exact probability density functions are unknown. We assume that the sources are real-valued, non-Gaussian distributed and statistically independent. The observation vector $\mathbf{x}(n) = [x_1(n), ..., x_N(n)]^T$ provides a convolutive combination of the N sources, i.e.,

$$\mathbf{x}(n) = \sum_{k=-\infty}^{\infty} \mathbf{A}(k)\mathbf{s}(n-k) \quad (1)$$

where $\mathbf{A}(k)$ is an unknown $N \times N$ matrix representing the mixing system.

In the frequency-domain, the convolutive mixture (1) takes the form

$$\mathbf{x}[\omega] = \mathbf{A}[\omega]\mathbf{s}[\omega] \quad (2)$$

where $\mathbf{x}[\omega]$, $\mathbf{s}[\omega]$ and the matrix $\mathbf{A}[\omega]$ represent the observations, the sources and the mixing coefficients in the frequency-domain, respectively. Note that the observation vector $\mathbf{x}[\omega]$ at each frequency corresponds to an instantaneous mixture of the sources $\mathbf{s}[\omega]$. Therefore, in order to recover the sources at each frequency, we can use a MIMO (Multiple Inputs-Multiple Outputs) system with output

$$\mathbf{y}[\omega] = \mathbf{W}^H[\omega]\mathbf{x}[\omega] \tag{3}$$

where $\mathbf{W}[\omega]$ is a $N \times N$ coefficients matrix which can be obtained using many existing algorithms proposed for separating instantaneous mixtures (see [2] and references therein). Combining both (2) and (3) together, we can express the outputs as follows

$$\mathbf{y}[\omega] = \mathbf{G}[\omega]\mathbf{s}[\omega] \tag{4}$$

where $\mathbf{G}[\omega] = \mathbf{W}^H[\omega]\mathbf{A}[\omega]$ is the overall mixing/separating matrix. The sources are optimally recovered when each output in vector $\mathbf{y}[\omega]$ extracts a single and different source. This means that the optimum matrix $\mathbf{G}[\omega]$ has the form

$$\mathbf{G}[\omega] = \Delta[\omega]\mathbf{P}[\omega] \tag{5}$$

where $\Delta[\omega]$ is a diagonal matrix and $\mathbf{P}[\omega]$ is a permutation matrix. Note that since the separating matrix at each frequency is independently obtained, the sources may be recovered in a different order (permutation indeterminacy) and with different amplitudes (amplitude indeterminacy) in some frequency bins. To remove both indeterminacies is a crucial task because the sources in the time-domain are recovered combining the outputs in different frequencies by the inverse Fourier transform.

3. SIMPLIFIED FREQUENCY-DOMAIN APPROACH

In order to recover the sources in the frequency-domain we propose to use the Simplified Frequency-Domain Approach (SFDA) shown in Figure 1. The convolutive mixture is transformed in several instantaneous mixtures by computing the Short-Time Fourier Transform (STFT) of zero-padded observations. Note that we only take the observations corresponding to two frequency bins. In the next stage, the mixtures in these frequency bins are separated and the permutation/amplitude indeterminacy is solved. As a consequence, we obtain the estimated sources in these frequency bins. In the paper, we show that the estimated frequency-domain sources are related to the temporal sources by an invertible matrix because of the use of zero-padding in the Fourier transform. Finally, the temporal sources are recovered multiplying the outputs by this invertible matrix instead to apply the Inverse Short-Time Fourier Transform (ISTFT). In the next subsections we describe each stage of SFDA in detail.

3.1. Instantaneous Mixing Separation

The first stage of the separating system consists in applying the Short-Time Fourier Transform to moving windows of observations. We split each particular observation, $x_l(t)$, in windows of K points, i.e., $\mathbf{x}_l(t_r) = [x_l(t_r), x_l(t_r+1), ..., x_l(t_r+K-1)]^T$, $t_r = 0, 1, ...$ Subsequently, we compute the L-points DFT ($L > K$ with zero-padding of $L-K$ points) of two frequency bins given by

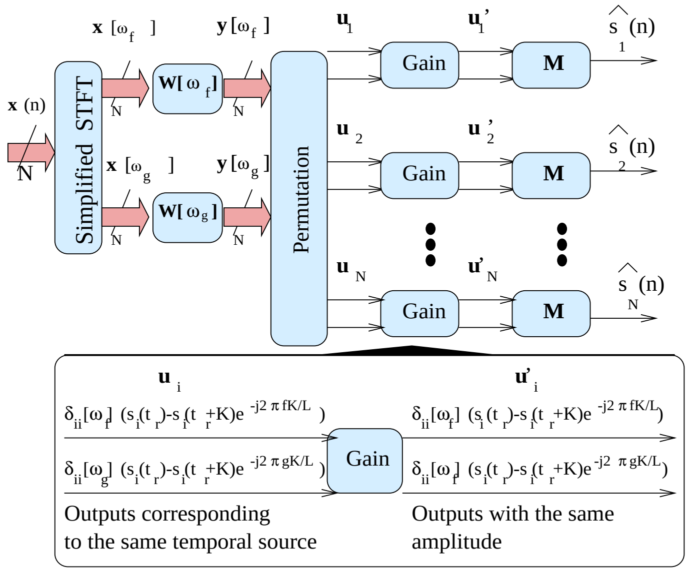

Fig. 1. Separating system

$$x_l[\omega_f, t_r] = \sum_{m=0}^{K-1} x_l(t_r+m)e^{-j\omega_f m}$$
$$x_l[\omega_g, t_r] = \sum_{m=0}^{K-1} x_l(t_r+m)e^{-j\omega_g m} \tag{6}$$

where $\omega_f = 2\pi f/L$ and $\omega_g = 2\pi g/L$ denote the two frequency bins. We will assume that the observations at each frequency bin are instantaneous mixtures of the sources, i.e.,

$$\mathbf{x}[\omega_f, t_r] = \mathbf{A}[\omega_f]\mathbf{s}[\omega_f, t_r]$$
$$\mathbf{x}[\omega_g, t_r] = \mathbf{A}[\omega_g]\mathbf{s}[\omega_g, t_r] \tag{7}$$

In the next step, these observations are independently processed by MIMO systems whose outputs have the form

$$\mathbf{y}[\omega_f, t_r] = \mathbf{W}^H[\omega_f]\mathbf{x}[\omega_f, t_r]$$
$$\mathbf{y}[\omega_g, t_r] = \mathbf{W}^H[\omega_g]\mathbf{x}[\omega_g, t_r] \tag{8}$$

Although in this paper the separating matrices will be found using the JADE (Joint Approximate Diagonalization of Eigen-matrices) algorithm proposed in [3] for complex-valued sources, another algorithms can be used (see [2] and references therein).

The objective of the BSS algorithms is to find the matrices $\mathbf{W}[\omega_f]$ and $\mathbf{W}[\omega_g]$ such as each output corresponds to a single and different source. This means that the sources are separated when the outputs have the following form

$$\begin{aligned} y_i[\omega_f, t_r] &= g_{il}[\omega_f]s_l[\omega_f, t_r] \\ &= g_{il}[\omega_f]\sum_{m=0}^{K-1} s_l(t_r+m)e^{-j2\pi\frac{fm}{L}} \\ y_i[\omega_g, t_r] &= g_{il}[\omega_g]s_l[\omega_g, t_r] \\ &= g_{il}[\omega_g]\sum_{m=0}^{K-1} s_l(t_r+m)e^{-j2\pi\frac{gm}{L}} \\ & \quad i, l = 1, ..., N \end{aligned} \tag{9}$$

and different outputs at the same frequency bin extract different sources. Here, $g_{il}[\omega_f]$ and $g_{il}[\omega_g]$ represent the gains introduced by the separating systems. Since the matrices $\mathbf{W}[\omega_f]$ and $\mathbf{W}[\omega_g]$ are independently computed, a permutation/amplitude correction must be performed in the two frequency bins.

3.2. Permutation Indeterminacy

In order to solve the permutation indeterminacy, we will use a method similar to the proposed in [1]. We filter the outputs $y_i[\omega_f, t_r]$ and $y_i[\omega_g, t_r]$ versus the index t_r using sliding Fourier transform with delay of one point

$$\begin{aligned} z_i[\omega_f, t_r] &= y_i[\omega_f, t_r] - y_i[\omega_f, t_r+1]e^{-j2\pi\frac{f}{L}} \\ z_i[\omega_g, t_r] &= y_i[\omega_g, t_r] - y_i[\omega_g, t_r+1]e^{-j2\pi\frac{g}{L}} \\ & i = 1, ..., N \end{aligned} \quad (10)$$

From the expression of the DFT in (9) and considering the redundancy in the sliding Fourier transform, we obtain

$$\begin{aligned} z_i[\omega_f, t_r] &= g_{il}[\omega_f](s_l(t_r) - s_l(t_r+K)e^{-j2\pi\frac{fK}{L}}) \\ z_q[\omega_g, t_r] &= g_{qp}[\omega_g](s_p(t_r) - s_p(t_r+K)e^{-j2\pi\frac{gK}{L}}) \end{aligned} \quad (11)$$

Note that this expression only depends on the gain introduced by the separating system and on the temporal sources $s(t_r)$ and $s(t_r + K)$ but there does not exist a dependence on the sources in the frequency-domain. The cross-correlation between $z_i[\omega_f, t_r]$ and $z_q[\omega_g, t_r]$ is given by

$$\begin{aligned} E[z_i[\omega_f, t_r]z_q^*[\omega_g, t_r]] = g_{il}[\omega_f]g_{qp}^*[\omega_g](E[s_l(t_r)s_p(t_r)] \\ -E[s_l(t_r+K)s_p(t_r)]e^{-j2\pi\frac{fK}{L}} \\ -E[s_l(t_r)s_p(t_r+K)]e^{j2\pi\frac{gK}{L}} \\ +E[s_l(t_r+K)s_p(t_r+K)]e^{j2\pi\frac{(g-f)K}{L}}) \end{aligned} \quad (12)$$

Since the sources are statistically independent in the time-domain, the expression (12) will be zero when the outputs $z_i[\omega_f, t_r]$ and $z_q[\omega_g, t_r]$ correspond to different sources, $l \neq p$. On the contrary, if the outputs extract the same source and the window length is sufficient large such as $E[s_l(t_r+K)s_l(t_r)] \approx 0$, the cross-correlation can be written as

$$\begin{aligned} E[z_i[\omega_f, t_r]z_q^*[\omega_g, t_r]] \approx \\ g_{il}[\omega_f]g_{ql}^*[\omega_g]E[s_l^2(t_r)](1 + e^{j2\pi\frac{K(g-f)}{L}}) \end{aligned} \quad (13)$$

This expression will be non-zero if $e^{j2\pi\frac{K(g-f)}{L}} \neq -1$.

From the explanation above, we can devise a simple method to solve the permutation indeterminacy. We apply the filter (10) to the outputs $y_i[\omega_f, t_r]$ and $y_i[\omega_g, t_r]$. Subsequently, for each filtered output at frequency ω_f, we compute the cross-correlation between $z_i[\omega_f, t_r]$ and each filtered output at frequency ω_g, $E[z_i[\omega_f, t_r]z_q^*[\omega_g, t_r]]$, $q = 1, ..., N$. Finally, we select the filtered output $z_q[\omega_g, t_r]$ corresponding to the maximum cross-correlation in absolute value. Using this procedure, we obtain a vector $\mathbf{u}_i$ whose components correspond to the same temporal source

$$\begin{aligned} u_i[\omega_f, t_r] &= z_i[\omega_f, t_r] \\ u_i[\omega_g, t_r] &= \max_{z_q[\omega_g, t_r]} |E[z_i[\omega_f, t_r]z_q^*[\omega_g, t_r]]| \end{aligned} \quad (14)$$

3.3. Amplitude Indeterminacy

Since the components into each vector $\mathbf{u}_i$ determined in the permutation stage depend on the same temporal source and on the gain introduced by the separating system, we can write

$$\begin{aligned} u_i[\omega_f, t_r] &= \delta_{ii}[\omega_f](s_i(t_r) - s_i(t_r+K)e^{-j2\pi\frac{fK}{L}}) \\ u_i[\omega_g, t_r] &= \delta_{ii}[\omega_g](s_i(t_r) - s_i(t_r+K)e^{-j2\pi\frac{gK}{L}}) \end{aligned} \quad (15)$$

where $\delta_{ii}[\omega_f]$ may be different to $\delta_{ii}[\omega_g]$. In order to solve the amplitude indeterminacy, we will obtain a new output $u_i'[\omega_g, t_r]$ with the same gain like $u_i'[\omega_f, t_r] = u_i[\omega_f, t_r]$. Towards this end, we compute

$$\begin{aligned} u_i'[\omega_g, t_r] &= \frac{\delta_{ii}[\omega_f]}{\delta_{ii}[\omega_g]}u_i[\omega_g, t_r] \\ &= \frac{\delta_{ii}[\omega_f]\delta_{ii}^*[\omega_g]}{|\delta_{ii}[\omega_g]|^2}u_i[\omega_g, t_r] \end{aligned} \quad (16)$$

The correction factor in (16) can be found using the cross-correlation between $u_i[\omega_f, t_r]$ and $u_i[\omega_g, t_r]$ given by (13). We obtain

$$\begin{aligned} \delta_{ii}[\omega_f]\delta_{ii}^*[\omega_g] &= \frac{E[u_i[\omega_f, t_r]u_i^*[\omega_g, t_r]]}{E[s_l^2(t_r)](1 + e^{j2\pi\frac{(g-f)K}{L}})} \\ |\delta_{ii}[\omega_g]|^2 &= \frac{E[|u_i[\omega_g]|^2]}{2E[s_l^2(t_r)]} \end{aligned} \quad (17)$$

Substituting in (16), the new output can be written as

$$u_i'[\omega_g, t_r] = \frac{2E[u_i[\omega_f, t_r]u_i^*[\omega_g, t_r]]}{1 + e^{j2\pi\frac{(g-f)K}{L}}}u_i[\omega_g, t_r] \quad (18)$$

3.4. Time-domain Recovering

The last stage of the separating system consists in recovering the sources in the time-domain. Recall that we have corrected the amplitudes of the outputs (15) by obtaining new vectors $\mathbf{u}_i'$, $i = 1, ..., N$ whose components are related to the the temporal sources by the following expression

$$\begin{aligned} u_i'[\omega_f, t_r] = \delta_{ii}[\omega_f](s_i(t_r) - s_i(t_r+K)e^{-j2\pi\frac{fK}{L}}) \\ u_i'[\omega_g, t_r] = \delta_{ii}[\omega_f](s_i(t_r) - s_i(t_r+K)e^{-j2\pi\frac{gK}{L}}) \end{aligned} \quad (19)$$

In a compact form, we can write

$$\mathbf{u}_i' = \mathbf{M}\hat{\mathbf{s}}_i \quad (20)$$

where $\hat{\mathbf{s}}_i = [\delta_{ii}[\omega_f]s_i(t_r), \delta_{ii}[\omega_f]s_i(t_r+K)]^T$ and $\mathbf{M}$ is a 2×2 matrix which depends on the value of the frequencies f and g. This matrix is given by

$$\mathbf{M} = \begin{bmatrix} 1 & -e^{-j2\pi\frac{fK}{L}} \\ 1 & -e^{-j2\pi\frac{gK}{L}} \end{bmatrix} \quad (21)$$

Since we have computed the DFT of the observations (6) with zero-padding of $L - K$ points ($L < K$), the condition $f \neq g + pL/K$ (where p is an integer number) guarantees that $\mathbf{M}$ is an invertible matrix and the sources can be recovered using

$$\hat{\mathbf{s}}_i = \mathbf{M}^{-1}\mathbf{u}_i', \quad i = 1, ..., N \quad (22)$$

Finally, the component corresponding to $\hat{s}_i(t_r)$ is taken. Note that we recover $\hat{s}_i(t_r) = \delta_{ii}[\omega_f]s_i(t_r)$ where $\delta_{ii}[\omega_f]$ may be complex-valued. If this occurs, only the real part must be considered.

4. APPLICATION I: THE COCKTAIL PARTY PROBLEM

The cocktail party problem deals with the recuperation of voice signals from the observations recorded by several microphones [8, 10, 11]. In our experiment, we have considered two sources recorded to 11kHz and two synthetic observations obtained by using the following mixing system

$$\mathbf{A}(z) = \begin{bmatrix} \frac{a_{11}+z^{-1}}{1+a_{11}z^{-1}} & \frac{a_{12}+z^{-1}}{1+a_{12}z^{-1}} \\ \frac{a_{21}+z^{-1}}{1+a_{21}z^{-1}} & -\frac{a_{22}+z^{-1}}{1+a_{22}z^{-1}} \end{bmatrix} \quad (23)$$

where the coefficients a_{ij} have been randomly generated.

In the separating system, the DFT of $L = 256$ points has been applied over windows of $K = 20$ observations. We have chosen the frequency bins $f = 10$ and $g = 11$, and we have solved the permutation and the amplitude indeterminacy using the solutions proposed in Section 3. In order to validate the accuracy of the proposed approach, we have also considered the theoretical solution (SFDA-TS) where the two instantaneous mixtures are separated using the inverse of the true mixing matrix. The performance has been measured in terms of the MSE (Mean Square Error) between the original temporal sources and the recovered temporal sources. The MSE has been averaged over 10 independent realizations. We have eliminated the gain $\lambda_{ii}[\omega_f]$ before computing the MSE of SFDA-JADE.

From the results in Table 1, we can conclude that both SFDA-JADE and SFDA-TS present a similar behavior. By listening the recovered signals, we have also tested the good performance of the two approaches. For instance, Figure 2 shows the sources, the observations and the recovered signals for a simulation where the MSE have been of -39.0385 dB for SFDA-TS and of -36.0185 dB for SFDA-JADE. Note the high quality of all the recovered signals. Finally, in order to verify the accuracy of the method proposed for solving the amplitude indeterminacy, Table 2 shows the true value and the estimated value of $\lambda_{ii}[\omega_f]/\lambda_{ii}[\omega_g]$.

The results above show that SFDA is an adequate solution to the cocktail-party problem. Also, it is interesting to note that the blind solution using JADE presents a similar performance to the theoretical solution where the true mixing matrix is used. We have obtained similar results considering another frequency bins.

	SFDA-TS	SFDA-JADE
Cocktail party	-36.6326 dB	-34.4974 dB
Rotating machines	-67.1731 dB	-45.3598 dB

Table 1. MSE obtained in the simulations

	$\lambda_{11}[\omega_f]/\lambda_{11}[\omega_g]$	$\lambda_{22}[\omega_f]/\lambda_{22}[\omega_g]$
True value	0.9429 + 0.0082i	-0.9172 + 0.0025i
Estimated value	0.9618 + 0.0002i	-0.9235 + 0.0002i

Table 2. Cocktail-party problem: true and estimated amplitudes

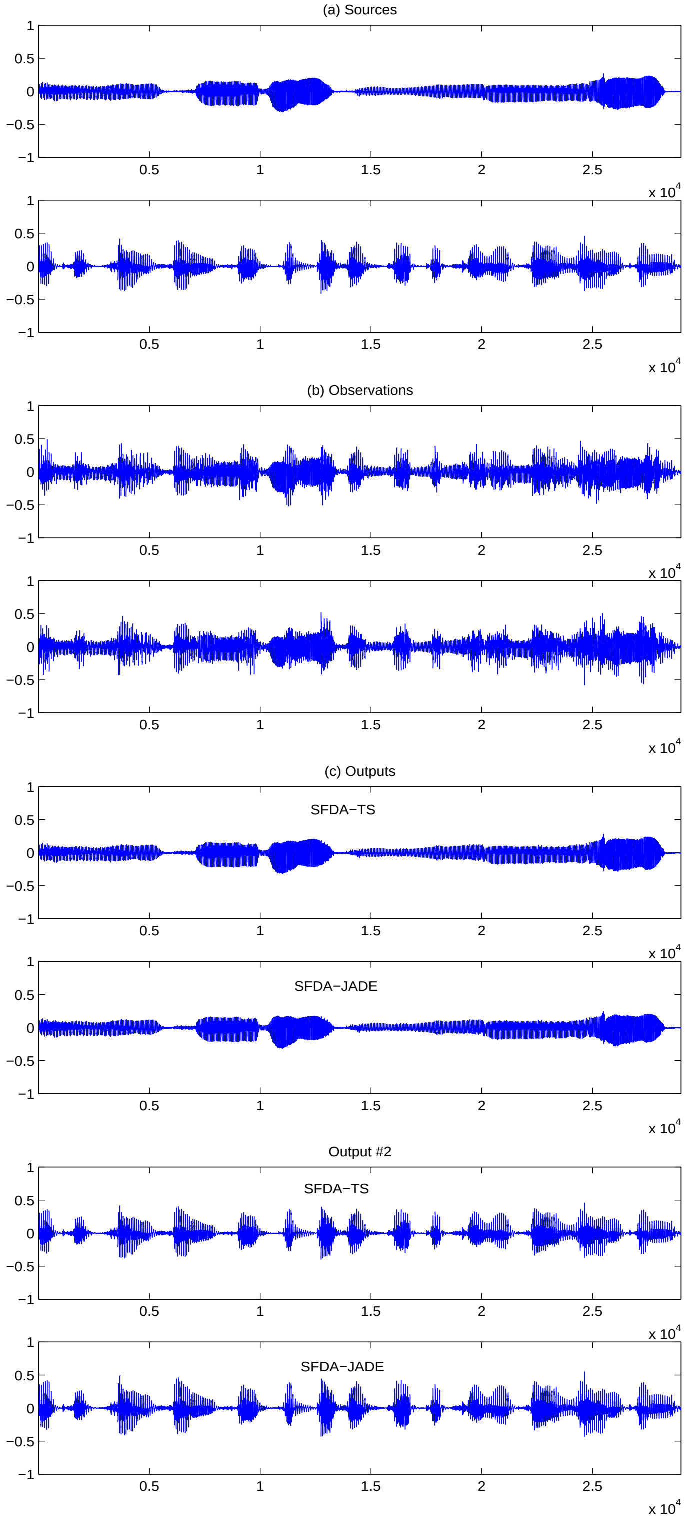

Fig. 2. Experimental results obtained using SFDA for solving the cocktail-party problem: (a) Temporal sources; (b) Observations and (c) Outputs obtained with SFDA-TS and SFDA-JADE.

5. APPLICATION II: ROTATING MACHINES MONITORING

There exists a great interest to apply BSS in mechanical system signals processing for monitoring and diagnosis purpose [5, 6]. The idea is to use BSS for recovering the signatures of several motors without having to stop them. From the signatures, it is possible to obtain important information about the motors such as, for example, the existence of faults.

In our experiment, we have considered two DC motors whose signatures are showed in Figure 3 (a). The motor $\#1$ has a rotation speed of 48.5 Hz. This motor is fed by a single phase wiring (rectified) which presents 100 Hz for fundamental frequency plus harmonics. Motor $\#2$ turns at 31.5 Hz and is fed by two phase wiring which present 100 and 200 Hz. Each motor is fitted out with two single row roller bearing and drives a main shaft equipped with two self aligning roller bearing. Roller bearing induce several defect frequencies: motor $\#1$ presents a fault at 207 Hz and motor $\#2$ presents three faults at 134 Hz, 179 Hz and 210 Hz. Details of the test bench can be consulted in [5]. We have used $20,000$ samples of the temporal sources recorded to 2 kHz. The sources are perturbed by Gaussian noise.

The sources have been passed thought the mixing system (23) to obtain the observations. In the separating system, we have used $K = 100$ and $L = 1024$. We have selected $f = 12$ and $g = 13$ because the sources have similar powers in these frequency bins. Since the objective is to recover the signatures of the sources, it is more suitable to measure the performance using the MSE between the original and the recovered signatures. Table 1 shows the MSE obtained using SFDA-TS and SFDA-JADE. Although both approaches have achieved a good separation, the performance of the blind algorithm JADE is far to the optimum value. We conjecture that this result is due to the presence of noise.

Figure 3 shows the Power Spectral Density (PSD) of the observations (part (b)) and of the recovered signals (part (c)) for a simulation where the obtained MSE has been of -63.5646 dB for SFDA-TS and of -45.0820 dB for SFDA-JADE. Each PSD has been normalized by its maximum value. In Figure 3 (c), we can see that the rotating frequency plus harmonics of the two motors have been recovered. However, like in the original signature of the motor $\#2$, only the rotating frequency and the first harmonic can be easily identified. The feeding frequencies (at 100 and 200 Hz) present in both sources have been also recovered. Concerning the bearing frequencies, the fault in 207 Hz is easily associated to motor $\#1$ and the faults at 134 Hz and 179 Hz are associated to motor $\#2$. It is difficult to associate the fault at 210 Hz but it also occurs in the original signatures. For this simulation, Table 2 shows the true value and the estimated value of $\lambda_{ii}[\omega_f]/\lambda_{ii}[\omega_g]$. It is apparent that again a good result has been obtained.

	$\lambda_{11}[\omega_f]/\lambda_{11}[\omega_g]$	$\lambda_{22}[\omega_f]/\lambda_{22}[\omega_g]$
True value	0.9998 + 0.0026i	1.1147 + 0.0026i
Estimated value	0.9887 - 0.0004i	1.1637 - 0.0012i

Table 3. Rotating machines: true and estimated amplitudes

6. CONCLUSION

In this paper, we have proposed a method for separating convolutive mixtures in the frequency-domain by using only two frequency bins. We have showed that each temporal source can be reconstructed multiplying the signals recovered in these frequency bins by a 2×2 matrix whose exact form depends on both the parameters of the DFT and the selected frequencies. The existence of this matrix is due to use zero-padding for computing the Fourier transform of the observations. The proposed system also solves the permutation/amplitude indeterminacy by using a novel method which exploits the statistically independence of the temporal sources. It is apparent that the computational cost of the proposed approach is reduced in comparison with previous frequency-domain approaches where all the frequency bins are considered. In addition, several simulations results show its good performance in different applications.

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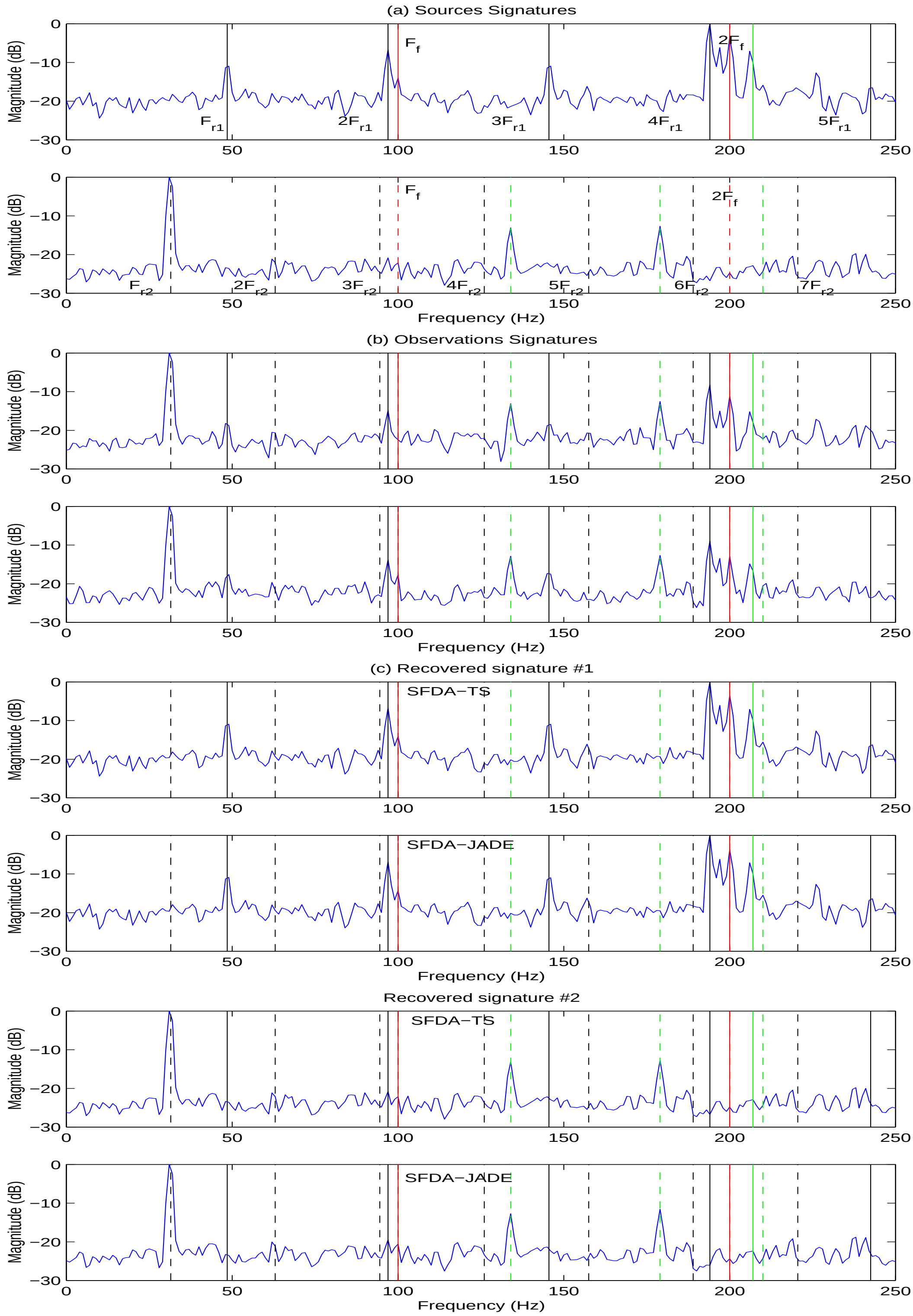

Fig. 3. Experimental results obtained using SFDA for rotating machines monitoring: (a) PSD of the sources; (b) PSD of the observations; (c) PSD of the outputs obtained with SFDA-TS and SFDA-JADE.