BLIND SEPARATION OF WIDE-BAND SOURCES : APPLICATION TO ROTATING MACHINE SIGNALS

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ABSTRACT

We propose an extension of the narrow band source separation algorithms to the case of wide band sources, which is developed in frequency domain. We mainly focus on the separation of convolutive mixtures of rotating machine noises and develop two specific points. In the first point, we study the feasibility of the separation of periodic signals, with regard to the hypothesis of random and non gaussian sources. The second point consists in the reconstruction of the spectra of the estimated sources from the signals identified at each frequency bin. Indeed, the source associated to the ith identified signal is not necessarily the same from one frequency bin to another. In this paper, we theoretically prove the feasibility of the separation of rotating machine noises and propose a solution in order to reconstruct the source spectra. The algorithm is then illustrated with experimental results, including the procedures of separation and reconstruction.

1. INTRODUCTION

The blind source separation issue has recently but largely been investigated as it arises in many fields (noise reduction, radar and sonar processing, speech enhancement, separation of rotating machine noises, localization in array processing, ...). Whatever its application, it consists in recovering the signals emitted by p sources $\underline{s}(t)$ from M observed linear mixtures $\underline{r}(t)$ of these sources. For that purpose, well known methods classically use the mere uncorrelation of the emitted source signals but need extra information to achieve their objective. For exemple, in a context of waves localization in array processing, the geometry of the wave front shapes is often supposed to be known. On the contrary, in a general context of source separation, this a priori knowledge is replaced with higher order statistic information. The only three assumptions are the non-gaussianity of the source signals, their mutual independence and the linearity and stationarity of the propagation.

Since ten years, many solutions have been proposed which test different measurements of the statistical independence. They are based on the use of fourth-order moments or cumulants, nonlinear functions, or contrast functions [1] [2] [3] [4] [5] [6] [7] [8]. Recently, a deflation procedure has been developed [9]. The linear filters (which caracterize the propagation fom the sources to the sensors) can be estimated using adaptive or nonadaptive algorithms minimizing or looking for zeros of different independence criteria. Some procedures are also based on the maximum likelihood principle [10] [11].

Most of these works reconstruct the source signals fom instantaneous mixtures. In a general case of convolutive mixtures, the problem has been treated with the help of adaptive algorithms in the time domain [4] [8]. Certain symmetrical fourth-order cumulants of the estimated sources are proposed to be canceled. Yet, it is proved that it is a sufficient condition to separate the sources only under the hypothesis of independent, identically distributed (i.i.d) processes with the same sign of kurtosis. As it has been pointed out in [4], in speech enhancement, these cumulants are not well conditioned and it seems better in that application to cancel dissymmetrical fourth-order cumulants, even if this may lead to spurious solutions.

In many applications, for exemple in the separation of rotating machines noises [12], the statistical properties of the source signals are far from the previous hypotheses which achieve the separation. Results on real data [12] proved that several problems (spurious solutions, local minima, influence of the initialization and low convergence speed) prevent from using these methods.

The source separation problem may also be treated in the frequency domain thanks to the use of multispectra [13]. In this approach, the general problem of convolutive mixtures comes to a problem of instantaneous mixtures of narrow-band sources in each frequency band. The mixtures in each band are then separated using one of the previous methods for complex mixtures [1] [2] [3].

2. MODELIZATION OF THE PROBLEM

In a general blind source separation problem, the observed M-dimensional data vector $\underline{r}(t)$ may be represented in frequency-domain by an instantaneous complex mixture for each frequency bin n, which leads to the following model:

(1) $\underline{Ri}(n) = \underline{\underline{A}}(n)\ \underline{Si}(n) + \underline{Vi}(n) \quad n=0, ..., N-1$

where $\underline{Ri}(n)$ is the N-point Discrete Fourier Transform (DFT) of the ith data block of the observation $\underline{r}(t)$. $\underline{Si}(n)$ represents the DFT of the ith data block of the p-dimensional data vector of the sources $\underline{s}(t)$. $\underline{\underline{A}}(n)$ is a matrix (M.p) which characterizes the linear propagation from sources to sensors and $\underline{Vi}(n)$ represents an additive

M-dimensional gaussian noise. The problem consists first in identifying the matrix $\underline{\underline{A}}(n)$. After a singular value decomposition, the mixing matrix $\underline{\underline{A}}(n)$ is expressed as the product of three matrices.

(2) $\underline{\underline{A}}(n) = \underline{\underline{F}}(n)\, \underline{\underline{D}}(n)\, \underline{\underline{\Pi}}(n)$

where $\underline{\underline{F}}(n)$ and $\underline{\underline{\Pi}}(n)$ are two (M.M) and (p.p) unitary matrices. $\underline{\underline{D}}(n)$ is a (M.p) diagonal matrix. The two matrices $\underline{\underline{F}}(n)$ and $\underline{\underline{D}}(n)$ are identified thanks to second-order statistic criteria. They respectively contain the eigenvectors and the eigenvalues of the spectral matrix of the observation $\underline{Ri}(n)$.

After projection of the observation vector $\underline{Ri}(n)$ in the signal subspace (which is spanned by the eigenvectors associated to the dominant eigenvalues) and normalization, the components of the p-dimensional vector, noted $\underline{Xi}(n)$, are uncorrelated and normalized. They are relied to the components of the normalized source vector, noted $\underline{s}'(t)$, by:

(3) $\underline{Xi}(n) = \underline{\underline{\Pi}}(n)\, \underline{S'i}(n)$

where $\underline{S'i}(n)$ is the DFT of $\underline{s}'(t)$.

$\underline{\underline{\Pi}}(n)$ may be expressed as a product of Givens rotations and estimated thanks to fourth-order criteria, by testing different measurements of the statistical independence [1] [2] [3] [4], as presented in §1.

3. PRESENTATION OF THE SPECIFIC PROBLEMS

We propose in this paper a generalization of the source separation problem to convolutive mixtures of wide-band sources in the frequency domain. We mainly focus on the separation of rotating machine noises and develop two points. The first one directly ensues from the frequency expression of the signals. The current methods in the field of source separation rest on the assumption that the emitted signals are random and non-gaussian sources. We discuss this point in §4 and prove the feasibility of the separation of rotating machine noises. The second point consists in the reconstruction of the estimated sources spectra from the signals identified at each frequency bin, as the source associated to the ith identified signal is not necessarily the same from one frequency bin to another. We discuss this point in §5 and propose an original method to solve the problem.

4. SEPARATION OF PERIODIC SIGNALS

This part of the paper is devoted to the feasibility of the separation of periodic signals, after Discrete Fourier Transform. As it has been shown before in §2 in the case of random signals, the source separation methods lay on the additional information provided by fourth-order statistics. This information only exists under the hypothesis of non gaussian sources. Whatever the chosen method, the variance of the estimator of matrix $\underline{\underline{\Pi}}(n)$ is inversely proportional to the kurtosis of the sources [14] [15] [16]. In a similar way, in frequency domain, we study the distance of the DFT to gaussianity thanks to the spectral kurtosis which is defined as a section of the general trispectrum of the normalized sources.

Let K(Si(n)) be the kurtosis of Si(n), defined by :

(4) $$K(Si(n)) = \frac{cum(Si(n), Si(n)^*, Si(n), Si(n)^*)}{cum(Si(n), Si(n)^*)}$$

where cum represents the cumulants of second and fourth orders and * the complex conjugate.

In practice, the source separation methods are applied on a particular realization of $\underline{Xi}(n)$, under the hypothesis of ergodic signal. Consequently, the algorithms lay on the non cancellation of the estimation K of the spectral kurtosis, where the statistical quantities are estimated by averaging over L different time data blocks.

(5) $$K = \frac{\frac{1}{L}\sum_{i=1}^{L} |Si(n)|^4 - \frac{1}{L}\left|\sum_{i=1}^{L} (Si(n))^2\right|^2}{\left(\frac{1}{L}\sum_{i=1}^{L} |Si(n)|^2\right)^2} - 2$$

In the case of periodic (thus deterministic) signals, the statistical kurtosis has non sense. However, as previously, the estimation K can always be computed by avering over L data blocks on each component of $\underline{Si}(n)$.

Let s(t) be a periodic signal with a period T. For example, let s(t) be a sinusoid of deterministic frequency and phase, noted ω and ϕ :

(6) $s(t) = A \sin(2\pi\omega t + \phi)$

Let us compute the DFT of s(t) on the ith data block of Si(n), for n close to ω :

(7) $$Si(n) = \frac{A}{2j}\exp\left(j(n + 2\pi\omega i + \pi(N-1)(\omega - \frac{n}{N})\right) \cdot \frac{\sin(\pi(\omega - \frac{n}{N})N)}{\sin(\pi(\omega - \frac{n}{N}))}$$

After some computations detailed in [17], K is equal to :

(8) $$K = -1 - \left|\frac{1}{L}\sum_{i=1}^{L} \exp(4\pi\omega i)\right|^2 = -1 - \frac{F}{L^2}$$

As the term F is bounded, the estimation of the kurtosis tends towards -1 when L is large enough for n close to ω. In the case of periodic signals, they may be decomposed in Fourier series and K tends towards -1 for the harmonic frequency bins. As a result, the non cancellation of K provides additional equations which allow the estimation of matrix $\underline{\underline{\Pi}}(n)$ in the harmonic frequencies. This point theoretically proves the feasibility of the source separation for rotating machines noises. Experimental results on this type of signals are shown in §6.

5. RECONSTRUCTION OF THE SOURCE SPECTRA

The crucial point consists in the reconstruction of the time sources sk(t) for (k=1, ..., p). After identification of the matrix $\underline{\underline{\Pi}}(n)$ with fourth-order criteria, p independent components of $\underline{Si}(n)$ are extracted in each frequency bin n.

More precisely, the identified matrix, noted $\hat{\underline{\underline{\Pi}}}(n)$, is relied to $\underline{\underline{\Pi}}(n)$ by :

(9) $\hat{\underline{\underline{\Pi}}}(n) = \underline{\underline{\Pi}}(n)\underline{\underline{P}}(n)\underline{\underline{\Delta}}(n)$

where $\underline{\underline{P}}(n)$ is a (p,p) permutation matrix and $\underline{\underline{\Delta}}(n)$ is a diagonal one. Due to the existence of this permutation matrix at each bin n, and since the methods independently treat each frequency bin, the kth identified component of $\underline{S}i(n)$ is not necessarily associated to the same time source sk(t), from one frequency bin to another.

In order to re-establish the continuity of the source spectra, several ideas have been investigated. The first one consists in examining the statistic relationship between the different estimated sources from one frequency bin to another. However, the correlation and the tricorrelation between two adjacent frequency bins of the same source depend on the shape of their spectral density and trispectrum [18]. In the particular case of rotating machine signals, it is impossible to define an absolute threshold from which the frequency components of two estimated signals would be attributed to the same temporal source or to two different sources. The second approach relies on the continuity of the unitary matrix $\underline{\underline{\Pi}}(n)$ from one frequency bin to another. As it requires the continuity of the mixing matrix $\underline{\underline{A}}(n)$ and also the source spectra, it cannot be envisaged in this particular application. These remarks show the interest of going back on a temporal expression of the sources.

The proposed method aims first at recovering the statistic relationship between the estimated sources at one frequency-bin n, $\underline{S}i(n)$, and the temporal sources $\underline{s}(t)$.

Recall the expression of the DFT of the kth component of $\underline{S}i(n)$, Si(n,k), on the ith data block :

(10) $$\mathrm{Si}(n,k) = \sum_{l=0}^{N-1} \mathrm{sk}(i+l)\exp(-2\pi j n \frac{l}{N})$$

Recall the expression of the DFT of the kth component of $\underline{S}i(n)$, on the (i+1)th data block, delayed for one sample :

(11) $$\mathrm{Si}+1(n,k) = \sum_{l=0}^{N-1} \mathrm{sk}(i+1+l)\exp(-2\pi j n \frac{l}{N})$$

We easily deduce from the two expressions (10) (11) a relation between an estimated source in frequency domain Si(n,k), at data blocks i and (i+1), and the associated temporal source sk(t): (12)

$$\mathrm{Si}+1(n,k)\exp(-2\pi j \frac{n}{N}) - \mathrm{Si}(n,k) = \mathrm{sk}(i+N) - \mathrm{sk}(i)$$

which directly ensues from the expression of the DFT. Consequently, it exists a specific MA filtering of $\underline{S}i(n)$ for each frequency bin n which is relied to a function of the time sources ($\underline{s}(t)$ - $\underline{s}(t-N)$).

Suppose now that the components of index i0, Si(n,io), and j0, Si(n+1,jo), are associated to the same time source s1(t). The previous MA filtering of Si(n,io), H(Si(n,io)), and of Si(n+1,jo), H(Si(n+1,jo)), will be equal to the same quantity (s1(i+N-1)-s1(i-1)), whatever the treated frequency bin n. Consequently, their coherence will be non zero and equal to one. On the contrary, if the two components are not associated to the same time source, H(Si(n,io)) H(Si(n+1,jo)), will be uncorrelated. Their coherence will then be zero. As a conclusion, a criterion based on the second order moments may be used to associate the N frequency components of s1(t) :

(13) $E\{H(Si(n,k)).H(Si(n+1,j))^*\} \neq 0 \, for (k,j) = (1,1)$
$= 2\,[\Gamma s1(0) - \Gamma s1(N)]$

where Γs1(k) represents the autocorrelation of the source s1(t).

(14) $E\{H(Si(n,k)).H(Si(n+1,j))^*\} = 0 \, for (k,j) \neq (1,1)$

This criterion is ambiguous in the only case where the source is periodic of period N, which is quite a particular case. Different algorithms of reconstruction are then possible, depending on the class of signals. If the spectra of the sources are continous, the reconstruction may be realized between each frequency bin and its previous bins. The contrast of the coherence between H(Si(n,io)), H(Si(n,jo)), and H(Si(n+1,k0)) allows to associate the k0-th component (at bin n+1) with the component i0 or j0 at bin n.

If the signal is a periodic one, the procedure of reconstruction is more robust if the reference bin is chosen at one of the harmonics. Indeed, the relations (13) and (14) are verified if the matrix $\underline{\underline{\Pi}}(n)$ is correctly estimated. Consequently, the quality of the reconstruction is closely linked to the quality of the separation. For the harmonics, the value of the spectral kurtosis (at -1) assumes a good separation. As a result, the contrast of the coherence between H(Si(n,io)), H(Si(n+1,jo)), and H(Si(n0,k0)), where n0 is a fixed reference bin allows to associate k0 with i0 or j0. This procedure is illustrated in §6 fig.2 on experimental data.

6. EXPERIMENTAL RESULTS

The simulation here after illustrates the results of a complete implementation of the algorithm in the frequency-domain, in the case of convolutive mixtures of two sources. The two real processes are rotating machine noises, mixed in a noisy context. In this particular experimentation, the real sources have been recorded.

We present in figure1 the coherences between the two observations and the two sources. It proves that the sources are actually mixed in the observations. After separation in frequency domain, two signals are identified in each frequency bin. They have been extracted, using a likelihood principle developed in [10]. We present in figure 2 the coherences between the two estimated sources after filtering by the specific filters proposed in §5 H(Si(n,1)), H(Si(n,2)) and one source estimated in a reference bin n0, H(Si(n0,1)). The reference bin is here fixed at 16. We remark that, for each frequency bin, one estimated source is correctly correlated with S1(n) since the second one is uncorrelated with it. This shows a very good quality of the separation procedure in all the frequency band. We present in figure 3 the coherences between the two right sources and the estimated ones after separation and reconstruction using the proposed technique in §5. The two curves close to 1 and the two curves close to 0 reveal a good quality of separation for each frequency bin and a good quality of reconstruction of the sources.

7. CONCLUSION

We propose in this paper a generalization of the source separation problem to convolutive mixtures of wide-band sources in the frequency domain. We mainly focus on the separation of convolutive mixtures of rotating machine noises and develop two specific points. In the first point, we study the feasibility of the separation of periodic signals, with regard to the hypothesis of random and non gaussian sources. The second point consists in the reconstruction of the estimated sources spectra from the signals identified at each frequency bin, since the sources associated to the ith identified signals are not necessarily the same from one frequency bin to another. We theoretically prove the feasibility of the separation of rotating machine noises and propose a solution in order to reconstruct the source spectra. Experimental results are also proposed, including the procedures of separation and reconstruction.

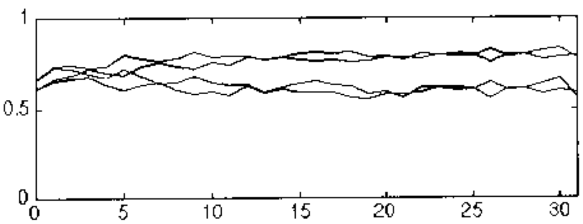

Fig1. Coherences between the observations and the right sources.

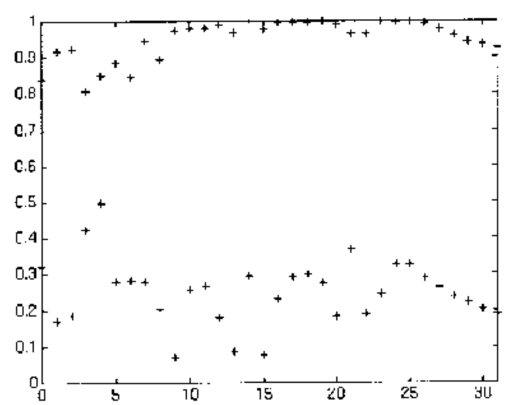

Fig2. Coherences between H(Si(n,1)), H(Si(n,2)) and one estmated source in the reference bin 16, H(Si(16,1)).

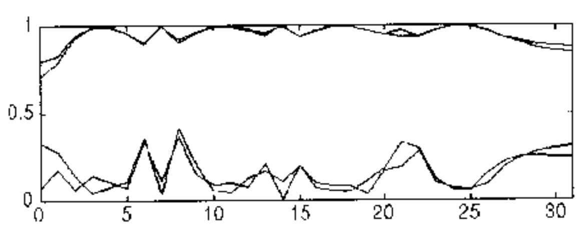

Fig3. Coherences between the right sources and the estimated ones

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