BSS FOR FAULT DETECTION AND MACHINE MONITORING

TIME OR FREQUENCY DOMAIN APPROACH ?

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ABSTRACT

There is a great interest to apply BSS methods in mechanical system signal processing for monitoring or diagnosis purpose. Actually, we show that BSS allows to recover the vibratory information issued from a single rotating machine working in a noisy environment by freeing the sensor signal from the contribution of other working machines. In that way, BSS can be used as a pre-processing step to rotating machine fault detection and diagnosis. In this paper, we compare two possible approaches to solve BSS problem of rotating machine signals, ie. temporal or frequential approach. The first method, initially developed to temporally white signals is used in an experimental context and we show that the results are comparable to frequential domain approach specially developed for rotating machine signals. These two approaches are tested on real signals arisen from a mechanical testing bench, and the implementation of different methods as well as their performances are discussed.

1. Introduction

Blind Source Separation (BSS) is a general signal processing method, which consists in recovering from a finite set of observations recorded by sensors, the contributions of different physical sources independently of the propagation medium and without any a priori knowledge of the sources. These methods have been successfully used in many fields of applied sciences and engineering including medicine, telecommunications, audio processing, noise reduction or data processing… [1]

Until now, BSS methods have seldom been used for the monitoring and diagnosis of mechanical system, such as the signal issued from rotating machines. Among the existing contributions on this field, we can mention [2] [3] [4] for a blind signal separation purpose, and also [5] for data analysis. However, it is a promising tool for non destructive monitoring because the signals recorded by sensors in an industrial application are often disrupted by the environment (ambient noise, other mechanical systems). Using BSS as a pre-processing step would enable the specific signature of each rotating system to be used for diagnose, thus isolating them from interference from the environment.

The purpose of this paper is the application of BSS to rotating machine signals separation and the comparison between temporal [3] and frequential [4] BSS approaches for convolutive mixtures. This comparison is realized on real world signals arisen from a test bench with two motors fixed to the same structure. The objective is to extract the signature of each machine from each sensor. We discuss the capability of these BSS methods to solve this problem as well as the advantages and drawbacks of temporal and frequential algorithms for this framework.

2. Blind source Separation model

Blind Source Separation is a class of signal processing methods by which unobserved signals, also called sources, are recovered from the observation of several mixtures. Typically, the observations are obtained as the output of a set of sensors, where each sensor receives a different combination of source signals. So, the adjective "blind" indicates that the source signals are not observed and also that no information is available about the mixture. This kind of approach is potentially most useful when no transfer model from the sources to the sensor is known. The lack of knowledge about the mixture and the sources is compensated by assuming the linearity of the mixing system and the statistical independence of the sources. The general model of BSS assumes the existence of *m* statistically independent signals $x_1(n),.......x_m(n)$ and the observations of *m* mixtures $y_1(n),.......y_m(n)$ such as :

$$Y(n) = [A(n)].X(n) + b(n) \tag{1}$$

In the most general case these mixtures are non-linear functions of several time lags and are commonly described by the mixing matrix *A(n)*. Nevertheless, in many fields such telecommunications or biomedicine the mixture is commonly assumed to be a linear combination of the sources. This is the case of memoryless mixing system also called instantaneous mixture. Mechanical systems are one example in which instantaneous assumption does not hold due to the transfer of the vibration through the structures. Usually, the model used for this application is a linear time dependent mixture, so called convolutive mixture. Two approaches can be used to solve the BSS problem, temporal or spectral estimation of the transfer filters.

2.1 Mixing model

Let us consider that the mixtures are linear and convolutive so that the received signals can be written :

$$y(n) = \sum_{k=0}^{\infty} A(k)x(n-k) + b(n) = [A(z)].x(n) + b(n) \tag{2}$$

where $[A(z)] = \sum_{k=0}^{\infty} A(k)z^{-k}$ represents the transfer function of the mixing system. For the case of two sources, this model can be decomposed as in figure 1. A_{ij} are linear unknown filters which are assumed to be different and dependent on the propagation medium, x_1 and x_2 are unknown sources ; we only assume that they are independent. y_1 and y_2 are sensor outputs and b_1 and b_2 are additive independent noises. BSS is achieved by estimating the inverse of the mixing matrix $A(z)$.

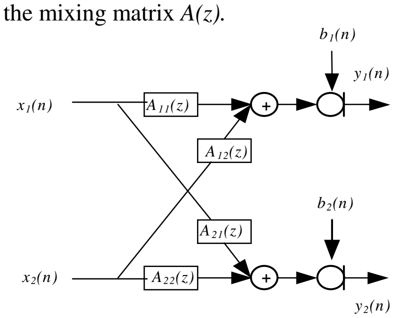

Figure 1 : Convolutive mixing model

2.2 Frequency domain mixing model

The convolutive mixture can be represented also in frequency-domain by an instantaneous complex mixture at each frequency bin f (figure2) as :

$$Y(n,f) = A(f)X(n,f) + B(n,f) \qquad f = 0,...,N-1 \tag{3}$$

where $Y(n,f)$ (respectively $X(n,f)$ and $B(n,f)$) is the N-point discrete Fourier transform (DFT) of the *n-th* data blocks of the 2-dimensional data vector $Y(n)$ (respectively $X(n)$ and $B(n)$).

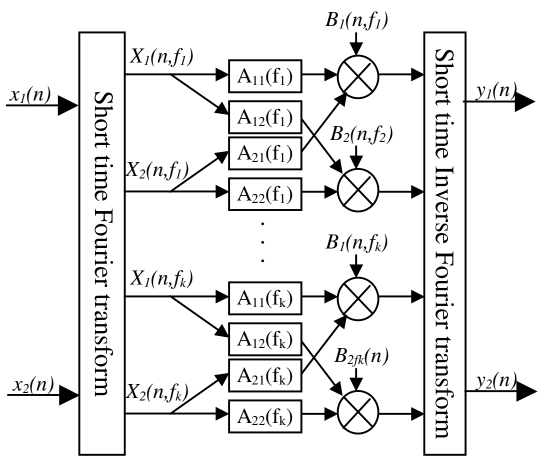

Figure 2 : spectral convolutive mixing model

The transfer matrix $A(f)$ characterizes the linear propagation from sources to sensors. It must be non singular to recover the sources at frequency bin f. The hypotheses of independence about sources and noises are assumed identically as for the temporal model.

3. Principle of separation

The basic assumption of BSS is the statistical independence between the sources. This assumption can be viewed as a strong condition about the sources, but, this assumption is really well suited to the fact that different physical processes lead to generate signals that are statistically independent to each other. This remark suggests that one way to recover sources is to restore the independence properties from signal mixtures by finding an appropriate linear transformation. In this communication, we assume the concept of BSS for instantaneous mixture (or ICA methods) well known .If is not the case, the reader is advised to refer to [6, 7]. Here, we recall only two inherent ambiguities due to the mathematical formulation of the blind separation procedure for instantaneous mixtures as well as convolutive ones. First, for instantaneous mixtures, we cannot determine the variance of the independent components. The reason is that both A and X are unknown and consequently, any scalar multiplier in one of the source x_i can be cancelled by dividing the corresponding column of the matrix A. A scaling indetermination on the source subsists, and an infinity of solution verifies the separation hypothesis. For convolutive BSS, the scaling indetermination becomes a filtering indetermination, and, equation (2) does not define the filters $A(z)$ uniquely (i.e they are not identifiable). Consequently, an infinity of solutions exists for couples $(A(z), X(n))$ such that the observation $Y(n)$ remains unchanged and the components of $X(n)$ are therefore estimated up to a linear filter. The second ambiguity of BSS problem, is that it is impossible to know the exact order of the sources and any permutation of the estimated sources gives a satisfactory solution. This indetermination remains for instantaneous or convolutive BSS.

Many approaches can be found in the literature to realize BSS with a convolutive mixing model. In this paper we stress on the 2 approaches early used in different papers. The first one is based on a temporal approach and implemented through an iterative algorithm. The second approach is based on spectral convolutive model and is implemented in frequency domain.

3.1 Temporal approach for BSS of convolutive mixtures

We emphasized previously that it is possible to restore the source signals except to a linear filtering. It is possible, however, to reduce the shape indeterminacy in the model (2) by setting a constraint either on matrices $A(z)$ (the diagonal terms of $A(z)$ are usually supposed to be unity) or on $X(n)$ (its components are generally assumed to have unit variance). The first constraint, (on $A(z)$), permits us to simplify the model shown in fig.2 for two sources. It is a realistic approximation if we assume that the sensors are as close to the sources as possible. Anyway, the ability to detect fault decreases with the distance between sensor and the fault source. Thus, it is very important for diagnosis that sensor is as close as possible to the engine being monitored. This simplified model is usually assumed when the linear filters are estimated in time-domain (the parameters A_{ij} are directly computed). So, the mixing matrix becomes :

$$A(z) = \begin{bmatrix} 1 & A_{12}(z) \\ A_{21}(z) & 1 \end{bmatrix} \tag{4}$$

In this case $A_{12}(z)$ and $A_{21}(z)$ represent the cross coupling filtering effect between the 2 processes. The second assumption to reduce the BSS problem is that $A_{ij}(z)$ are assumed to be linear and causal filters with a finite impulse response (FIR). Then the coefficient $A_{ij}(z)$ can be written as :

$$A_{ij}(z) = \sum_{k=0}^{M_{ij}-1} a_{ij}(k).z^{-k} \tag{5}$$

where M_{ij} is the filter length. This assumption is not necessary to solve our problem, but we show below that it is necessary to free from the permutation of the restored sources. Now, the general idea of convolutive temporal BSS consists in identifying an inverse matrix *of* $[A(z)]$ like :

$$C(z)=\frac{1}{D(z)}\begin{bmatrix}1 & -C_{12}(z)\\ -C_{21}(z) & 1\end{bmatrix} \qquad (6)$$

with $D(z)=1-A_{12}(z)A_{21}(z)\neq 0$ to respect the condition of invertibility of [$A(z)$]. The sources will be reconstituted by filtering signals from the sensors through this transfer matrix (6). The two unknown filters can be identified by a back propagation or recurrent procedure as shown on Figure 3 :

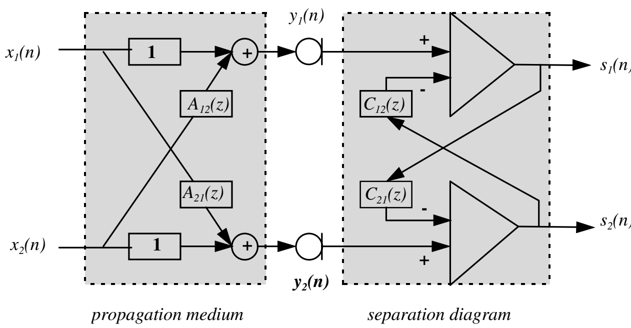

Figure 3 : recurrent procedure for BSS

The solution of this system can be obtained from :

$$s_i(n)=y_i(n)-C_{ij}(n)*s_j(n)=y_i(n)-\sum_{k=0}^{M_{ij}-1}C_{ij}(n,k).s_j(n-k) \qquad (7)$$

with $i\neq j$ and $i, j \in [1,2]$ for two sources and M_{ij} is the length of the filter C_{ij}. This solution can be written in matrix formulation as :

$$S(n)=[C(z)].Y(n)$$

$$S(n)=\frac{1}{D(z)}\begin{bmatrix}1-C_{12}(z)A_{21}(z) & A_{12}(z)-C_{12}(z)\\ A_{21}(z)-C_{21}(z) & 1-C_{21}(z)A_{12}(z)\end{bmatrix}.X(n) \qquad (8)$$

System stability will be ensured if the zeros of the polynomial $D(z)$ remain within the unit circle, i.e. if the filter $1-C_{12}(z)C_{21}(z)$ is minimum phase.

Separation is obtained when *Si* equal to *Xi* up to a permutation matrix and a linear filtering (independence of the sources). Here, (8) yields two solutions following this constraint :

- Either, $C_{12}(z)=A_{12}(z)$ and $C_{21}(z)=A_{21}(z)$ and we have the perfect theoretical solution, $s_1(z)$ equal to $x_1(z)$ and $s_2(z)$ equal to $x_2(z)$.

-The solution $C_{12}(z)=1/A_{21}(z)$ and $C_{21}(z)=1/A_{12}(z)$ is also possible to lead to independent sources. In this case, the solution $Si(z)$ is equal to $-X_j(z) / A_{ji}(z)$. However, this solution implies that the filters are infinite impulse response (IIR), then, this solution is inconsistent with our hypothesis.

The aim of BSS, is now to estimate the filters A_{12} and A_{21} (which are assumed to be unknown), and then, x_1 and x_2 could be recovered from y_1 and y_2 by inverse filtering. The method used afterwards consists in finding estimates C_{12} and C_{21} of A_{12} and A_{21} by maximizing a criterion function of the system outputs (7) through a stochastic iteration :

$$c_{ij}(n+1,k)=c_{ij}(n,k)+\mu_{ij}(n)\Phi_{ij}(n,k) \qquad (9)$$

where $\Phi_{ij}(n,k)$ is a function maximizing the independence of $S(n)$.

Many approaches to quantify the independence of $S(n)$ can be found in the literature. We can note principally three separation criteria which will be implemented on this application :

- Output decorrelation [8]

A1: $$\Phi_{ij}(n,k)=E[s_i(n).s_j(n-k)] \qquad (10)$$

- Output non linear function cancellation [9]

A2 : $$\Phi_{ij}(n,k)=E[f(s_i(n)).g(s_j(n-k))] \qquad (11)$$

- Output Cross cumulants cancellation [9]

A3 : $$\Phi_{ij}(n,k)=-sign\frac{\partial Cum31[si(n),sj(n-k)]}{\partial c_{ij}(n,k)}Cum31[si(n),sj(n-k)] \qquad (12)$$

for $i\neq j$ and i,j $\in$ [1,2] , and $0\leq k < M$, $M=max(M_{ij})$

A recent study of A1 and A2 was presented in [10], including stability analysis and asymptotic behavior, for a large class of separating functions. The authors show that the stability conditions are related to the sources statistics, the separating functions and the mixing filters for independent identically distributed (*iid*) random sequences.

For a good implementation of these classes of algorithms it is necessary to formulate some remarks. The independence between the output *i* at time *n* and the output *j* at a different time *(n-k)* is tested to obtain as many equations as coefficients in filters (*2M*). However the output independence test will be sufficient if these *2M* equations are independent. Therefore :

$$\Phi_{ij}(n,k)\neq\Phi_{ij}(n,k-1) \qquad (13)$$

This condition is verified if the signals have sufficiently broad band spectra and if the sampling frequency (*Fe*) is not too high, so that $s_j(n)$ and $s_j(n-1)$ can be actually independent. Otherwise, over-sampling would damage the algorithm because it would generate adaptation equations that are too similar.

3.2 Frequential approach for convolutive BSS

In frequency domain, the convolutive mixture is reduced to an instantaneous complex mixture for each frequency bin. The scaling indetermination is eliminated here by setting a constraint on the source power. The source components are assumed to have unit variance. The mixing matrix $A(f)$ is then expressed as the product of three matrices, after a singular value decomposition:

$$A(f)=V(f).\Delta(f)^{1/2}.\Pi(f) \qquad (14)$$

$V(f)$ and $\Pi(f)$ are two (2.2) unitary matrices. $\Delta(f)$ is a (2.2) diagonal matrix. The two matrices $V(f)$ and $\Pi(f)$ are identified using only second order statistic criteria. They respectively contain the eigenvectors and the eigenvalues of the spectral matrix of the observation $Y(n)$. After projection of the observation $Y(n,f)$ in the subspace spanned by the eigenvectors and normalization, the data $Z(n,f)$ are whitened. They are linked to the components of the source vector after $X(n,f)$ by a remaining unitary transformation:

$$Z(n,f)=\Pi(f).X(n,f) \qquad (15)$$

The matrix $\Pi(f)$ can be expressed as a product of Givens rotations. It cannot be identified from the use of the mere uncorrelation of the sources, as $\Pi(f)$ is not observable from the covariance matrix of the data $Y(n,f)$. It is clear that additional information is necessary, which is provided by assuming the statistical independence between the source components [6,7,11] or some temporal correlation of the sources [12, 13].

Concerning the temporal correlation of the sources, we prove that matrix $\Pi(f)$ results on the diagonalization of delayed interspectral matrix [13]. Concerning statistical independence, the additional information exists only under the hypothesis of non gaussian sources. Fourier transform is often thought to converge towards gaussianity, but it was shown in [14] that this assertion is not valid for spectral lines signals like those of rotating machines. More precisely, the spectral kurtosis is equal to (-1) at all the harmonic bins. Hence, for these latters, any higher order based source separation algorithm for instantaneous complex mixtures can be used in each frequency bin. Here, we apply a maximum likelihood based method [11] to estimate $\Pi(f)$. In the case of two sources, $\Pi(f)$ is a complex Givens rotation, parameterized with two angles. The maximum likelihood function is computed, using a Gram-Charlier expansion of the sources probability laws. The expansion is stopped at the fourth order and $\Pi(f)$ is expressed with fourth-order cumulants of the observations.

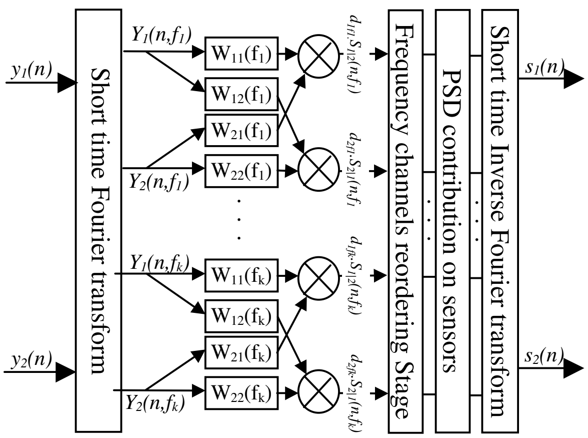

Figure 4 : Frequential BSS separation

After the separation step, each frequency bin contains two independent non gaussian components. The mixing matrix is recovered up to a permutation matrix. Hence we estimate a matrix $W(f)$, such that :

$$W(f)A(f) = D(f)P(f) \tag{16}$$

where $P(f)$ is a permutation matrix and $D(f)$ is a diagonal complex one. The permutation indeterminacies can be removed by the reordering step described in [14]. It aims at recovering the statistical relationship between the estimated sources at one frequency bin and the temporal sources $x_i(n)$. It uses the redundant information between $S_i(n,f)$ *and* $S_i(n+1,f)$ on the temporal source. Indeed, it exists an MA filtering of $S_i(n,f)$ versus the temporal index n which reconstitutes the temporal signal $(x_i(n)\ -\ x_i(n-N))$. The permutations are then detected and removed, comparing the coherence of the filtered estimated sources between different frequency bins f.

A constraint is then applied to $X(n)$ by an energy normalization of $S_i(n,f)$ in each frequency bin followed by a correlation measure between $S_i(n,f)$ and $Y_j(n,f)$ for $j=1,2$. In that way, filter indeterminacy can be partially circumvented by restoring the PSD contribution of each source on each sensor. This approach is equivalent to that described in §3.1 when sensors are actually nearby the sources. The figure 4 presents the synopsis of the frequency domain approach.

4. Application to rotating machine vibrations

4.1 Experimental context

The experiments were done on a test bed bearing to two DC motors (1.4 kW and 1.1 kW) with varying rotation speed. The 2 motors were fixed to the same frame as in Figure 4. Two accelerometers were glued on each motor to measure vibrations.

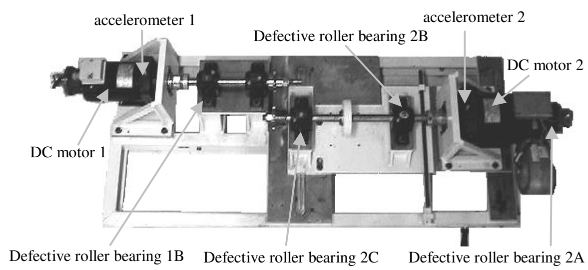

Figure 5 : test bench

The contributions of the two motors were received by each sensor. The problem illustrated by this experiment is for example a factory in which two rotating machines operate simultaneously, but each machine must be diagnosed separately. Thus, according to the superposition principle, signals received by sensors placed on each machine are disrupted by those from the other machines. There is a great interest to use BSS methods as part of the diagnostic process because BSS should allow to be free to the noisy environment ie. restoring on each sensor the signature of its own machine without having to stop them which would be damaging to the production. So, BSS can be viewed as a pre-processing step (denoising) that allows to improve the diagnosis. Traditional methods of fault detection could then be applied to the specific signatures of the system to be diagnosed.

With real world recordings, it is very difficult to measure the separation quality. Here, we used the a priory knowledge on the sources, and equally the signals recorded on each sources separately in the real environment (called reference). In a first step, we describe this two reference signals shown in fig 6. Afterwards, the motor which has for rotation speed 48.5 Hz is called “motor 1” and the one which turns at 31.5 Hz “motor 2”. Motor 1 is feeded by a single phase wiring (rectified) which presents 100 Hz for fundamental frequency plus the harmonics. The motor 2 is feeded by a three phase wiring (rectified) which presents 100, 200 and 300 Hz frequencies. These wiring frequencies are represented in all the next figure in dash dotted line. The harmonics of the low rotating frequency (motor 1) are drawn in dotted lines and thus for high rotating frequency (motor 2) are drawn in dashed lines. Each motor is fitted out with two single row roller bearing (6203 RS C3) and drives a main shaft equipped with two self aligning roller bearing (2207 KTV C3). Roller bearing 2A, 2B, 2C, and 1B were found to be faulty and induce two defect frequencies at 134Hz (outer race fault on 2C), 179Hz (outer race fault on 2A), 207Hz (outer race fault on 1B) and 210Hz (inner race fault on 2B). These frequencies are marked on figures 6, 7 and 8 in solid lines. 20000 samples were recorded at Fs=2 kHz and resampled for temporal approach to 500 Hz. Figure 7 presents the PSD (Welch averaged method) of the two records obtained on each sensor. Each PSD was normalized by its maximal value.

4.2 Separation results

- Settings :

Concerning the temporal methods, the number of filter coefficients *M* for the mixture was experimentally estimated by impulse response method equal to 100 for a sampling frequency equal to 500 Hz. All temporal algorithms were implemented with a constant gain (for different *n*) but with multiple pass of the observations for different value of μ_{ij} in order to refine the results around the separating solution. Both adapting step μ_{ij} were set to [0.2, 0.1, 0.01, 0.001]. For the frequency domain method, the mixing matrix have been estimated on 256 frequency bins in the frequency band [0-250] Hz. 20.000 samples were considered for each frequency channel to perform separation.

- Experimental Results :

The results obtained with the four approaches are depicted in figure 8. For legibility, each plot is shifted with respect to frequency domain results.

- Firstly, Figure 8 indicates that all the methods excepted cross-cumulants cancellation give satisfactory results for the 2 motor rotating frequencies plus harmonics (position and magnitude) excepted for the 5th harmonic of motor 1 for which temporal BSS was not efficient. Decorrelation criterion seems to provide a slightly better results for the fundamental frequency of motor 2 and is the more accurate temporal method to solve this BSS problem. Another remarks allow to favor this solution is that rotating machine signals are present obviously highly temporal correlation and all the temporal methods used in this paper are dedicated to white signals. Second order criterion seems to be less sensitive to this strong assumption on the sources.

- Concerning the feeding frequencies (k.100Hz) present in both sources but prevalent on the motor1, frequency domain method provides better separation, actually, temporal approach leads to attribute one feeding harmonic in each source.

- Concerning the bearing frequencies, most of faults are clearly re-associated with its driving shaft. However, the fault connected with the bearing 2C (outer race), which is more distant from the sensor seems to be attributed to the good source only with frequential approach. For temporal methods, no BSS is performed at this frequency. Plausible hypothesis is that the faulty bearing corresponding to this frequency stands away from the principal vibratory sources (ie. the motors). In this case, it seems that the faulty bearing acts like a third source towards the sensors. The minimum sensor requirement towards the sources is not respected and no separation is performed. Frequential domain approach is insensitive to this fact due to the presence of the faulty bearing frequency only in one frequency bin. Concerning the others faults related to bearing (outer race of 1 B : 207 Hz and inner race of 2A : 210 Hz), no problem occurs in the separation step for both temporal and frequential domain approaches because of their closeness to the motors. In that case, the condition of sources punctuality is respected and the quality of separation at these frequencies allow to detect and to locate the presence of faults more easily than in the mixtures (figure 7).

- Practical point of view :

From a practical point of view, we must mention that the frequency domain algorithm is really computationally difficult to implement. The good results obtained with decorrelation approach and the attractive computational cost seems to be a good alternative for our objective. However, to obtain a very good separation quality in few frequency bins, frequency domain method seems to be more accurate. A combination of these two methods could be a good alternative neither too computational cost nor too accuracy.

5. Conclusion

The experimental results provided by this paper allow to consider BSS as a promising tool pre-processing in mechanical fault diagnosis applications. In this framework, we show that temporal and frequential BSS approaches for convolutive mixture give rise to very close results. However the high computational cost of the frequential approach with respect to temporal one is prohibitive for an implementation for the whole frequency bins. On the other hand, this method seems to be less sensitive about the gap from model hypothesis as shown in §4.2.

6. References

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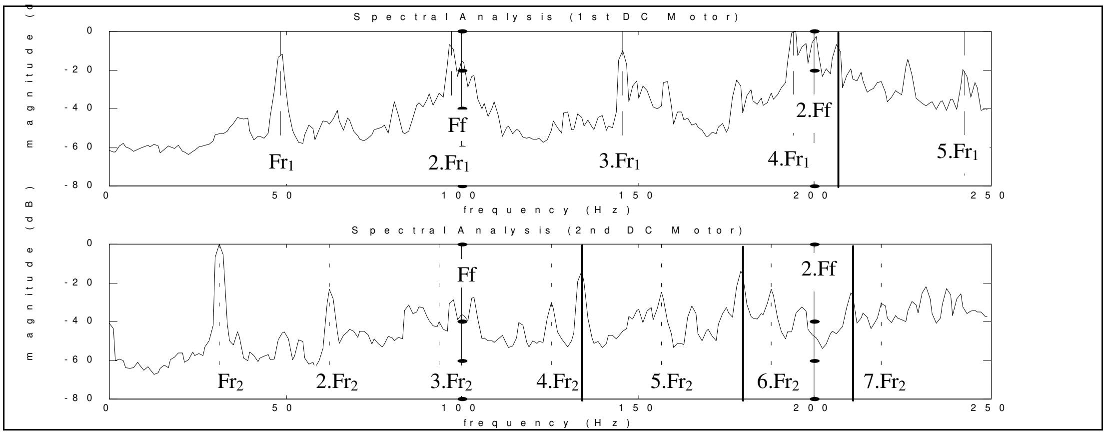

Figure 6 : Source references

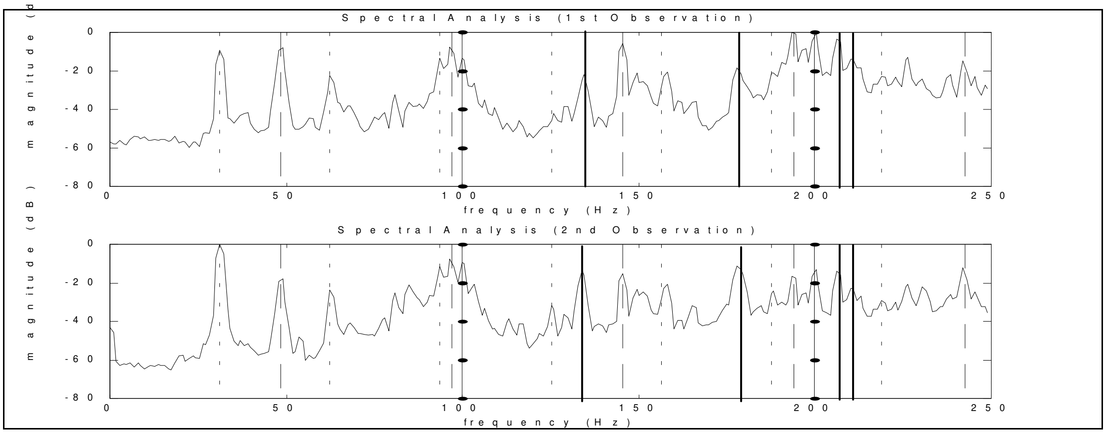

Figure 7 : Sensor signals (mixture)

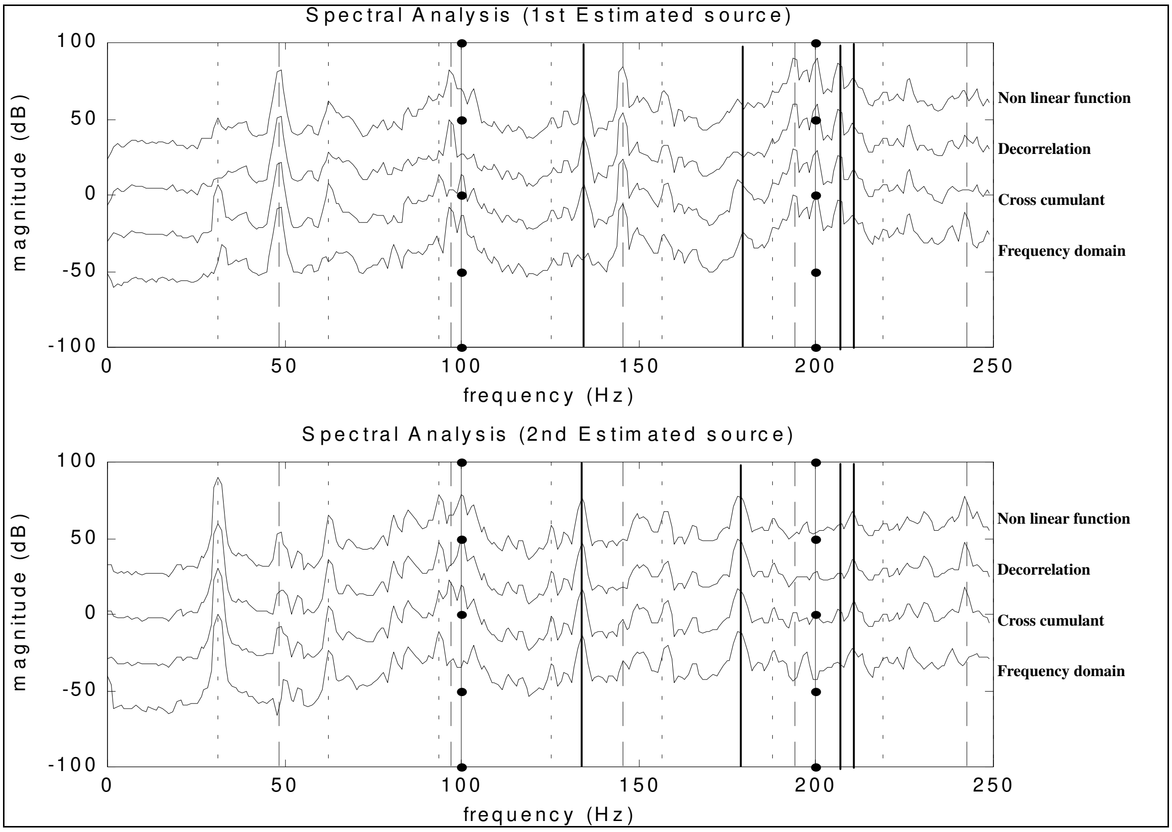

Figure 8 : estimated sources