Analysis of vibration responses of defective rolling bearings using Blind Source Serparation

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Abstract: Separating vibration signals generated by defective rolling bearings is of major importance for rotating machinery health monitoring, since rolling bearings of the same type are quite frequently encountered in the industrial environment, especially in large machines, critical in the production process. For this reason, Blind Source Separation (BSS) is considered for application on vibration signals, which may include characteristic simulated defective bearing responses under different types of bearing faults. It is demonstrated that the BSS method, properly implemented, is quite able to decompose the measured signal into a number of independent components, each one corresponding to the vibration induced by an individual bearing.

Key-words: Blind Source Separation, Independent Component Analysis, bearings,vibration analysis

1 Introduction

Bearings are the most important components in the vast majority of machines and exacting demands are made upon their carrying capacity and reliability. Therefore it is quite natural that rolling bearings should have come to play such a prominent part and that over the years they have been the subject of extensive research.

It has been found that defects in rolling bearings can be identified and quantified with vibration analysis. Bearing defects cause bearing impacts at frequencies governed by the operating speed of the unit and the geometry of the bearings. Excessive wear and defects cause the bearing to ring at its natural frequencies, a phenomenon utilized in high-frequency demodulation (*enveloping*) techniques [1].

However, although monitoring and fault diagnosis of rotating machines based on their vibratory and acoustical response is the dominating industrial practice, many practical problems are encountered, since the vibration and especially the acoustical response is usually corrupted by other interfering sources and noise.

A frequently encountered industrial case is the separation of vibration responses of the same type of bearings inside the same machine, mounted for e.g. on the same shaft. In this case, methods for the decomposition of the measured the signals into a number of independent components is quite important, so that the individual bearing sources can be analysed separately.

An ideal canditate for this reason, are *Blind Source Separation* methods, already used in statistical signal processing [6, 9, 10, 11, 12, 13].

They first emerged as an extension to the well-known principal component analysis *(PCA)* by Comon [2]. Comon's original studies were not specially on source separation but on finding domain decompositions producing basis sets that are statistically independent. In this approach, first, *PCA* is used to achieve independence up to second-order statistics, then higher order cumulants are calculated, such as the third and fourth order cumulants.

Herault and Jutten [3] introduced a neuromimetic approach. Their algorithm worked as a neural network, in which certain weights were trained. A specific constraint on the network is the requirement that the inputs should have a zero mean.

Bell and Sejnowski [8] have developed an unsupervised learning algorithm based on entropy maximization in a single-layer feed forward neural network. The algorithm is effective in separating sources that have super-Gaussian distributions. The self-organizing learning rule maximizes the information transferred in a network of non-linear units.

Amari et al. [7] derive a new on-line learning algorithm that minimizes a statistical dependency among outputs for blind separation of mixed signals. The dependency is measured by the average mutual information of the outputs. The Gram-Charlier expansion instead of the Edgeworth expansion is used in evaluating the mutual information. The natural gradient approach is used to minimize the mutual information. A novel activation function is proposed for the on-line learning rule.

Cichocki et al. [5] present several modifications of blind separation adaptive algorithms, which have significant advantages over the Herault-Jutten learning algorithm in handing ill-conditioned signals. The proposed algorithm is more stable and converges to the correct solutions in cases where previous algorithms did not.

In this paper the sources of interest are separated, using the learning algorithm proposed by the quite recent algorithm of Te-Won Lee et al. [4], due to its general application.

In section 2, an introduction on the principles of *Blind Source Separation* is performed, followed by the proposed learning rule. In section 3, signals resulting from the simulation of defective rolling elements of the same type are examined, in order to check the validity and performance of the learning algorithms.

2 Principles of Blind Source Separation

Blind Source Separation is critically related to *Independent Component Analysis (ICA)*, a recently developed signal processing technique for analysing noisy mixtures of signals as a linear combination of statistically independent signals. This method is a class of signal processing methods by which unobserved signals (*sources*) are recovered from the observation of several mixtures. The observations are obtained as the output of a set of sensors, where each sensor receives a different combination of source signals. The adjective *'blind'* indicates that the source signals are not observed and also that no information is available about the mixture. The basic assumption is that the mutual independence of the sources compensates the lack of knowledge about the mixture and the sources. From the mathematical point of view, the solution to the *BSS* problem is a separating matrix *A* which transforms the mixture signals into signals with a maximal degree of independence estimating the original source signals.

The simplest *BSS* model assumes N unknown, independent signals $s_1(t),\ s_2(t),\ \ldots,\ s_n(t)$. These sources are instantaneously mixed with an unknown linear *NxN* matrix *A*, which produces observation signals $x_1(t),\ x_2(t),\ \ldots,\ x_n(t)$.

Source signals are denoted by a N*x1* vector:

$$s(t)=[s_1(t),\ \ldots\ ,\ s_n(t)]^T,\ t=0,1,2,\ldots \tag{1}$$

and it is assumed that each component of $s(t)$ is independent of each other. The independence of the sources is defined by:

$$p[s_1(t),\ \ldots,s_1(t-\tau),s_2(t),\ \ldots,s_2(t-\tau)]=$$

$$=\Pi p[s_i(t),s_i(t-1),\ldots,s_i(t-\tau)] \tag{2}$$

for any τ. Equation (2) implies that the joint distribution of signals can be factored by the propability functions used. The source signals $s(t)$ are assumed to be of zero mean.

Observations are presented by a vector:

$$x(t)=[x_1(t),\ \ldots\ ,\ x_n(t)]^T,\ t=0,1,2,\ldots \tag{3}$$

They correspond to the measured signals. In the basic *BSS* problem, the observed signals are linear mixtures of the source signals:

$$x(t)=A*s(t) \tag{4}$$

where *A* is an unknown linear operator.

The goal of the *Blind Source Separation* is to find a linear *NxN* separating matrix *B* such that the components of the reconstructed signals:

$$y(t)=B*x(t) \tag{5}$$

are matually independent, without knowing the matrix *A* and the probability distribution of the source signals $s(t)$.

The source separation criterion focuses on finding the spatial diversity of signals that are gathered from several different sensors. The time structure is ignored and the goal is to determine the probability distribution of vector x, given a sample distribution. The mixing matrix *A* is assumed to have linearly independent columns, which allows one to define algorithms with uniform performance whose behaviors are independent of a specific mixture. The input sources are taken to be matually independent, meaning that signal $s_i(t)$ is not influenced by $s_j(t)$. The techniques for separating such sources are widely available. These techniques vary depending on the assumptions of the source distributions.

The separating technique that is chosen for implementation, is an extension of the infomax algorithm of Bell and Sejnowski [8], which is able to blindly separate mixed signals with sub- and super-Gaussian source distribution [4]. This is achived by using a simple type of learning rule, first derived by Girolami [4] by chosing negentropy as a projection pursuit index. Probability distributions that have sub- and super-Gaussian regimes are used to derive a general learning rule that preserves the simple architecture produced by Bell and Sejnowski. The method is optimized using the natural gradient by Amari [7], and uses the stability analysis of Gardoso et al. [14] to switch between sub- and super-Gaussian regimes.

The learning rule for strictily sub-Gaussian sources is:

$$dB/dt=[1+tanh(y)y^T-yy^T]B \tag{6}$$

The learning rule for super-Gaussian sources is:

$$dB/dt=[1-tanh(y)y^T-yy^T]B \tag{7}$$

The difference between the sub- and super-Gaussian leaning rule is the sign before the tanh function and can be determined using a switching criterion.

The switching between the sub- and the super-Gaussian learning rule is:

$$dB/dt=[1-ktanh(y)y^T-yy^T]B \tag{8}$$

and:

$$\begin{array}{l} k_i=1: \text{super-Gaussian} \\ k_i=-1: \text{sub-Gaussian} \end{array} \tag{9}$$

where:

k_i are elements of the N dimensional diagonal matrix K.

In order to ensure that the elements:

$$k_i>0 \tag{10}$$

the learning rule of equation (8) is used, where the elements k_i are defined as:

$$K_i=sign\{E[sech^2(y_i)]E(y_i^2)-E[(tanh(y_i))y_i]\} \tag{11}$$

3 Analysis of bearing vibration signals

A wear on a rolling element bearing component produces a train of impacts that occur periodically at frequencies characterized by the nature of the bearing defect, the bearing geometry and the rotation speed. The impacts cause resonances at the natural frequencies of the installed rolling element bearing or even of the entire machine. When the wear progresses, more frequencies around these resonances appear, which are sidebands of the machine rotation speed, as well as modulating peaks, spaced at the characteristic bearing defect frequencies.

In order to check the validity and the performance of the above adaptive algorithms, as defined by Eqs. (8), (9), (10) and (11), simulated signals are used, corresponding to the above characteristic vibration response, resulting from the same type of rolling elements under a different defect, which are assumed to operate inside the same machine (for e.g. mounted on the same shaft).

The first signal $s_1(t)$ corresponds to a typical response of a bearing with an outer race defect. The ball passing frequency outer race of the bearing *(BPFO)* is chosen equal to 74 Hz and the structural natural frequency w, assumed to be excited, is chosen equal to 1186 Hz. The sampling frequency of the simulated signal is 10 KHz, its length is equal to 4096 samples and the sfaft rotation speed f_{shaft} is assumed to be equal to 22 Hz.

Figure 1(a) illustrates the waveform of the signal, and Fig. 2(a) presents its Power Spectrum. The highest peak in the spectrum is the eigenfrequency w, which is surrounded by sidebands of the *BPFO* defect frequency. This pattern in the Fourier analysis of the signal provides an initial evidence of the modulation of the natural frequency by the bearing defect frequency *BPFO*.

The second signal $s_2(t)$ presents a typical vibration response, generated at a rolling element bearing with an inner race fault. The sampling rate of the simulated signal is 10 KHz, its length is equal to 4096 samples, the rotation speed f_{shaft} is 22 Hz, the eigenfrequency z is 2385 Hz and the defect frequency *BPFI* is equal to 113 Hz.

Figure 1(b) presents the waveform of the signal, and fig. 2(b) displays the spectrum analysis of this signal. The spectrum presents sidebands of the defect and the rotational frequency around the eigenfrequency z. This frequency pattern could be indicative of a modulation effect, present in the signal.

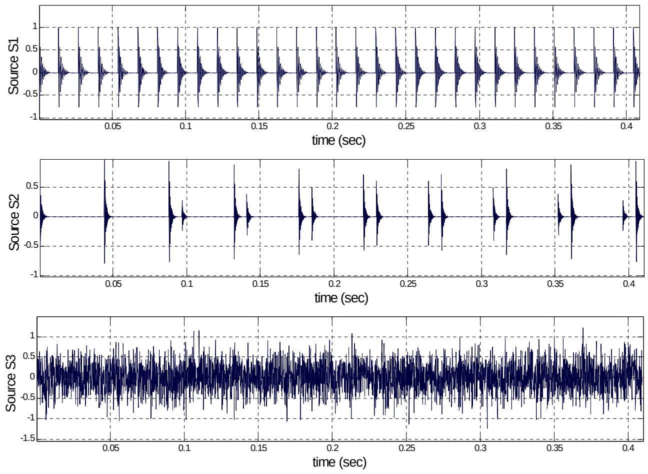

Figure 1: Waveforms presenting simulated signals of the response of a rolling element bearing with (a) an outer race defect and (b) an inner race defect, and (c) white noise.

The last simulated signal $s_3(t)$ represents noise, generated accidentally by other interfering sources. This signal is assumed to corrupt the bearing fault signals. The sampling rate of the simulated signal is also 10 KHz and its length is equal to 4096 samples. Figure 1(c) presents the waveform of the noise, and fig. 2(c) illustrates the spectrum analysis of this signal.

In all cases the code of the algorithm that is used for the computation of the simulated signals has been developed under the *MATLAB* programming environment. The Blind Source Seraration analysis of the simulated signals was also implemented with the aid of the *MATLAB* signal processing toolbox.

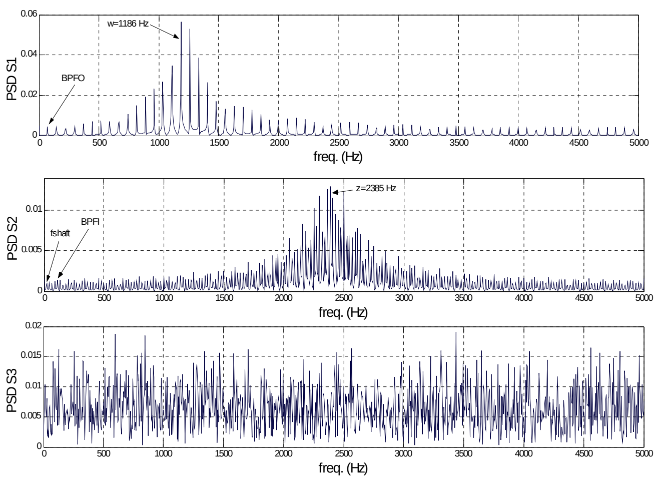

Figure 2: Power Spectral density (*PSD*) of the signals in Fig. 1.

The mixing matrix A is chosen to be nearly singular:

$$A = \begin{bmatrix} 1.7 & 2.6 & 1 \\ 2.5 & 1.3 & 1 \\ 1.2 & 1.5 & 2.3 \end{bmatrix} \qquad (11)$$

It was assumed that only the combined sensor signals $x_1(t)$, $x_2(t)$ and $x_3(t)$ are observable. The observed signals are shown in figure 3. The sensors that measure the signals $x_1(t)$ and $x_2(t)$ are mounted close to the sources that transmit the signals $s_2(t)$ and $s_1(t)$ respectively, whilst the sensor that measures the signal $x_3(t)$ is mounted close to the source that transmits the noise signal $s_3(t)$.

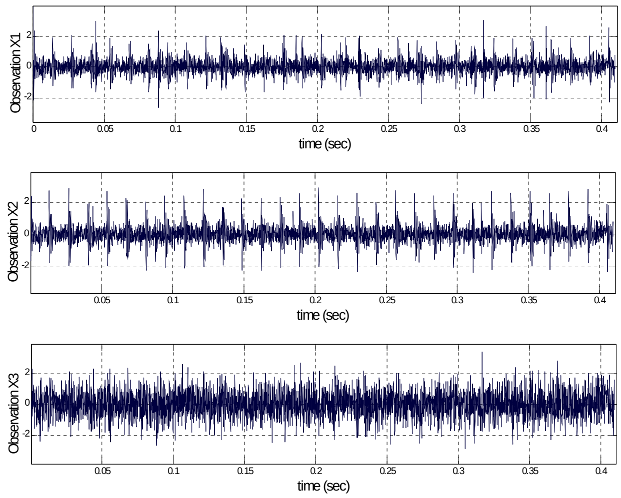

Figure 3: Waveforms presenting the measured signals (a) $x_1(t)$, (b) $x_2(t)$ and (c) $x_3(t)$.

The frequency analysis of the observed signal $x_1(t)$ is shown in figure 4(a). Several peaks appear at the power spectral density of the signal. As an experienced analyst might recognize, the most important ones correspond to the sidebands around the natural frequencies of $w = 1186$ Hz and $z = 2385$ Hz, and the defect frequencies *BPFO* and *BPFI*. The spacing between the frequency components, that surround the eigen-frequencies w and z, is equal to the defect frequency *BPFO* and the shaft speed f_{shaft}. Therefore, this frequency pattern could be indicative for modulation effects present in the signal and characterizing an outer and inner race fault of the bearing.

The frequency analysis of the other odserved signals $x_2(t)$ [fig. 4(b)]and $x_3(t)$ [fig. 4(c)] present similar results to the ones mentioned above. It should be noted, that the weak source signal (*BPFI*) is not clearly visible neither in the observed signals nor in their frequency analysis. Additionally, it is difficult to recognize the bearing with the inner race defect and the bearing with the outer race defect, since they are of the same type and assumed to be mounted on the same shaft.

The *Blind Source Separation* algorithm of the observations $x_1(t)$, $x_2(t)$ and $x_3(t)$ of fig.3 is then implemented in order to separate the source signals $s_1(t)$, $s_2(t)$ and $s_3(t)$, and to identify the defect type of each bearing. The BSS algorithm has converged to the desired solution almost immediately, only after 500 iterations. As illustrated in figure 5, the source signals are successfully and completely retrieved.

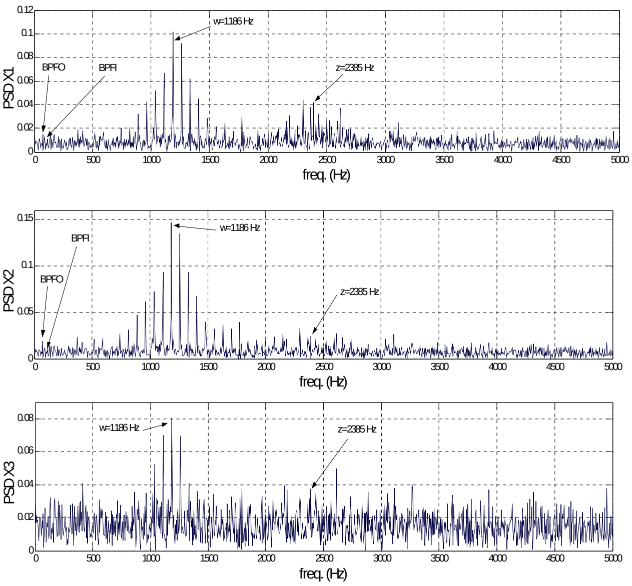

Figure 4: Frequency analysis of the observations (a) $x_1(t)$, (b) $x_2(t)$ and (c) $x_3(t)$.

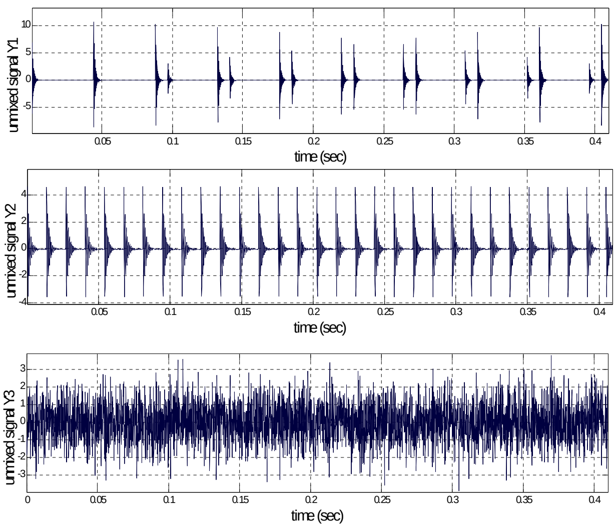

Figure 5: Waveforms presenting the serarated source signals (a) $y_1(t)$, (b) $y_2(t)$ and (c) $y_3(t)$.

Additionally to the separation of the individual signals, the method is also able to identify their spatial source, using the calculated scale factors of the mixing matrix A. They are indicative of the distance between the sensor and the source. The closer to the source, the greater is the scale factor.

The first output signal [fig. 5(a)] of the *BSS* analysis corresponds to a typical response of a bearing with an inner race defect, and has been contributed by the rolling bearing that is closer to the sensor measuring the observation x_1.

The second output signal [fig. 5(b)] corresponds to a typical response of a bearing with an outer race defect, and has been contributed by the rolling bearing that is closer to the sensor measuring the observation x_2.

Likewise, the last signal, shown in figure 5(c) corresponds, to the added noise and has been transmited by other interfering noise sources, which are closed to the sensor measuring the observation x_3.

Figure 6 presents the frequency analysis of the output signals and confirms the results of the implementation of the *BSS* algorithm, regarding the sourse signals.

As derived and confirmed by the numerical simulations, the *BSS* algorithm can provide solutions in the case where we cannot obtain measurements close enough to the source. *BSS* is a technique that allows the recovery of source signals and the detection of the source from observed signals in the case where bearings of the same type are mounted inside the same machine, or even on the same shaft.

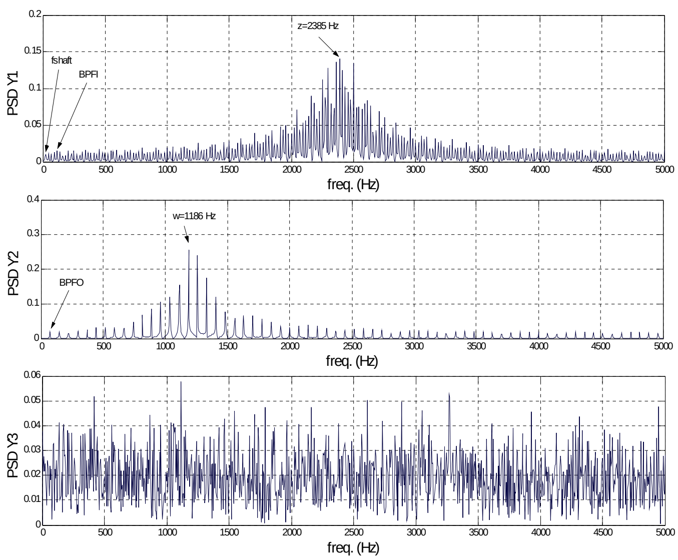

Figure 6: Power Spectral density (*PSD*) of the output signals of figure 5.

4 Conclusion

The problem of separating fault signals generated by defective rolling bearing bearings of the same type, and which are mounted inside the same machine is successfully adressed, using the *Blind Source Separation* technique. This method, is able to recover the contribution of different physical sources from a finite set of observations, recorded by sensors, independent of the propagation medium and without any prior knowledge of the sources. The learning algorithm has the capability not only to separate the source signals but, also, to detect the sources where each signal is emitted.

Thus, the implementation of the proposed method is an efficient and significant tool that aids and enhances the application of the other signal processing methods.

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