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Combination of Single Channel Blind Source Separation Method and Normal Distribution for Diagnosis of Bearing Faults

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Abstract

In most industrial environments, vibration analysis is widely used for fault diagnosis of rolling bearings. The vibration signal measured from a bearing represents a mixture of motor vibration, rolling vibration, noise, and other sources. Due to the high cost of devices and limited space, only one sensor can be installed to measure this signal. In this paper, a feature extraction method based on Single Channel Blind Source Separation (SCBSS) and Normal Distribution (ND) is proposed for vibration monitoring of rolling element bearings. To decompose the bearing signal, SCBSS is applied for separating the different sources. Because ND is sensitive to the type of fault, it is used as criterion to find an output that contains the maximum information about the fault by removing the other sources. In fact, the obtained signal contains other vibrations which affect the correct source of fault. A second SCBSS filter is, therefore, proposed to decompose the selected source and thus improves the performance of fault diagnosis. The application of the proposed method is carried out on a deep groove ball bearing with outer race fault, ball fault, and inner race fault in order to better validate the diagnosis results.

Keywords: Vibration analysis, Fault diagnosis, Single Channel Blind Separation Source, Normal Distribution, Rolling bearing.

1. Introduction

The vibration monitoring and fault diagnosis of rotating machines is the most important strategy to guaranty the operating conditions of such equipment [1-2-3]. The main objective is to monitor and know the state of the machines at all times in order to detect a failure early [4-5].

The rolling element bearing is the most important components of rotating machines and their load capacity and reliability are subject to high demands. The malfunction of rolling bearings may cause abnormal vibration and undesirable noise [6]. Their monitoring is therefore a serious subject for researchers to improve the bearing performance.

In the industrial field, the measured vibration signal of rolling bearings is a mixture of vibration from motor, rolling element, other sources and the noise [7]. The Blind Source Separation (BSS) method, called also ICA algorithm (Independent Component Analysis), is one of the most effective methods for solving the multi-component or multi-source signal problems [8], and it is used to separate or recover unknown source signals through the signals observed in cases where the source signals cannot be acquired precisely [9].

In many cases, only one sensor can be installed for monitoring mechanical equipment due to the high cost of devices and limited space. Therefore, research on adequate single-channel separation methods to separate the sources from each other using only one sensor, is of great interest [10]. Among them we find the Single Channel Blind Source Separation method (SCBSS) [11]. SCBSS is a special case of BSS, which must satisfy the condition that the number of sensor signals is less than the number of source signals [12]. Especially, it requires only a single sensor to separate multiple source signals [13]. A large number of SCBSS applications has been studied and documented, e.g. Sun et al [14] Used an adaptive multiscale generalized morphology filter (AMGMF) combined with adaptive fast ensemble empirical mode decomposition (AFEEMD) for diagnosis of the composite failure of the rotor system. Xu et al [15] combined EEMD, PCA and Robust ICA for diagnosing of bearing faults. Xiong et al [16] proposed an algorithm based on SCBSS, Complementary EEMD and PCA for motion artifact reduction in ambulatory ECG signals. He et al [17] presented a new SCBSS based on the multi-channel mapping and Independent Component Analysis (ICA) to separate the mixed signal. In the same context, the SCBSS method is widely used in industry, especially for combined fault problems [15-17]. It effectively isolates the mechanical fault for each part individually [18]. Compared to EEMD. Although EEMD algorithm can effectively reduce the mode mixing problem, there are still problems such as empirical selection of parameters and time consuming [19]. In addition, rotating mechanical sampling signals often contain

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strong background noise, in which the impact signal is the main cause of EEMD aliasing. Therefore, it is necessary to filter the signal in order to reduce noise interference before EEMD decomposition

In fact, the vibration signal of rolling bearings, even without noise, is a signal with several sources or components [7]. For this purpose, there should be close attention paid to the decomposition and analysis of multi-components signals. There are several methods of decomposition exist such as: Empirical Mode decomposition [20], Wavelet Decomposition [1-21] and BSS. In the present work, the SCBSS method is applied for separating or decomposing the multi-components bearing signal into different sources in order to extract the source with useful information by eliminating the unwanted signals and interferences.

In this paper, we propose to use a combination between SCBSS and ND as a selection criterion. First, a SCBSS filter is used to decompose the measured vibration signal into a series of sources, and then the ND and its mean are employed to select the source component that contains the most characteristic fault information. The envelope spectrum is applied to explore the fault information upon the appearance of the fault characteristic frequencies.

Knowing that the signal of a bearing has several components, so there is an unclear extraction of the fault characteristics in the frequency spectrum, which affects the performance of the bearing fault diagnosis. To overcome this difficulty, the resulting signal from the SCBSS filter is again injected into the same filter. Finally, to assess the quality of recovered signal; the kurtosis, Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE) are calculated for each SCBSS output.

The remaining sections are organized as follows. Section 2 presents the proposed method and the mathematical formulations of SCBSS and ND. Section 3 describes the bearing test rig and the bearing characteristic frequencies. Section 4 discusses the obtained diagnosis results and evaluates the proposed method by calculating the kurtosis, the SNR and the MSE. Finally, Section 5 presents our concluding remarks.

2. Theoretical Descriptions:

2.1. Blind Source Separation (BSS):

BSS is a signal processing technique, addressed specially for recovering multiple independent sources from their mixtures. It is closely related to Independent Component Analysis (ICA) [11]. When monitoring and fault diagnosis of mechanical equipment, the M observations, which represent the outputs of the M sensors, are the linear combinations of the N sources. In this way, the output observation of the ith sensors is defined as:

$$X_i = \sum_{j=1}^{N} a_{ij} s_j + n_i, i = 1,2,...M \tag{1}$$

Where $X_{1,..M}$ denote the observations, $s_{1,...N}$ denote the sources, a_{ij} is the linear combination coefficient and n_i denotes the environment noise received by the ith sensor.

The noise may be considered as a source signal, in this way, the mathematical model of BSS could be shown as: ith sensor.

The linear BSS can be expressed as follows:

$$X(t) = AS(t) \tag{2}$$

Where $X \in R^{M+1}$ is the observation vector, $A \in R^{M*N}$ the unknown mixing matrix, $S \in R^{N+1}$ the unknown source vector.

Here, assuming the mixing matrix A is invertible and the sources are statistically independent. The hypothesis of independence between the sources is physically possible because their origins are different.

The BSS is based on the estimation of the separation matrix B to calculate Y, which can be expressed as follows:

$$Y(t) = BX(t) = BAS(t) \tag{3}$$

Where Y (t) is an estimate vector of the source signal S (t) and B is the separating matrix. The basic principle of the BSS method is illustrated in Figure (1).

2.2. Normal Distribution (ND):

ND is a super Gaussian shape [22]. It is applied, in the present work, as a selection criterion to find the source that has more information about the defect of the rolling element bearing. The ND function is given as [23]:

$$h = f(\frac{s}{\mu,\sigma}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(S-\mu)^2}{2\sigma^2}} \tag{4}$$

Where S [s_1, s_2….,s_N] is a vector, μ the mean of vector S and σ its standard deviation. They are defined as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{5}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - \mu)^2} \tag{6}$$

2.3. Proposed Method:

The Figure (2) illustrates the steps of the proposed algorithm. Its principle is described as follows: first, we insert a segment of the input signal into the SCBSS filter in order to reduce the calculation time; this segment must contain the same characteristics of the original signal. After applying SCBSS filter, two outputs are resulted. In order to extract the source that contains most of the fault information and removes the unwanted signal, the ND and its mean is applied to each output. The selected signal is again injected into the SCBSS filter to obtain a clear source with useful information.

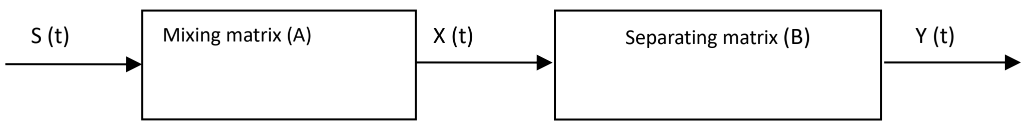

Figure 1. Principle of BSS method.

3. Experimental setup

In this study, we used the vibration data obtained from the Case Western Reserve University Bearing Data Center [24]. As illustrated in Figure (3), vibration data was collected using accelerometers, which are attached to the housing with magnetic bases. The unit of measurement is mm/s^2 (Gravity) and the duration of each vibration signal was 10 seconds. The vibration data were collected at 12000 samples per second, for four different bearing conditions: (1) Bearing without fault i.e. Normal state (N); (2) Bearing with Outer Race Fault (ORF); (3) Bearing with Ball Fault (BF) and (4) Bearing with Inner Race Fault (IRF). For ball and inner race cases, the sizes of the different faults are: 0.1778, 0.3556, and 0.5334 mm. For outer race case, the sizes of the faults are either 0.1778 or 0.5334 mm. The vibration data was recorded with four rotation speeds; 1797, 1772, 1750 and 1730 rpm corresponding respectively to 30, 29.5, 29.1 and 28.8 Hz.

The characteristic frequencies of defective bearing with ORF, BF and IRF computed at rotation frequency of 30 Hz, are respectively 107.8 Hz, 139 Hz and 161.8 Hz. The Figure (4) shows the segments of their time measurements.

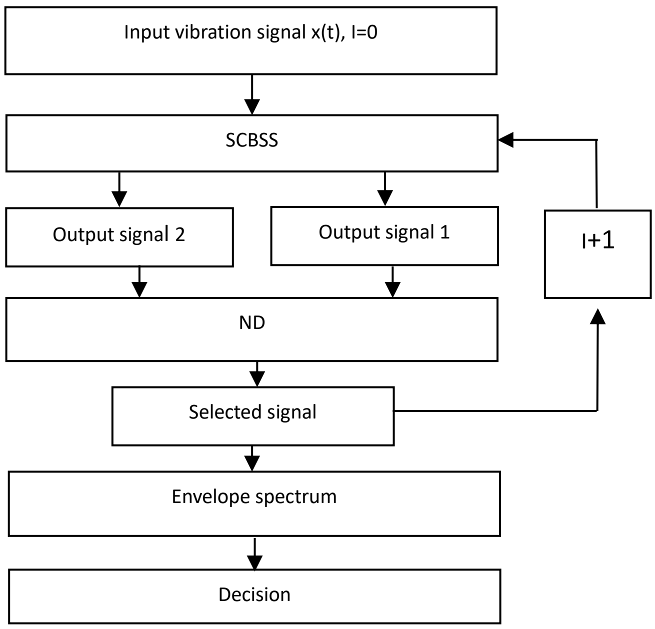

Figure 2. SCBSS-ND algorithm

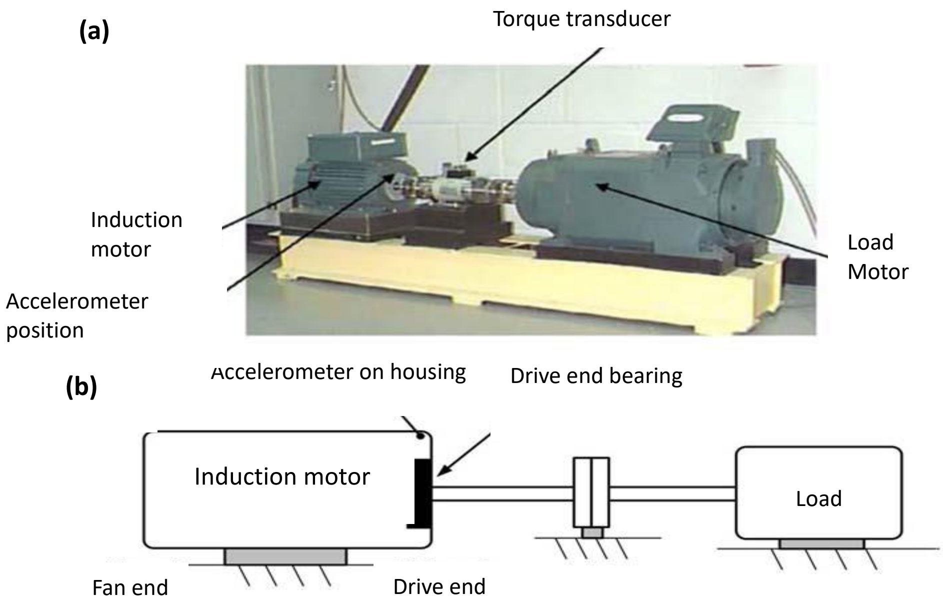

Figure 3. (a) Bearing test rig and (b) its schematic description.

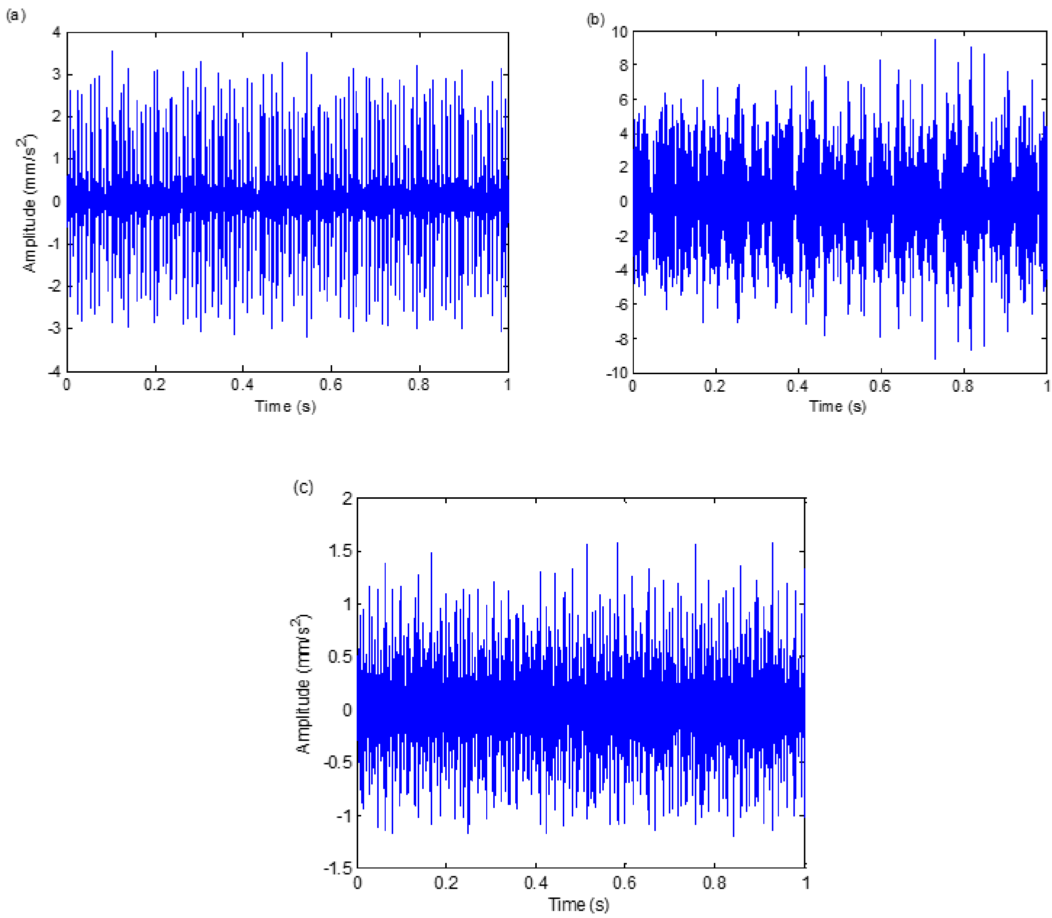

Figure 4. Measured vibration signals: (a) ORF, (b) BF and (c) IRF

4. Results and Discussion

In this section, we validate the effectiveness of the proposed method by using the SCBSS-ND algorithm and the bearing experimental signals mentioned previously. In fact, to separate the different sources by inserting the complete raw vibration signal into the SCBSS filter takes a lot of computing time. For this purpose, we truncate the original signal into segments of length, at least, 6 complete rotations as long as the motor speed is ranging from 1730 to 1797 rpm, in order to have the same characteristics of the full signal. Here the segment of length 8192 point is selected and a Blackman window to adjust this truncation is applied.

The selected signal is injected into the SCBSS filter with good control over its properties, in which the window length of this filter is 1024 and the format of the extracted sources is the same as the truncation window (Blackman window). In this section, the proposed algorithm is applied to analyze the vibration signals acquired from the rolling element bearing with the three considered conditions; ORF, BF and IRF. The shaft rotation speed is 1797 rpm (30 Hz) and the characteristic frequencies of defective bearing are 107.8 Hz for ORF, 139 Hz for BF and 161.8 Hz for IRF. The measured vibration signals are plotted in the experimental part (section 3, Figure (4) (a, b and c)).

First, the SCBSS method is used to decompose the raw fault signals acquired from a single sensor, into temporal sources in order to select, among them, the most informative. For the considered cases of rolling bearing, two outputs are resulted; source1 and source2, which are illustrated in Figure (5). This indicates physical that the measured vibration signal of rolling bearings is a multi-component signal which includes many sources and noise. The noise component is an independent source in relation to other vibration signals. Although, the vibration measured from the rolling bearing, even without noise, is a signal with several sources or components.

The ND and its mean are used to analyze the fault information of each source; they are presented in Figure (6) (a, b and c) and listed in Table (1). Based on the largest normal distribution mean values which are 1.8651, 1.0917 and 2.0682 for ORF, BF and IRF respectively, the first source, which contains the most characteristic information about the fault, is selected for all considered cases, as shown in the Table (1), the normal distributions of the source1 remain constant in all cases, and it is also symmetrical around μ on x axis, where the shape of the distribution curve is Gaussian (see, Figure (6) (left) (a, b and c)), while the normal distribution curves of the source 2 are not constant in all cases. Besides being heterogeneous and irregular, they do not have the same beginning and the same end, and they are also not symmetrical around μ on x axis (Figure (6) (right) (a, b and c)), which justify our choice of the source1, the measured vibration signal is periodic shocks contaminated by noise. For this reason, the ND of source1 is regular, while the noise distribution is random and irregular.

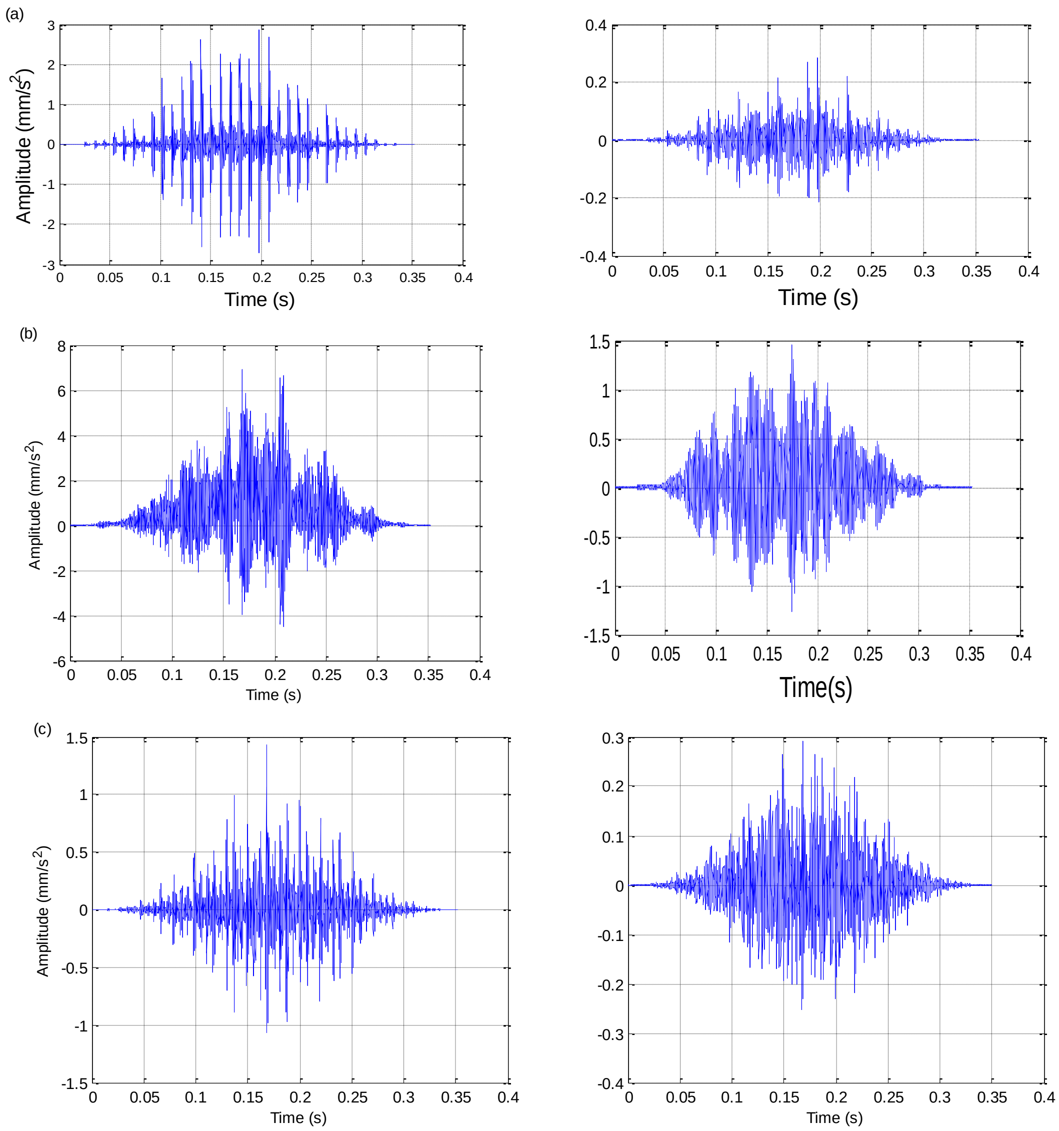

Figure 5. Temporal representation of source1 (left) and source2 (right) for the bearing with: (a) ORF, (b) BF and (c) IRF.

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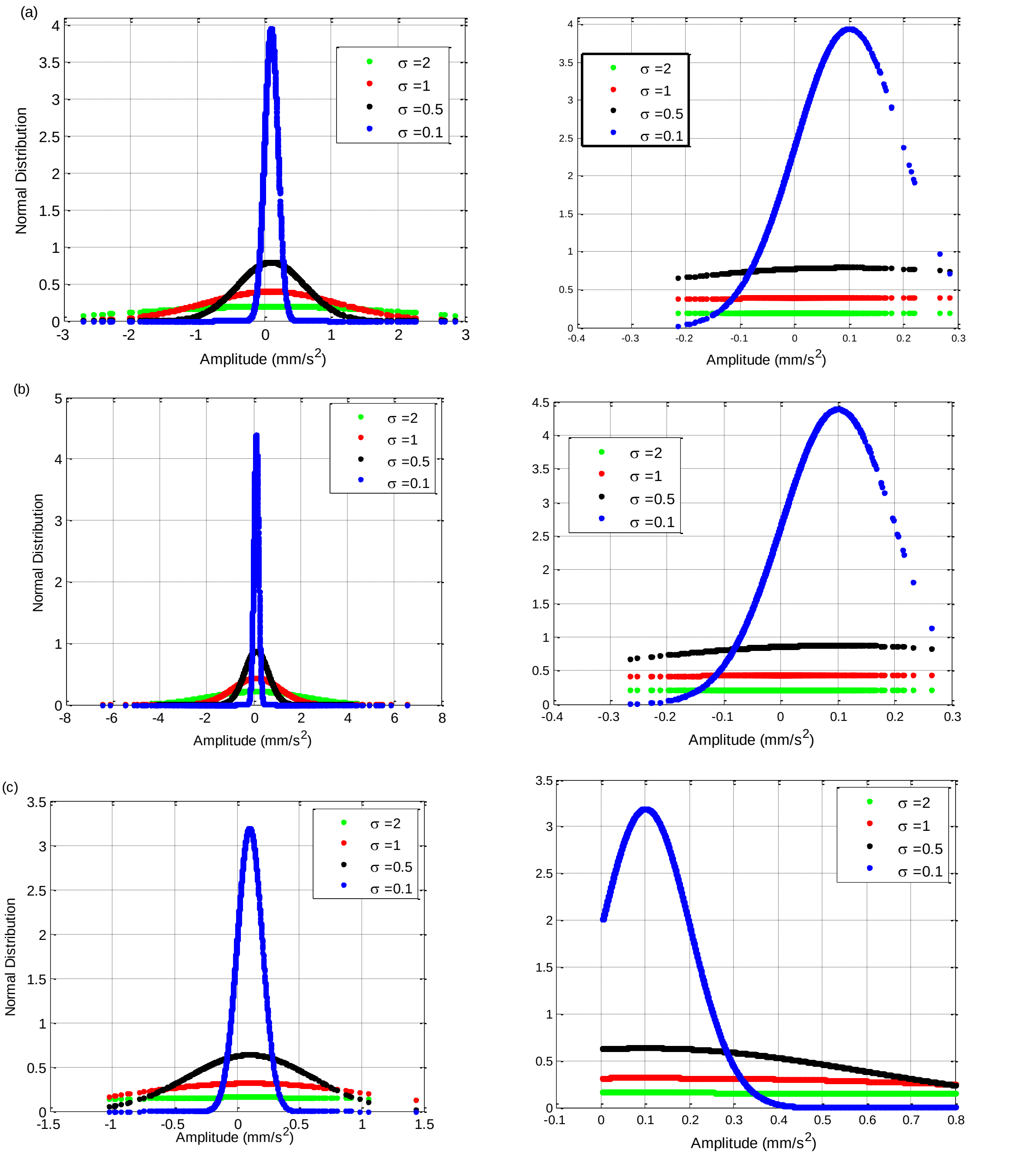

Figure 6. Normal distributions, with μ=0.1, of source1 (left) and source2 (right) for the bearing with: (a) ORF, (b) BF and (c) IRF.

Table 1. Mean of ND of the two sources (μ=0.1).

	ORF		BF		IRF	
	Source1	Source2	Source1	Source2	Source1	Source2
σ=2	0.1963	0.1992	0.1987	0.1933	0.1986	0.1533
σ=1	0.3797	0.3966	0.3464	0.3517	0.3925	0.2762
σ=0.5	0.7798	0.7071	0.5637	0.4839	0.7529	0.4113
σ=0.1	1.8651	0.6429	1.0917	0.2279	2.0682	0.5775

Figure (7) represents the envelope spectra of source1 of the rolling bearing with ORF, BF and IRF. The characteristic frequency of ORF (fORF) and its seven successive harmonics are clearly noted (see, Figure (7) (a)). These frequency components are not well detected in their exact positions as shown in Table (2). In this table, the calculated delta represents the difference between the theoretical frequency and the detected frequency of the bearing fault. On the envelope spectra of the selected source of BF and IRF cases of Figure (7) (b) and (c) respectively, the characteristic frequencies of BF and IRF are clearly detected and their first harmonics can barely be recognized with the presence of some spectral interference lines. The computed values of delta index, listed in Table (2), show that the principal harmonics are not detected in their exact positions. The presence of shocks in the signal clearly indicates the presence of the defect. They are represented on the spectrum by synchronous peaks.

The selected source, even without noise, is a multi-components signal which is again injected into the SCBSS filter to eliminate the unwanted signals in order to further improve the obtained results, are often produced by interference of vibration from motor, rolling element and other sources. The Figure (8) (a, b and c) represents respectively the time domain of source1 of the defective bearing with ORF, BF and IRF. From this figure, there is a significant decrease in parasites and the emergence of pulses appears clear and harmonious, especially in Figure (8) (a) and Figure (8) (c), as well as the noise is almost entirely eliminated, which will be more apparent on the spectrum.

The envelope spectrum of the resulting signal is illustrated in Figure (9). From Figure (9) (a), it is clear that the ORF frequency (fORF) and its two harmonics (2□fORF and 3□fORF) are exactly identified. In Figure (9) (b), the peak frequencies of BF are clearly detected, in which the first and second harmonic frequencies are also precisely identified. Finally, the characteristic frequency of IRF (fIRF) and its two successive harmonics (2□fIRF, 3□fIRF) are correctly identified (see, Figure (9) (c)). In addition, we also note from the Table (3) that the calculated values of the delta decrease for each harmonic frequency.

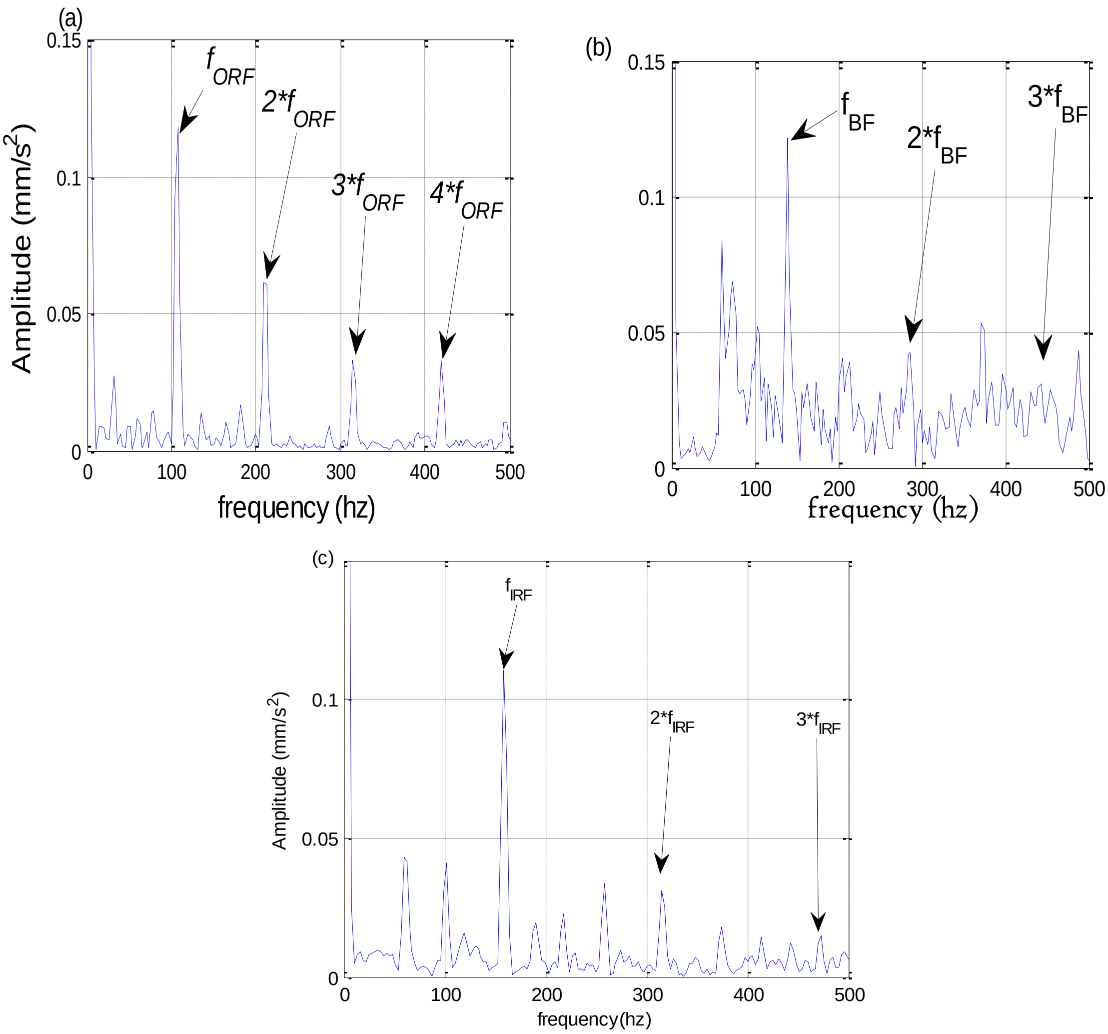

Figure 7. Frequency spectrum of source1 resulting from the first SCBSS filter: (a) ORF, (b) BF and (c) IRF.

Table 2. ORF, BF and IRF frequencies detected from the first SCBSS filter.

ORF		BF		IRF	
f_{ORF} and harmonics (Hz)	Delta (Hz)	f_{BF} and harmonics (Hz)	Delta (Hz)	f_{IRF} and harmonics (Hz)	Delta (Hz)
107.8	0	139	0	161.8	0
209.9	5.7	286.5	8.5	323.6	0
314.9	8.5	420.6	3.6	486.79	1.39
419.9	11.3	544.7	11.3	658.4	11.2

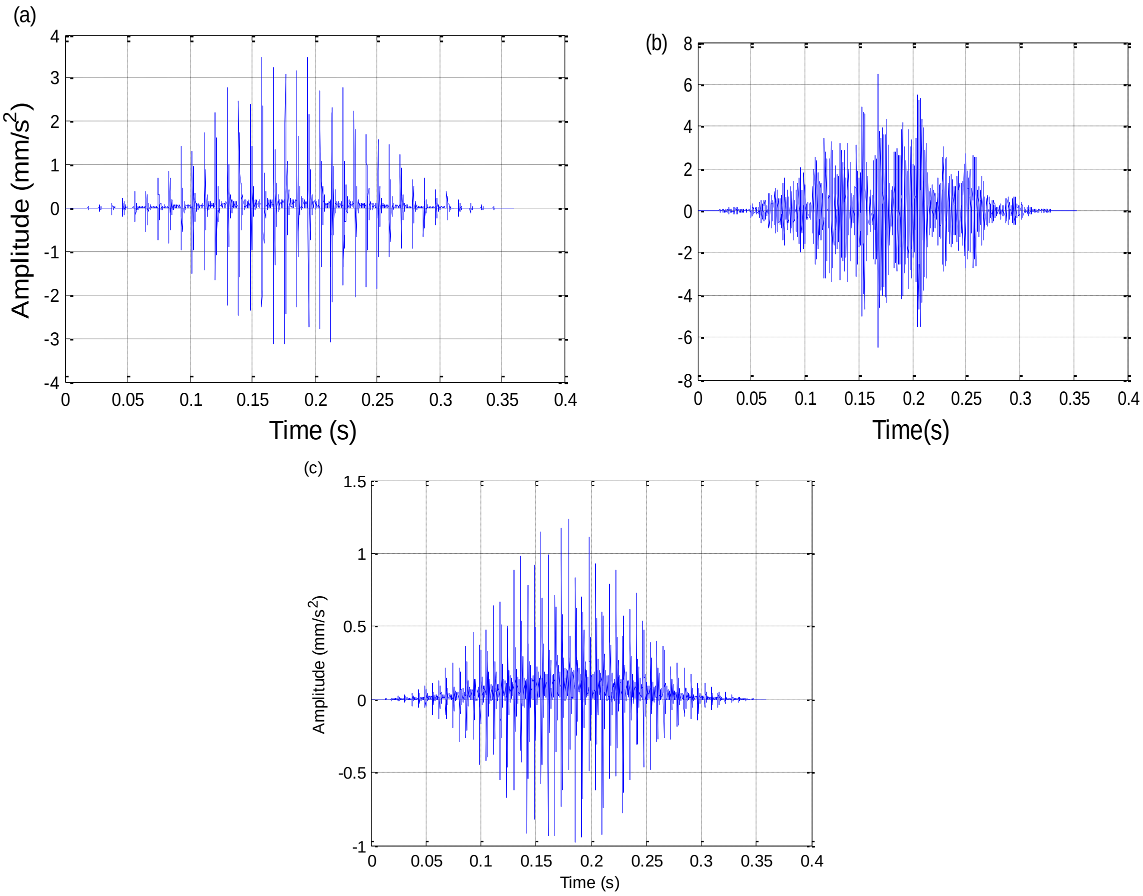

Figure 8. Temporal representation of source1 obtained from the second SCBSS filter: (a) ORF, (b) BF and (c) IRF.

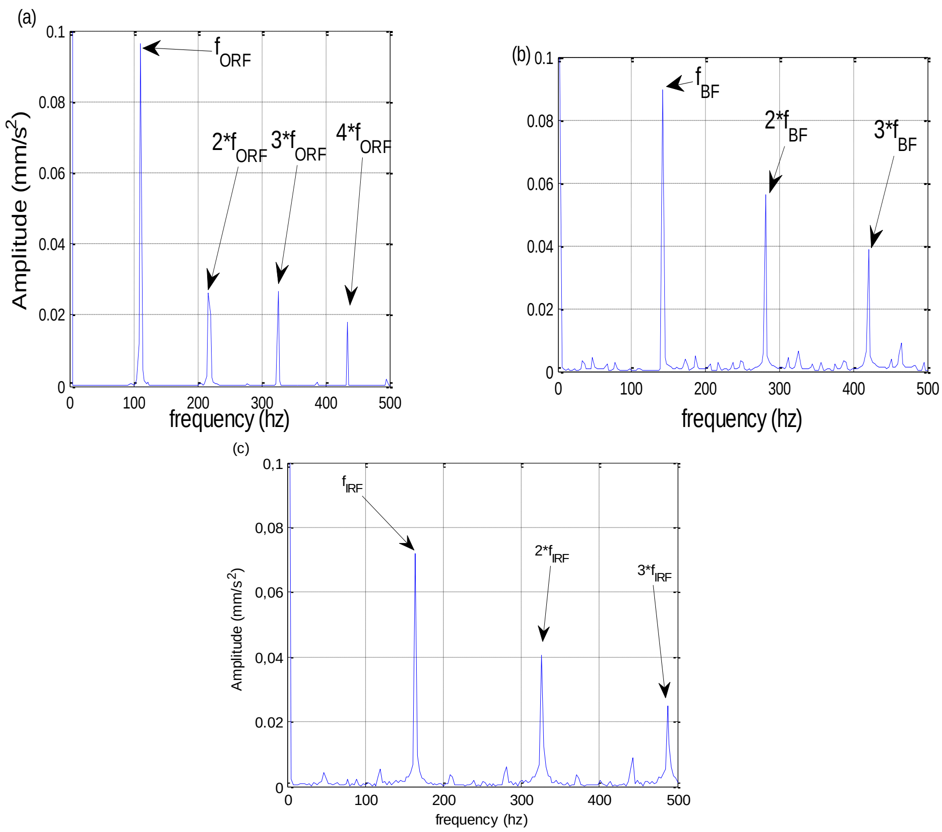

Figure 9. Frequency spectrum of source1 resulting from the second SCBSS filter :(a) ORF, (b) BF and (c) IRF.

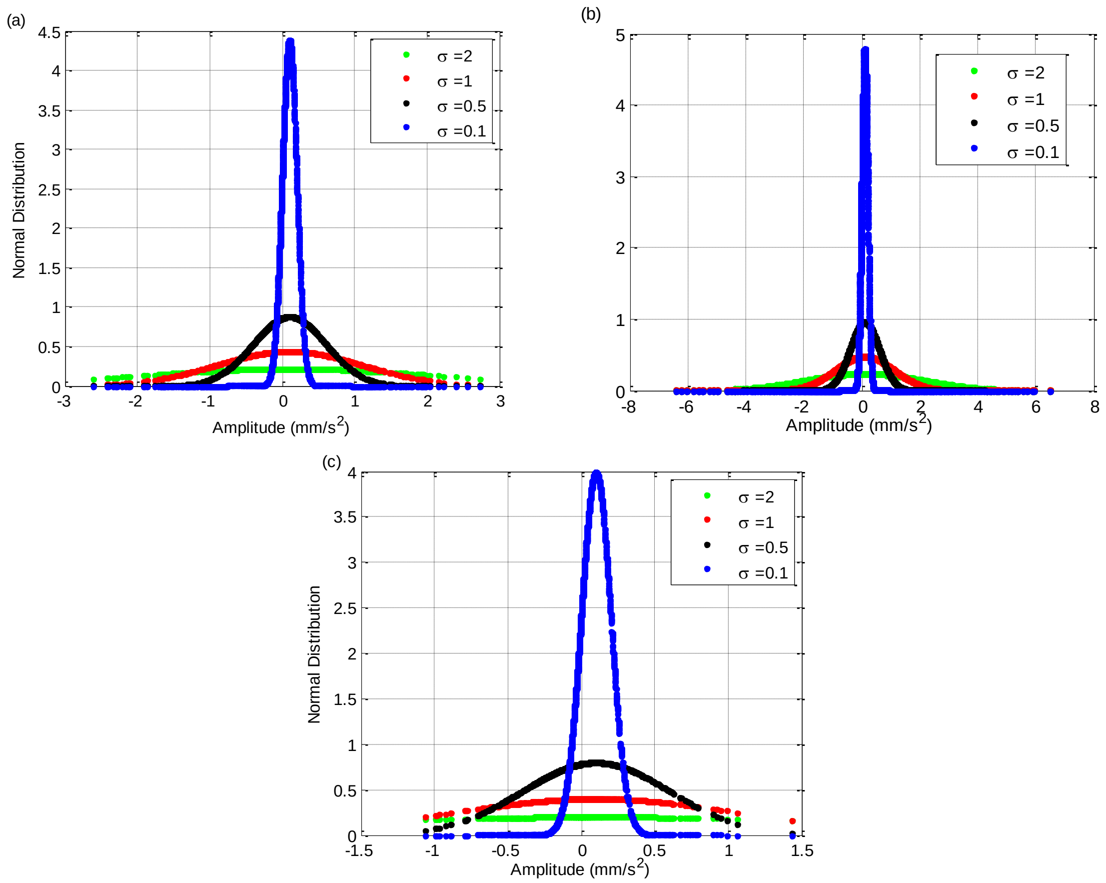

Figure 10. Normal distributions of the signal resulting from the second SCBSS filter, with μ=0, of: (a) ORF, (b) BF and (c) IRF.

Table 3. ORF, BF and IRF frequencies obtained from the second SCBSS filter.

ORF		BF		IRF	
f_{ORF} and harmonics (Hz)	Delta (Hz)	f_{BF} and harmonics (Hz)	Delta (Hz)	f_{IRF} and harmonics (Hz)	Delta (Hz)
107.8	0	139	0	161.8	0
215.6	0	278	0	323.6	0
323.4	0	420.3	3.3	485.49	0
425.5	5.7	559.4	3.4	648.4	1.2

Table 4. Mean of ND of the signal obtained from the second SCBSS filter (μ=0.1).

	ORF	BF	IRF
σ=2	0.2186	0.2191	0.1992
σ=1	0.4326	0.4361	0.3966
σ=0.5	0.8354	0.8564	0.7793
σ=0.1	2.4313	2.3767	2.3856

By comparing normal distributions and their means of vibration signals resulting from first and second SCBSS filters, the Figure (10) (a, b and c) shows that the distribution of the second signal increases over the y axis, also it is more accurate and symmetrical around μ on the x axis. Table (4) summarizes the calculated values of the means of the distributions; it shows that the obtained values from the second SCBSS filter are larger than those calculated from the first filter (see Table (1)).

In order to verify the quality of the resulting signal from SCBSS filters, Table (5) shows respectively the computed values of kurtosis, SNR and MSE. From all obtained results, the signal containing only information about rolling bearing fault is correctly recovered.

Table 5. Kurtosis, SNR and MSE values for each SCBSS.

	Kurtosis	SNR	MSE
Before applying BSS	7.706	-	-
First SCBSS	17.07	11db	8.38 *10-6
Second SCBSS	20.34	23db	2.56*10-11

5. Conclusion

This paper presents a combined method based on Single Channel Blind Source Separation (SCBSS) and Normal Distribution (ND) to analyze and detect bearing degradation. SCBSS filters are used to decompose the vibration signals measured from defective bearings with outer race fault, ball fault and inner race fault, into a series of sources. To select the source that contains the significant information about the fault, the ND and its mean are used as principal criterion.

The validation of the obtained results by the calculation of kurtosis, SNR and MSE parameters showed a precise detection of the characteristic frequencies of the bearing faults and their harmonics, by eliminating the various interferences. By comparing with BSS alone and EMD, the method proposed, in this paper, leads to the best separation performances for most types of mixture with an extraction precision of the characteristic frequencies of the bearing faults and their harmonics in the shortest possible time.

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