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## **DIAGNOSIS OF BEARING FAULTS IN COMPLEX MACHINERY USING SPATIAL DISTRIBUTION OF SENSORS AND FOURIER TRANSFORMS**

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### **ABSTRACT**

This paper addresses a statistical energy analysis in diagnosis of bearing faults in complex machinery. The principle of this method is based on the fact that each sensor, with respect to its location in the system, collects a different version of the vibration produced in the system. By applying a short time Fourier transform to the signals collected by multiple sensors and making use of a priori knowledge of the spatial distribution of sensor locations with respect to the components, the source of the peaks on the frequency spectra of the signals can be identified and attributed to the components. The performance of the method was verified using a series of experimental tests on synthetic signals and real laboratory signals collected from different bearings and the results confirmed the efficacy of the method.

**Keywords:** Fourier transforms, source separation, multisensory vibration acquisition

### **INTRODUCTION**

A difficulty in diagnosis of faults in components of rotating machinery using vibration signals is that these signals are always a cluttered mixture of ambient noise and vibration produced by different parts. This problem is encountered in its most severe form when diagnosis of certain components in a compact complex system such as an engine is desired. In this case, in order to lessen the effect of vibration from neighbor components, it is necessary to place the sensors as close as possible to the components of interest. However, due to restrictions such as the manufacturer's warranty policy and inaccessibility, it is not always practical to place the sensors as such. The only choice is therefore to place the sensors on the innermost possible surface of the structure. As a result, even if the sensors are positioned very close to the components, they collect signals not just from one specific component but from other components as well. That is to say, signals collected by each sensor are a combination of the vibration produced by different components in addition to ambient noise. This makes it difficult to determine which component dominates the collected signals. The first challenge in diagnosis of faults in a complex system is therefore to decompose the signals into components corresponding to the system's individual components. In other words, determining what signals come from which components. This concept is referred to in the literature as "source separation" and in the case where components of the system are not well identified it is called "blind source separation." A number of mathematical methods exist to solve this blind source separation problem, among which the independent component analysis (ICA) [Comon *et al.*,

2009; Serviere *et al.*, 2005, and Antoni 2005] method is the most dominant. In this study, we sought to develop a method that presents the distribution of vibration energy with regard to location of vibration sources and sensors and based on the mechanical behavior of the structure. This method adopts some key concepts from statistical energy analysis (SEA) to support the fact that each sensor collects a different version of the oscillations produced in the system with respect to its location in the system. Applying a Fourier transform to the signals and making use of a priori knowledge of the spatial distribution of sensors and components, the original vibration signals can be recovered through comparison between the frequency representations (Fourier transform) of signals received by each sensor. The proposed method was verified with synthetic and experimental data.

## DEVELOPMENT

### Multi-Sensor Data Acquisition

In blind source separation, it is usually necessary to have at least as many sensors as the number of components in the system. In some applications, determining the number of components is obscure due to the definition of a component (Antoni, 2005). For example, a ball bearing can be considered a single component, which is usually the case, or as a number of parts (i.e., balls, outer race, and inner race). For fault diagnosis, the following definition may be implemented based on a practical point of view: A component is a part of a structure, machine, etc. that is either repairable or replaceable during maintenance. Although the number of components may be approximated based on the above definition, it does not necessarily follow that a “component” will act as though it is a single source. A replaceable part may consist of different elements, each of which can produce statistically independent vibration signals. Fortunately, this problem is less likely to arise in the proposed method. In fact, this method is based on the concept of subsystems where recordings from different subsystems are compared to one another. Therefore, as long as a component and its element are considered to be in a subsystem and the sensors used for comparison are mounted in other subsystems the abovementioned problem will not affect the results. In other words, all the elements of the component will have the same characteristics as far as the proposed method is concerned. To determine the number of sensors for this method, the same criterion applies, i.e., the number of sensors must be at least equal to the number of “components.”

### Methodology

The procedure for the proposed method is outlined as: given  $N$  as the number of sensors and  $X_i(f)$  are the Fourier transform of the signals  $x_i(t)$  (where  $i=1, \dots, N$ ). For each frequency bin denoted by  $f$ , the intensities are set to zero except for the maximum intensity (i.e.  $\text{argmax} X_i(f)$ ) among all the signals from different sensors. Using this approach, at each frequency the intensities of  $N$  spectra are either zero or the maximum. Finally, using the spatial diversity of sensor locations with respect to the subsystems and the components, each sensor together with its modified frequency representation is associated with a component. It is noted that in this method, the spectral density does not contain any temporal information about the signal, and consequently certain random and transient fluctuations can cause misinterpretation. One way to get around this problem is to utilize short time Fourier transforms (STFT), and apply the aforementioned procedure to each short window and then average the results of all windows.

## EXPERIMENT CASE STUDIES AND RESULTS

In order to verify the viability of the proposed method, two case studies are carried out using vibration signals taken from two different test facilities. The description of each test facility and the discussion of the results for each case are represented in the following sections.

### Experimental Setup and Data Acquisition of the First Case Study

Vibration signals were collected from a test setup at Ecole Polytechnique de Montreal consisting of a 2 HP motor coupled to a shaft supported by two different bearings. One bearing was an overhauled roller bearing (PWC15) provided by Pratt & Whitney Canada from one of their engines. The other bearing was an SKF ball bearing (1217 K). Each bearing was encompassed by a housing that was bolted to an adjustment base; which was also bolted to the main base. This way, each housing together with the bearing inside can be considered a subsystem that is connected through another subsystem (adjustment base) to the main base. Four accelerometers were used, one mounted on each bearing housing and two on the main base as shown in Figure 1. Signals were gathered at a sampling frequency of 2 kHz for a period of 10 seconds while the shaft was running at a speed of 900 RPM (15Hz).

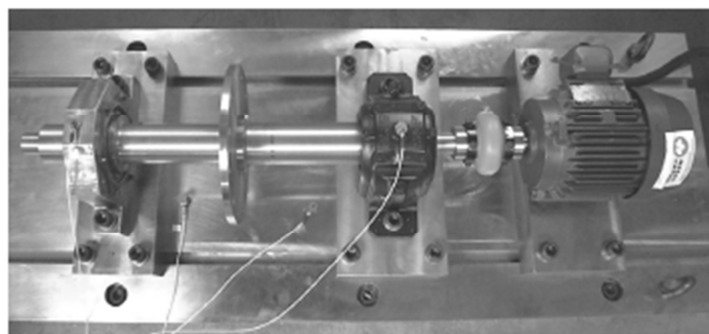


Fig. 1 - Test setup with a PWC15 bearing mounted on the left end of the shaft

### Results and Discussion for the First Case Study

The short time Fourier transforms of the signals with window length and time steps of, respectively, 512 and 32 points were obtained. The Fourier transforms of signals gathered by each accelerometer are shown in Figure 2.

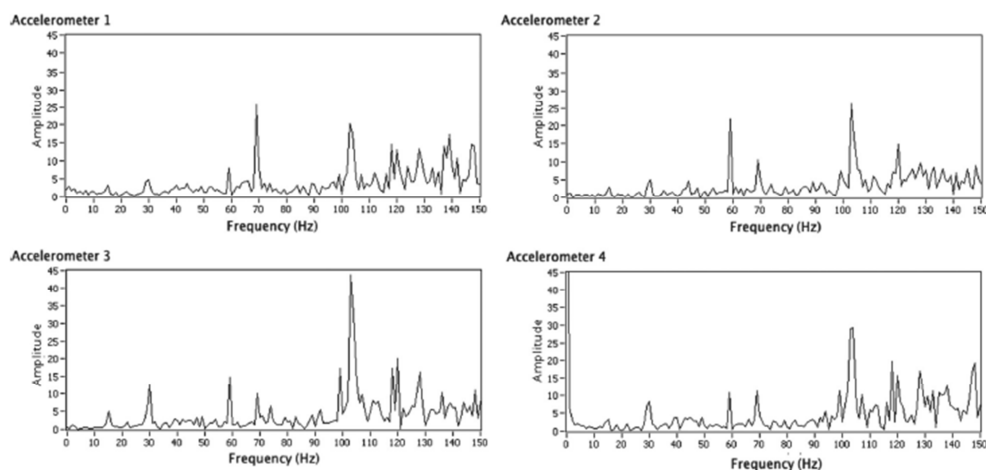


Fig. 2 - Frequency representation of signals collected by four accelerometers

The four frequency representations show certain distinguishable peaks at different frequencies. However, it is not clear if the peaks are noise or actual oscillations caused by a component. Also, it is not possible to determine the source of each peak. The separation results up to 150 Hz are shown in Figure 3. The results are plotted in different styles. Each style represents the signals pertaining to an accelerometer. For the profile pertaining to accelerometer (located on the PWC15 roller bearing housing) two dominant peaks, one at around 69 Hz and another at around 138 Hz can be singled out. Further, for accelerometer 2 (located on the 1217KSKF bearing) except for one peak at 30 Hz there is another dominant peak at 59 Hz. For other accelerometers on the base there are a number of peaks, mostly occurring in the range from 100 to 150 Hz.

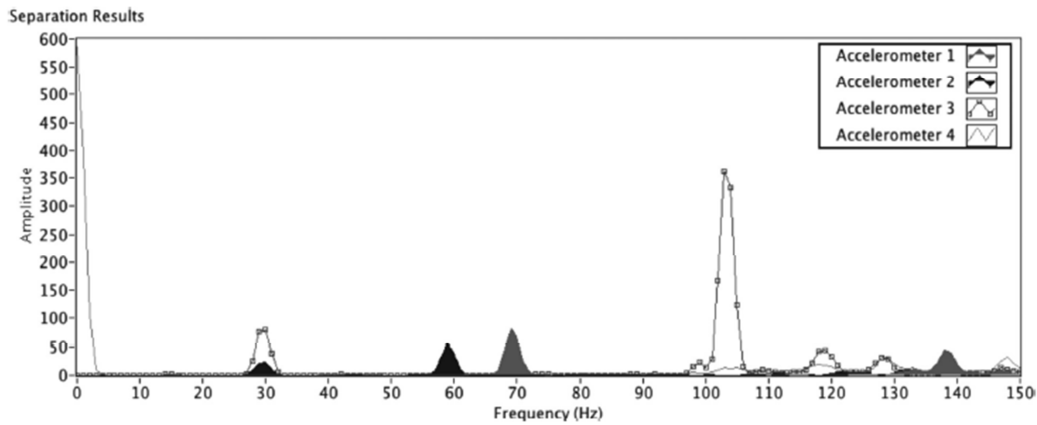


Fig. 3 - Separation results of PWC15 and 1217K SKF bearings

The characteristic frequencies of the bearings (Table 1) were calculated using following equations (Shahan, and Kamperman, 1976):

$$\text{Rotational frequency of rolling element assembly: } f_c = \frac{f_s}{2} \left( 1 - \frac{D_B}{D_P} \cos\theta \right)$$

$$\text{Rotational frequency of rolling element: } f_r = \frac{f_s D_P}{2 D_B} \left( 1 - \frac{D_B^2}{D_P^2} \cos^2\theta \right)$$

$$\text{Over rolling frequency of one point on inner ring: } f_{ip} = \frac{f_s}{2} N_B \left( 1 + \frac{D_B}{D_P} \cos\theta \right)$$

$$\text{Over rolling frequency of one point on outer ring: } f_{ep} = \frac{f_s}{2} N_B \left( 1 - \frac{D_B}{D_P} \cos\theta \right)$$

$$\text{Over rolling frequency of one point on rolling element: } f_{rp} = \frac{f_s D_P}{D_B} \left( 1 - \frac{D_B^2}{D_P^2} \cos^2\theta \right)$$

where:

$f_s$  (shaft rotation speed in Hz),  $D_B$  (diameter of the ball),  $D_P$  (distance between the centre of two opposing balls "pitch"),  $N_B$  (number of the balls),  $\theta$  (contact angle of the ball).

Table 1 - Characteristic frequencies of the bearings used in the experiments

Bearing	PWC	SKF 1217K	SKF1216K	Rexnord
Rotational frequency of rolling element assembly (Hz), $f_c$	5.77	6.6	6.65	14.8
Rotational frequency of a rolling element (Hz), $f_r$	30.7	61.2	65	140
Over-rolling frequency of one point on inner ring (Hz), $f_{ip}$	111	176	184	297
Over-rolling frequency of one point on outer ring (Hz), $f_{ep}$	69.2	139	146	236
Over-rolling frequency of one point on rolling element (Hz), $f_{rp}$	61.5	122	130	280

In comparison with the separation results, it can be noticed that the peak at 69 Hz relating to the closest component to accelerometer 1 (i.e., PWC15 bearing) equals the over-rolling frequency of one point on the outer ring of the PWC15 bearing. The existence of such a fault on the outer ring of the PWC15 bearing was confirmed by visual inspection the bearing after the test. Further, at around 60 Hz, which is very close to the rotational frequency of a rolling element of the SKF bearing, there is a peak related to a component in the vicinity of accelerometer 2.

Contrary to the abovementioned concurrences, there is a peak at around 139 Hz related to accelerometer 1 and supposedly to the PWC15 bearing that matches with the 1217K SKF bearing’s frequency of one point on the outer ring. This might be considered as a misconstrue but, as mentioned before, the SKF 1217K bearing was a new bearing and an outer race fault is very unlikely. Moreover, this peak occurs at 139 Hz which is, not accidentally, twice the frequency of the outer ring fault of PWC15. In order to further investigation, a separate test session was carried out in which the PWC15 bearing was replaced with a 1216K SKF bearing.

The separation results are demonstrated in Figure 4. The two peaks at 69 Hz and 139 Hz no longer exist, showing that they most probably emanated from PWC15 in the previous test. Another significant difference with the previous test is that the high amplitude peaks ranging from 100 to 150 Hz disappeared. Instead, there are peaks at frequencies equal to the rotation frequency and its harmonics. These frequencies are mostly related to wellness of the shaft mount and bearings, the imbalance disk, etc. Even with further adjustments in the shaft mount it is possible that the frequency peak at 59 Hz might have been provoked in the bearing by shaft misalignment.

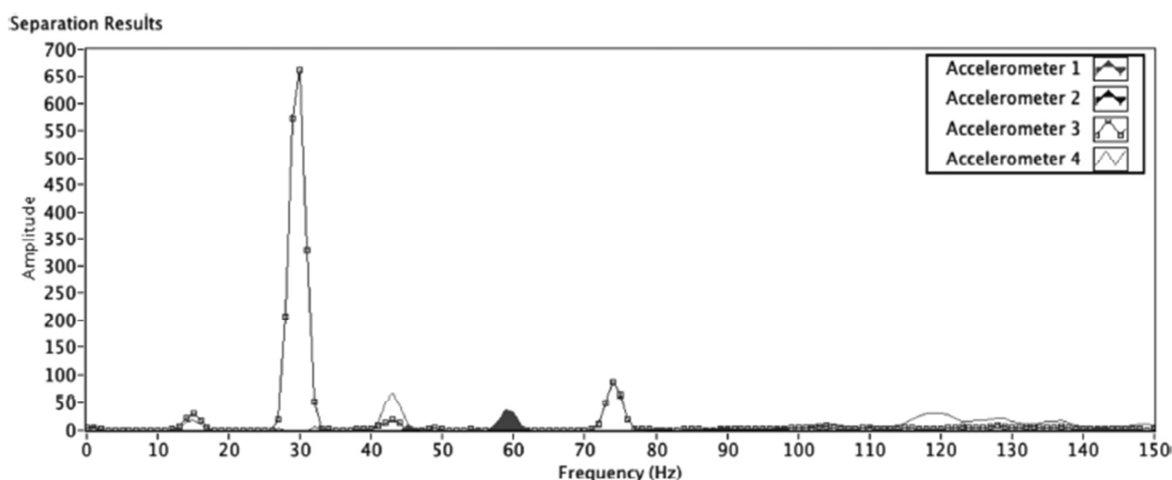


Fig. 4 - Separation results for case of 1216K SKF and 1217 K SKF bearings

### Experimental Setup and Data Acquisition of the Second Case Study

In order to further validation of the proposed method, a bearing data set provided by the Center for Intelligent Maintenance Systems (IMS) of University of Cincinnati through NASA Ames Prognostics Data Repository (Lee *et al.*, 2007) was used. In this test, four double row Rexnord ZA-2115 bearings were mounted on a shaft driven by an AC motor (Figure 5).

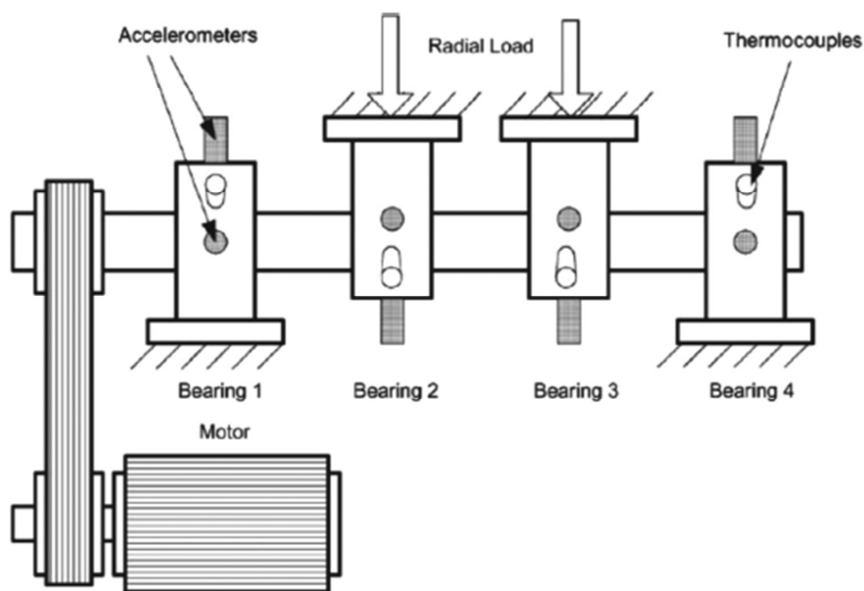


Fig. 5 - Schema of the test rig at IMS of University of Cincinnati [by courtesy of Ref. (Qiu *et al.*, 2006)]

Vibration data were gathered using four accelerometers, one on each bearing housing, at a sampling rate of 20 kHz. A spring mechanism exerted a radial load of 6000lb on the rotating shaft and the bearing. Data snippets of approximately one second in duration were gathered at ten minutes intervals throughout a run-to-failure test. In this study, one of the snippets was selected in which an outer race fault on the third bearing was clearly discernible.

### Results and Discussion

Separation results for this case are shown in Figure 6. The same window length and time steps were used with a higher number of frequency bins to attain better frequency resolution.

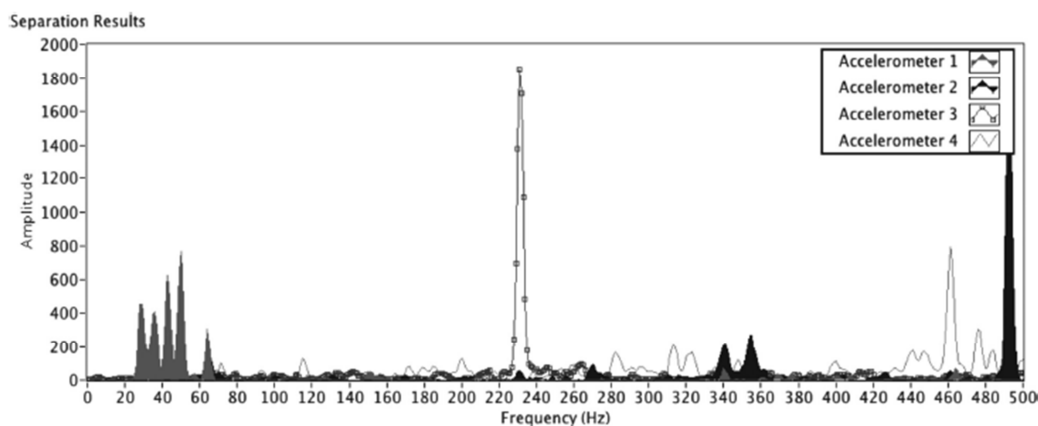


Fig. 6 - Separation results for case of Rexnord bearings

According to Table 1, due to a fault on the outer race of the third bearing, a peak at 236 Hz is expected in the resulting profile corresponding to accelerometer 3. In Figure 6, this peak occurs on the right profile but with a slightly lower frequency. This error has also been reported in (Qiu *et al.*, 2006). It is shown that the results are consistent with the proposed method for this case as well.

## CONCLUSION

A separation method based on frequency signatures obtained from signals gathered from multiple sensors positioned in different locations of the system was presented. This method has a simple yet solid theoretical basis driven by the concept of statistical energy analysis. The performance of the method was verified using a series of experimental tests on synthetic signals and real laboratory signals collected from different bearings. Despite its simplicity, the results confirmed the efficacy of the method. Some shortcomings associated with this method were also discussed. To summarize: this method may not be very effective or accurate in systems with transitory behavior. Also, in systems with very densely mounted components, determining the subsystems, and therefore, the best location for the sensors can be very challenging.

## ACKNOWLEDGMENTS

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