Bearing Fault Diagnosis Using Time Encoded Signal Processing and Recognition

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Abstract

Many novel condition monitoring techniques have been invented in recent years, and the challenge lies in coming up with a highly reliable and cost efficient monitoring system which should be capable of tracking down and give an early indication of machinery's faults. The focus of this paper is to develop advanced approaches based on advanced intelligent computations to diagnosis and prognosis bearing condition. TESPAR (Time Encoded Signal Processing and Recognition) is an effective and direct way for describing complex waveforms in digital terms. It is the generic terms set to a collection of novel signal analysis, recognition and classification approaches that can be applied to describe and classify various ranges of complicated band limited signals. The results show that vibration signal waveforms of bearing faults can be digitized and analyzed in terms of its epochs' duration and shape which are the main parameters of the TESPAR technique that provides an accurate separation between different bearing faults with different degree of severity.

Keywords: TESPAR, Fault detection, Condition monitoring, Bearing faults.

1. Introduction

Condition monitoring of machines has become increasingly essential to improve their reliability and to avoid catastrophic failures. Many novel condition monitoring techniques have been invented in recent years, such as the indication of temperature, acoustic emissions, debris in lubricant, instantaneous angular speed airborne acoustics and structural borne vibration techniques. One of the key tasks in using these techniques is to apply effective data analysis techniques for accurate detection and diagnosis feature extraction.

In bearing condition monitoring, vibration based envelop analysis is considered as the most common method for monitoring various faults up to now. However, this technique involves complicated operations such as Fast Fourier Transforms (FFT) and digital filtering implemented using an expensive Digital Signal Processing (DSP) board. In addition, it also needs large memory space due to a very high sampling rate requirement in envelope analysis and hence also requires high power to operate it. These high resource demands make it difficult to implement in an intelligent sensor node which has very limited in computational capability, storage and power resources [1].

This research explores an alternative method to vibration data analysis in bearing fault monitoring. The TESPAR (Time Encoded Signal Processing and Recognition) describes different signal waveforms in terms of their shape and differentiates between them. The technique is simple but is able to code time varying signals without the need to use complex FFT and has been used for analysing speech signals. Recent practical experience [2, 3] confirms that the TESPAR and neural network combination produces very powerful classification methods, achieving system performance previously considered infeasible using conventional methods. Therefore, this work evaluates the performance of this technique in condition monitoring by applying it to bearing vibration signals from different bearings conditions.

2. Time Encoded Signal Processing and Recognition (TESPAR)

TESPAR is a new simplified digital language, first proposed by King and Gosling [4] for coding speech signals. TESPAR technique is based on an accurate numerical representation of waveforms, concerning polynomial theory that explains how a signal illustrates solely depending on its real and complex zeros locations. It differs from conventional techniques that are based on amplitude sampling at regular intervals that have been illustrated by several researchers such as Fourier. The TESPAR and Fourier transform are computationally equivalent, they result in 2TW (where the T is the time and W is the bandwidth) of digital sample data points explaining the waveform [5].

A TESPAR quantisation process has been promoted to code the signal waveform in its real and complex zeros [6, 7]. The interval between two closest zero-crossings is called an epoch. Every epoch can be described by two parameters that are obtained from its limits: D, the duration represents the samples number and its shape, S, is the number of negative maxima or positive minima featured. As shown in Figure 1, the signal between two zero crossings can be encoded into D=14 and S=1.

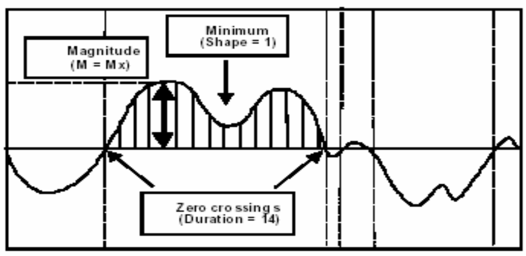

Figure 1 TESPAR coding within one epoch (D=14, S=1)

It is possible for the majority of applications to be coded and expressed into a small sequence of discrete numerical descriptors identified as a symbol stream of the TESPAR [8, 9], typically in the range 1 to 29. Base on these small number of symbols classification can be implemented. The model TESPAR symbol alphabet consists of 28 different symbols and has been proven that it is sufficient to characterise signal waveforms to a given approximation.

The sequence of the symbols can be represented in two data formats: 1-Dimensional (vector) or 2-Dimensional (matrix) and named as “S-Matrices” and “A-Matrices” respectively. The S-matrix approximates to a histogram of TESPAR symbols which records the number of times each TESPAR alphabet symbol appears in the TESPAR symbol stream. A-matrix represents the temporal relationship between consecutive pairs of symbols. It is a two dimensional 28x28 vector matrix that records the number of times each pair of symbols in the alphabet appears *n* symbols apart in the symbol stream [7]. Parameter *n* is known as the delay between symbols. $n < 10$ is used for characterizing the fast oscillating content of the signal while and $n > 10$ is used for characterizing the slow fast oscillating content of the signal. Discrimination between TESPAR matrices has been always obtained through different applications [10].

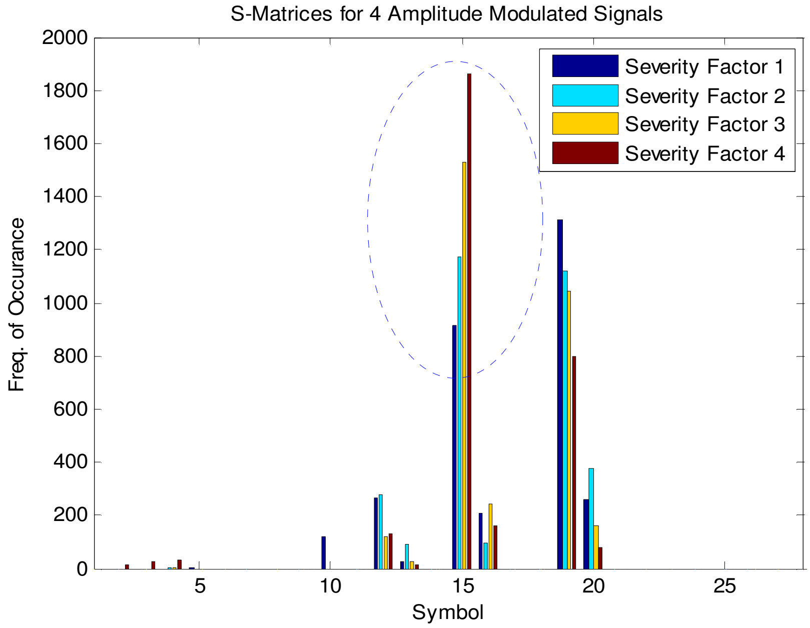

Figure 2 S-Matrices from amplitude modulation signals with 4 modulation factors

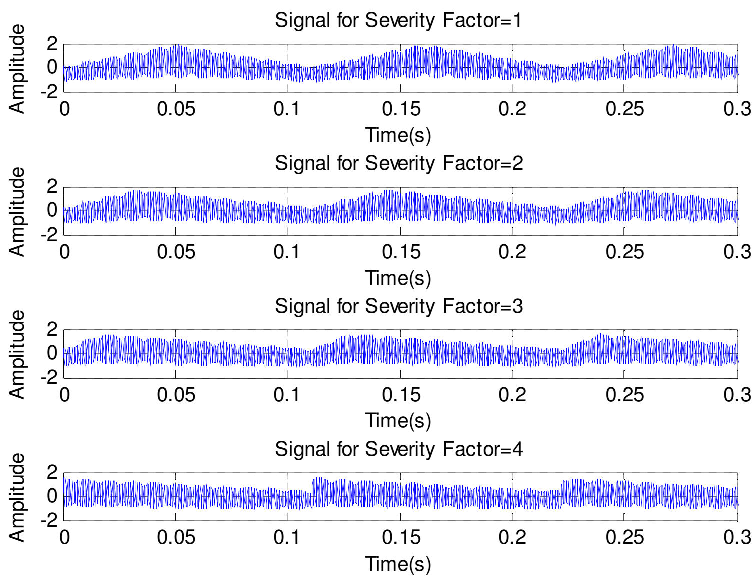

Figure 3 Raw signals from 4 modulation factors

Figure 2 shows four examples of S-Matrices for 4 sets of amplitude modulation signals respectively. It is clear that the amplitude for symbol 15 and 19 are very high for all four signals. Interestingly, the amplitudes for symbol 15 have a gradual increase trend, showing that some of the signal components have an internal connection and changes gradually over the four cases.

Actually these four signals are generated by changing the shape of a triangle modulating signal in a linear way. The four factors represent values: 0.45, 0.3, 0.15 and 0 respectively. Each of them is a fraction of 2π at which the maximum of the triangle wave occurs. As shown in Figure 3, Factor 1 is from a fraction value 0.45. So the modulating process starts slowly whereas Factor 4 is for the value 0 and the modulating starts very quick. With such modulating characteristics, these 4 simulated signals may reflect different degrees of severities included in vibration signals from different bearing faults. The quick modulation may represent high impacts due to large deep dents on bearing races whereas the slow one may represent small impacts from small shallow dents. Therefore, the amplitudes for symbol 15 in S-Matrix can be used to differentiate the signal contents and hence used for classification of fault severity.

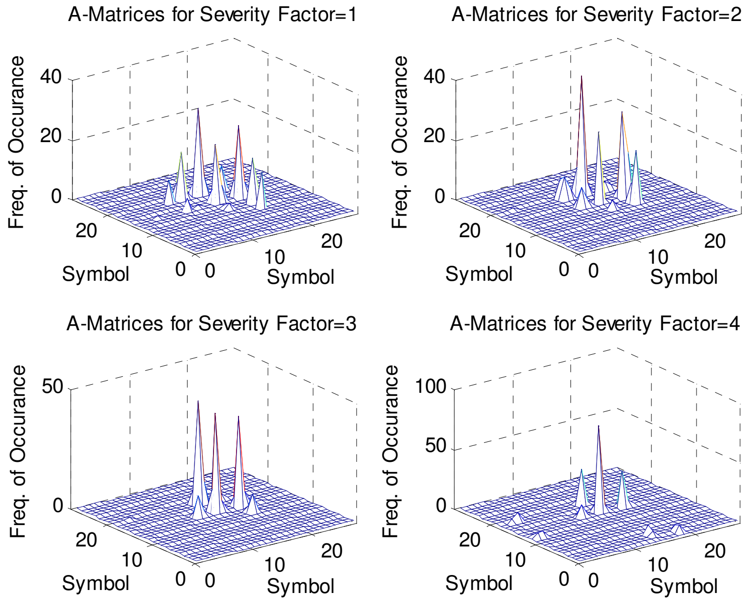

Figure 4 A-Matrices from amplitude modulation signals with 4 modulation factors

In a similar way TESPAR A-matrices can be also used to differentiate the four cases. As shown in Figure 4, the number of distinctive peaks in A-matrices becomes small as the severity factor increases. Therefore, this number can be a feature for severity classification.

From this study, TESPAR methods have been understood to be capable of classifying signals with amplitude modulations. Vibrations of faulty bearings often exhibit these characteristics. So TESPAR can be used to analyse bearing vibrations for condition monitoring.

3. Bearing Vibration Measurement

To examine the performance TESPAR in monitoring bearing faults, bearing vibration data was acquired from a research bearing test rig illustrated in Figure 5. It comprises of a 3-phase electrical induction motor coupled with a dynamic brake, the stator of which is free to move so that torque measurements may be taken. The motor is connected to the brake through 2 shafts that are coupled by three pairs of matched flexible couplings.

These two shafts are held in two bearing housings, each has one roller and one captive ball bearing. It is the roller bearing that is tested with different faults in this study.

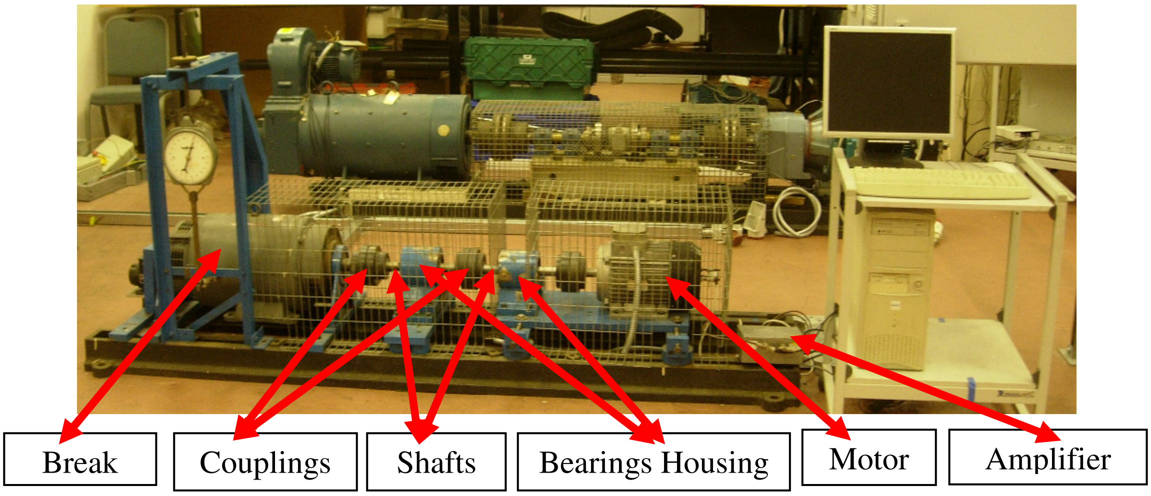

Figure 5 Image of bearing test rig

3.1. Test Bearings

Table 1 lists the specification of the roller bearing. It is a common bearing used to undertake high radial load only. Characteristic frequencies in the table are usually based to diagnose faults from this bearing in envelope spectrum analysis. Because this type of bearing can be separated easily into different parts, various faults can be created conveniently for study.

Table 1 Roller bearing characteristic frequencies at a shaft frequency of 24.3Hz

Elements	Dimension	Fault	Frequency(Hz)
Roller diameter	14mm	Cage	9.3
Number of roller	9	Outer race	83.3
Contact angle	0°	Inner race	135.1
Pitch diameter	59mm	Roller	48.3

In this study, four faulty bearings were tested under a shaft rotational speed of 1461.7rpm or frequency of 24.3Hz under no load condition. Bearings 1 and 2 were introduced to a small fault and a large fault respectively by making small and large scratches on the out races. In the same way, Bearing 3 and 4 were created with a small and a large fault on their inner races respectively.

3.2. Data sets

Four tests were conducted for studying bearing fault detection and diagnosis. Each test acquired data at a sampling rate of 62.5 kHz. In addition, the data length for each test recorded is 960,000 points and three such records were obtained for each bearing case. This is the typical requirement for envelope based bearing analysis, which allows envelope signals to be obtained in high frequency range and the spectrum average to be carried out with high numbers and hence produces reliable results for bearing fault diagnosis.

Figure 6 shows the envelope spectra of vibration for the four bearings. It is clearly demonstrated that the first two bearings have different amplitudes at 83.3Hz, showing the typical feature of an out race fault, whereas bearing 3 and 4 show different spectral amplitudes at 135.1Hz, showing the typical faults at the inner race. In addition, the spectral amplitudes for each type of fault increase with the size of scratches on the races. Therefore, it is confirmed that the datasets contain the desired fault characteristics and severity for TESPAR methods evaluation.

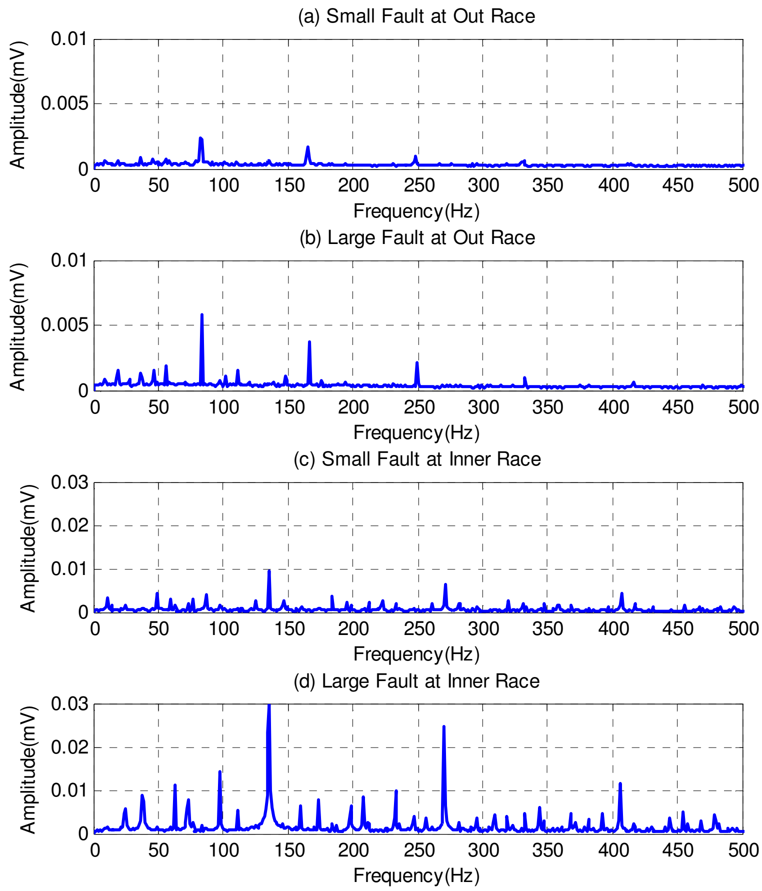

Figure 6 Envelope spectra of tested bearings

4. TESPAR Result and Discussion

Once vibration datasets have been obtained for the four cases, they are encoded into their TESPAR symbol streams and their S and A-Matrices are constructed by a program written in Matlab. For comparison over different cases, the matrices are normalised by the total number of symbol occurrence with respecting to each case.

In addition, two sets of matrices are obtained for evaluation. The first set is the raw data directly where the second is from the envelope signals of the raw data. As the envelope signals are obtained in the same frequency range as that of envelope spectrum analysis, results from the second matrices thus allow a comparison with the detection results from envelope spectra.

4.1 Matrices of raw vibration signals

By comparing the S-Matrices, shown in Figure 7, between all bearing conditions tested;

clear differences can be observed in TESPAR symbol 2, 4, 5 and 6. In particular, the amplitude differences in symbol 2 and 4 can be combined to differentiate between different types of faults and different degrees of faults for each type. This demonstrates that it is possible to use S-Matrices alone to diagnose these for bearing cases completely but it needs to use two features.

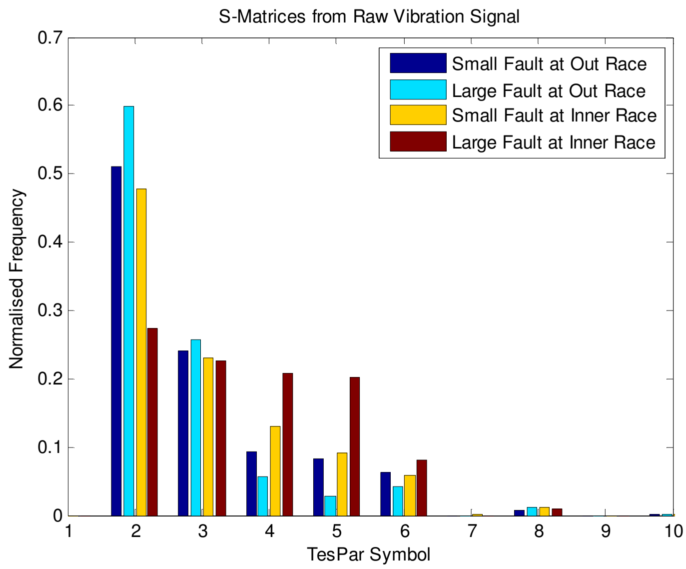

Figure 7 S-Matrices from raw signal for four faulty bearings

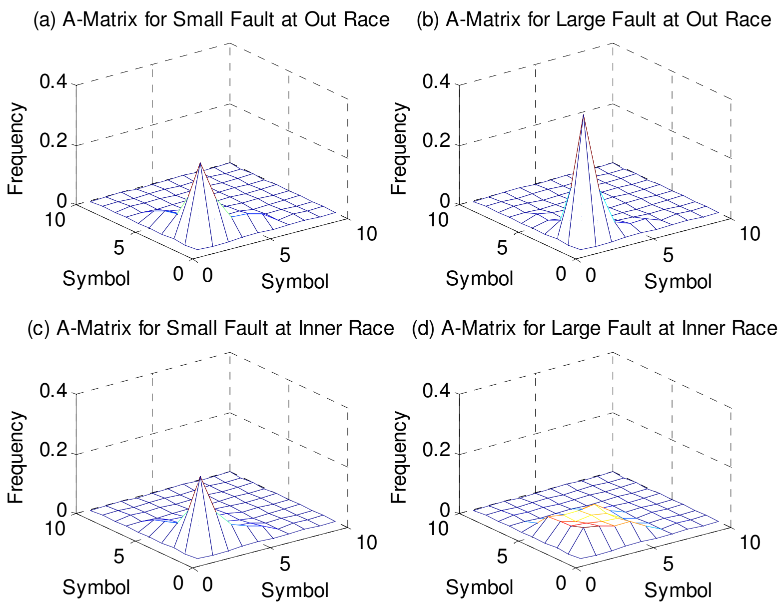

Figure 8 A-Matrices from raw signals for four faulty bearings

A-Matrices for raw signals are shown in Figure 8. The pattern's differences permit the differentiation between small and large severities for each type of fault. However, because the patterns of Figures (a) and (c) are very similar, it is difficult to analyse differences between two types of faults under the cases of small severities. This means that A-Matrices cannot provide a full separation between the cases tested even if it has large number of features

4.2 Matrices of envelope signals

S-Matrices in Figure 9 exhibit similar patterns as that of Figure 7. So with the same method, the amplitude in TESPAR symbol 2 and 4 can be relied on for the separation of fault cases completely. Moreover, amplitudes in either symbol 5 and 8 exhibit a pattern that can be used to separate between different types of faults and different degrees of severity for each fault, showing that only one feature is needed for fault diagnosis.

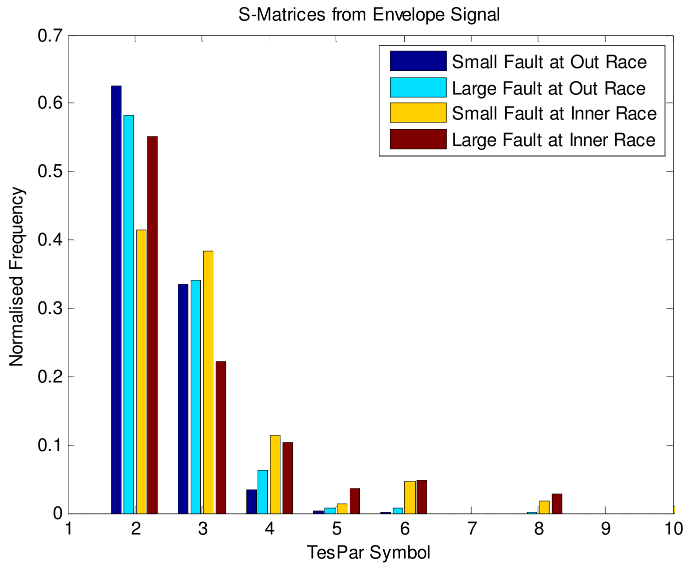

Figure 9 S-Matrices from enveloped signals for four faulty bearings

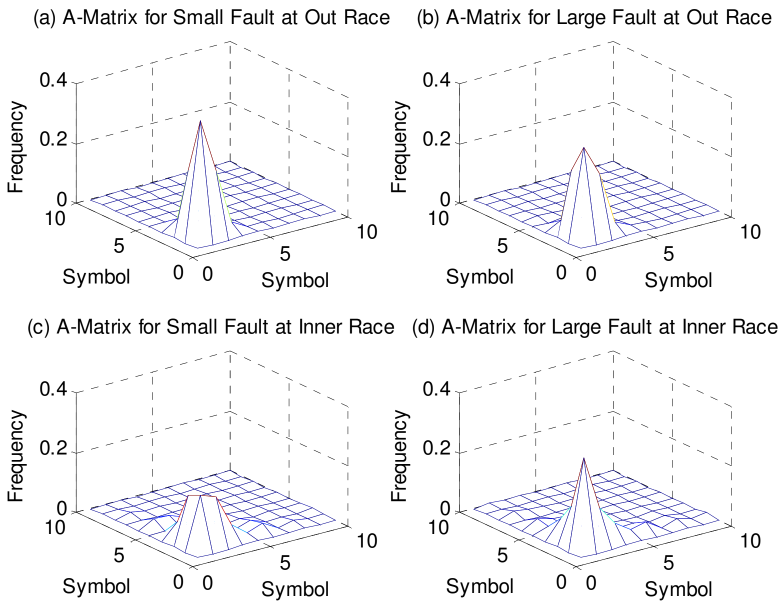

Figure 10 A- Matrices from enveloped signals for four faulty bearings

In addition, patterns in A-Matrices shown in Figure 10 also provide good differences for a full separation between the four fault cases. For the out race faults, two patterns are very similar but with different peak values, which indicates signal contents are close for the same type of bearing faults. This features also exhibits for the cases of two inner race faults. In addition, patterns between the two different types are quite different, showing the diversity of the signal contents. Nevertheless, the results from enveloped signals show better performance than the raw signals because envelope signals have a higher sign to noise ratio. This also indicates that TESPAR method is sensitive to noise and noise suppression is needed before applying these methods.

5. Conclusion

The performance of TESPAR in monitoring bearing faults has been evaluated with both raw and envelope signals. From the results obtained based on raw signals it shows that S-Matrices allow the diagnosis of the faults simulated but needs more than two features. However, A-Matrices cannot produce full diagnosis results in classifying fault types. The reason for this lower performance is that the signal to noise ratio is low in the raw data sets. Therefore, enveloped signals obtained by filtering away some noisy components allow TESPAR to produce a full diagnosis of the bearing faults with using just one detection feature.

6. Reference

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