DETECTION OF MACHINERY FAILURE BY USING TIME-FREQUENCY ANALYSIS

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ABSTRACT

We present a new method for detection of machinery failure based on evolutionary spectral analysis of machine vibrations. Evolutionary spectral method is one of the time-frequency analysis techniques which provides a means for identifying spectral variations in the vibrations produced by machines. In this work, vibrations generated by different electrical machines are recorded by using accelerometers. Then vibrations are classified into two groups based on their evolutionary spectra: first one being the healthy operation and second one having an abnormality. A method is also presented for automatic detection of abnormality in these machine vibrations using their joint time–frequency moments and neural networks. Simulation results are given to illustrate the performance our algorithm.

1. INTRODUCTION

Health condition monitoring of electric machines is a growing research area as the early determination of failures is very important from reliability and economics point of view [1, 2]. One of the methods widely used is spectral analysis of recorded machine vibrations [3] where the machine health information is characterized in frequency domain. Machine health condition information can also be extracted from time–domain signal by using statistical methods [4]. Recently, methods based on time–frequency (TF) analysis have been extensively used to determine more reliable and sensitive results [3, 5, 6]. Most of the studies on machine condition monitoring focuses on detecting defects in asynchronous motors. It has been observed in the previous studies that more than half of those defects are caused by bearing failure and shaft imbalance [7, 8]. In this work, we present a new method based on evolutionary spectral analysis for detection of bearing failure in asynchronous motors.

The machine vibrations, like many other non-stationary signals, such as speech, music and biological signals exhibit time–varying, or non–stationary characteristics. Time frequency representations (TFRs) have been successfully applied to such signals to study their changing spectral properties. Intuitively, using high resolution TFRs for the classification of non–stationary signals should improve the classification performance. However, many of the TF methods producing a high degree of detail inhibits effective integration with trainable classifiers, such as neural networks, due to the dimensionality problem. That is, for an N-point discrete–time signal, the TFR is an $N \times N$ matrix. Hence, more data will be used for TFR based classification than other methods. In this work, we use Evolutionary Spectrum (ES) that is calculated by the multi–window Gabor coefficients [9] as the TFR for the signal. Then, we solve the dimensionality problem by using joint TF moments calculated from the ES estimate of the signal. The joint TF moments have been extensively used for recognition purposes in image processing [4, 10]. In our approach, a set of joint moments of a TFR for each labeled time series in the training set is computed, and then normalized. These feature sets consisting of normalized joint moments are used to train a neural network to classify unlabeled data from two classes: vibrations from (i) healthy motor, (ii) motor with a bearing failure.

This work was supported by The Research Fund of The University of Istanbul, Project number: T-779/251099.

2. EVOLUTIONARY SPECTRAL ANALYSIS BY USING THE MULTI–WINDOW GABOR EXPANSION

In this section, we briefly present the connection between the evolutionary spectral analysis and the multi–window Gabor expansion. This will allow us to obtain a TFR for the signal as well as its time dependent spectrum.

2.1. The Multi–window Gabor Expansion

The multi–window Gabor expansion for a finite–support signal $x(n), 0 \leq n \leq N-1$ is given in [9] as

$$x(n) = \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} \sum_{k=0}^{K-1} a_{i,m,k} \; h_{i,m,k}(n), \tag{1}$$

where the logons are

$$h_{i,m,k}(n) = h_i(n - mL) \; e^{j\omega_k n}, \tag{2}$$

and $\omega_k = 2\pi k L'/N$. The parameters M, K, L, L' are positive integers constrained by $ML = KL' = N$ where M and K are the number of analysis samples in time and frequency, respectively, and L and L' are the time and frequency steps, respectively. Existence, uniqueness and numerical stability of the representation depend on the choice of parameters L and L'. For numerically stable representations, L and L' must satisfy $L\,L' \leq N$, or equivalently that $L \leq K$. When $L = K$, we have the critical sampling, and when $L < K$ we have the over-sampling.

The synthesis window $h_i(n)$ is generated by contracting a unit-energy mother Gabor window $g(n)$, i.e.,

$$h_i(n) = 2^{i/2}\; g(2^i n), \qquad 0 \leq n \leq N-1, \tag{3}$$

for $i = 0, 1, ..I-1$. The scaling factor 2^i changes the support of the window, and I is the number of scaled windows used to analyze the signal. The Gabor coefficients are evaluated by

$$a_{i,m,k} = \sum_{n=0}^{N-1} x(n)\; \gamma_i^*(n - mL)\; e^{-j\omega_k n}, \tag{4}$$

where the analysis window $\gamma_i(n)$ is solved from the bi-orthogonality condition between $h_i(n)$ and $\gamma_i(n)$ as in the discrete Gabor expansion [9].

Notice that equation (1) is the average of I representations of $x(n)$. However, each of these expansions represents some of the signal components better than others. Hence the TF resolution of this representation is improved by averaging several representations obtained from scaled windows.

2.2. Evolutionary Spectral Analysis

We consider the following discrete–time, discrete – frequency model for finite–extent, deterministic signals:

$$x(n) = \sum_{k=0}^{K-1} A(n, \omega_k) e^{j\omega_k n}, \qquad 0 \leq n \leq N-1, \tag{5}$$

where $\omega_k = 2\pi k/K$. The multi–window Gabor expansion in (1) can be written as

$$\begin{aligned} x(n) &= \sum_{k=0}^{K-1} \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} a_{i,m,k}\; h_i(n - mL)\; e^{j\omega_k n} \\ &= \sum_{k=0}^{K-1} A(n, \omega_k)\; e^{j\omega_k n}. \end{aligned} \tag{6}$$

We then have that the kernel

$$\begin{aligned} A(n, \omega_k) &= \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} a_{i,m,k}\; h_i(n - mL) \\ &= \frac{1}{I} \sum_{i=0}^{I-1} A_i(n, \omega_k). \end{aligned} \tag{7}$$

Replacing the coefficients $\{a_{i,m,k}\}$ of equation (4) we obtain also that

$$A(n, \omega_k) = \sum_{\ell=0}^{N-1} x(\ell)\; \mathrm{w}(n, \ell)\; e^{-j\omega_k \ell}, \tag{8}$$

where we defined the time–varying window

$$\mathrm{w}(n, \ell) = \frac{1}{I} \sum_{i=0}^{I-1} \sum_{m=0}^{M-1} \gamma_i^*(\ell - mL) h_i(n - mL). \tag{9}$$

Then the evolutionary spectrum of $x(n)$ is obtained according to

$$S_{ES}(n, \omega_k) = \frac{1}{K}\; |A(n, \omega_k)|^2, \tag{10}$$

where the factor $1/K$ is used for proper energy normalization.

In [9] two ways to calculate the evolutionary spectrum is presented: one is using (8) and (10), and the other is by calculating the $\{A_i(n, \omega_k)\}$ from (7), and combining the corresponding spectra $\{S_i(n, \omega_k)\}$ using existing averaging techniques. It is also shown in [9] that normalizing the window $\mathrm{w}(n, \ell)$ to unit energy, the total energy of the signal is preserved. Furthermore, $S_{ES}(n, \omega_k)$ is always non–negative and approximates the marginal conditions [11], hence, in contrast to many time–frequency distributions, interpretable as TF energy density function [9]. In the next figures, we show the time and frequency marginals calculated from an ES estimate of a motor vibration signal. Fig. 1-a shows the correct time marginal of the signal (solid line) together with the time marginal calculated from the ES (dashed line). Frequency marginal of the signal (solid line) and that of the ES (dashed line) are given in Fig. 1-b. It is concluded that ES, having no negative values, preserving the total signal energy, and approximating the correct marginals, can be used as TF density function when calculating the joint TF moments. In the next section we employ evolutionary spectra to obtain the joint TF moments of machine vibration signals.

3. DETECTION OF MACHINERY FAILURE

It was reported that TFRs have been successfully applied to non–stationary signals for revealing their time-varying characteristic features [12]. Machine vibrations also have time-varying characteristics, as such, it is natural to expect an enhanced classification performance for TFR based classification [12, 13]. We propose to use the ES for the detection of machinery failure, i.e., classification into two groups: vibrations generated by (*i*) the normal operation and (*ii*) the unhealthy operation. However, for an N-point signal, $S_{ES}(n, \omega_k)$ is an $N \times N$ matrix. This means that far more data will be calculated for ES based classification than other methods such as template matching and temporal, or spectral moment based classification [4, 10], hence increasing the computational cost. This dimensionality problem is overcome in [12] by using a reduced feature set including joint TF moments instead of the whole matrix with successful results.

In this study, we also use the same approach for the detection of machinery failure: for each data in the training set, ES is calculated and normalized to unit–energy. Then several joint moments are calculated from ES and used as futures for the classification.

Temporal and spectral moments of a signal $x(t)$ are given by [11]

$$< t^i >= \int_{-\infty}^{\infty} t^i \; |x(t)|^2 dt \qquad i = 1, 2, ...$$

$$< \omega^j >= \int_{-\infty}^{\infty} \omega^j \; |X(\omega)|^2 d\omega \qquad j = 1, 2, ... \qquad (11)$$

respectively where $X(\omega)$ is the Fourier transform of $x(t)$. The joint TF moments are given by

$$< t^i, \omega^j >= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} t^i \; \omega^j \; X(t, \omega) \; dt \; d\omega \qquad (12)$$

for $i, j = 1, 2, ...$, where $X(t, \omega)$ is the TF density function of the signal [11]. In our experiments, we calculate joint moments of machine vibrations by using $S_{ES}(n, \omega_k)$ and numerical approximations for the integrations in (12). The joint moments are then log–normalized as in [12] by

$$\overline{< t^i, \omega^j >} = \log \left(\frac{< t^i, \omega^j >}{i!j!} \right) \qquad i, j = 1, 2, ... \qquad (13)$$

to reduce their dynamic range. The future set $\{ \overline{< t^i, \omega^j >} \}$ is then used to train a neural network for the detection of machinery failure [10].

4. SIMULATION RESULTS

Vibrations from 24 (3 healthy and 21 damaged) electric motors were recorded by accelerometers for 250 msec. and digitized. After ES of each data computed, joint TF moments are obtained for $i, j = 1, 2, 3$. Then a neural network, with 9 inputs (one for each TF moments), 2 outputs (one designating healthy and one for failure) and one hidden layer, is trained by using the back-propagation learning algorithm [10]. After completing the training, the net is tested on training set with 100 % performance. Then the net is tested by using joint TF moment sets from healthy motors and from motors with a sign of bearing failure. Healthy vibrations are identified successfully and failures are detected with 90 % performance rate. We also applied spectral moment based classification [4] to our data and compared the classification performance of these methods in Table 1. As shown, joint TF moment based classification yields higher performance rate than other method which only uses spectral moment information. In Fig. 2, we present ES estimates of healthy and failed vibrations. Fig. 2-a is an ES estimate of a vibration from a healthy motor, and Fig. 2-b shows ES estimate of a vibration from a motor with a small level of bearing failure. As shown, energy of the healthy motor vibration is concentrated in low frequency range (up to 2000 Hz), whereas failure shows energy in 2500–4500 Hz band as well. Another vibration from a motor with a higher level of failure is analyzed and ES is given in Fig. 2-c. As shown in the last two figures, higher level of fault in the machine is demonstrated by more energy in the high frequency range.

Table 1. Classification performance on test data.

Vibration type	Joint Moment (%)	Spectral Moment (%)
healthy	100	80
failure	90	50

5. CONCLUSIONS

In this paper, we studied detection of bearing failure which is one of the most common failure types that may occur in electrical machines widely used in industry. A method based on evolutionary spectra is presented for detection of bearing failure. ES is calculated from coefficients of a multi–window Gabor expansion. This multi–window analysis provides representation of narrow–band, wide–band, and time varying frequency components of electrical machine vibrations with enhanced TF resolution. We presented an automatic detection algorithm which uses the joint TF moments as features of the vibrations. TF moments of labeled data are used to train a neural network. Performance of the detection is tested on unlabeled data from both classes, and obtained encouraging results.

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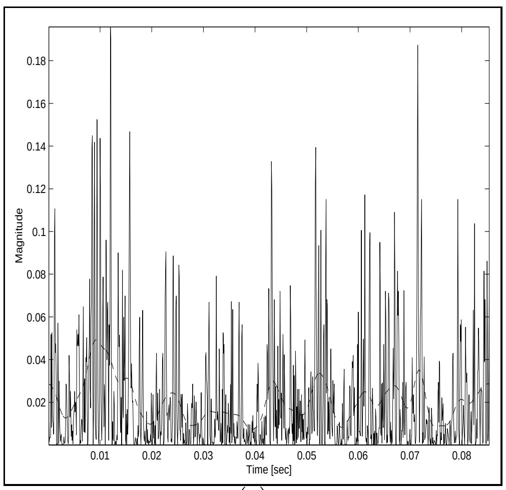
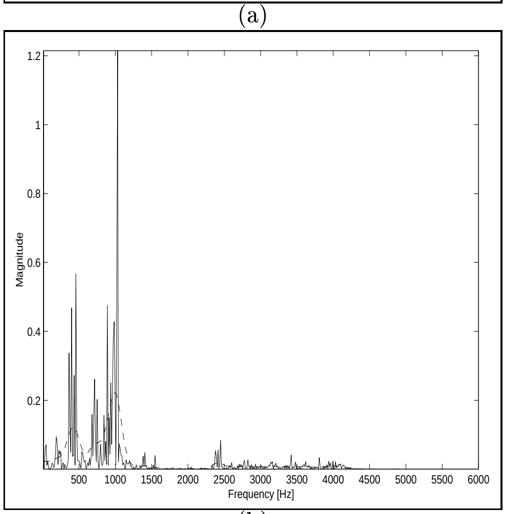
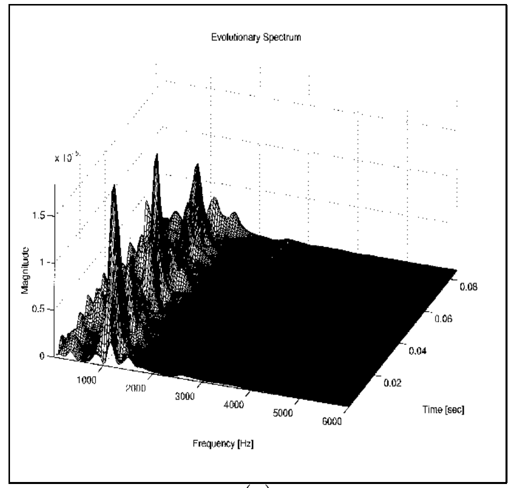


(a)



(b)

Figure 1: a) Time marginal, b) Frequency marginal of vibration recorded from a motor with bearing failure.



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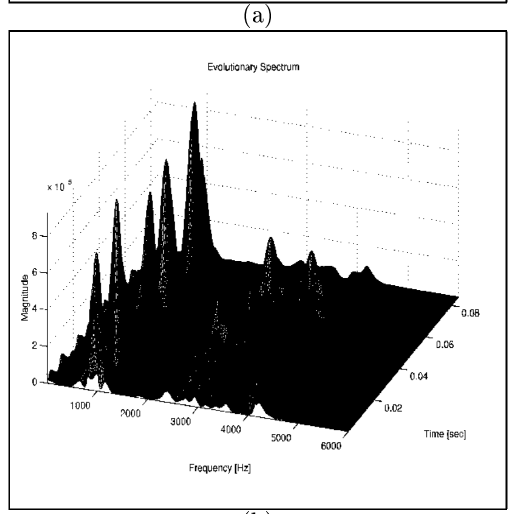

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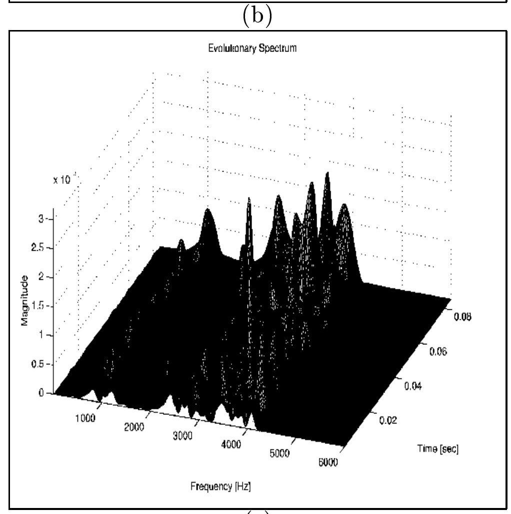

(c)

Figure 2: ES estimates of a vibration from a) a healthy motor, b) a motor with a small level of bearing failure, c) a motor with a higher level of bearing failure.