A Method for the Investigation of Bearing Vibration Based on Spectrogram Image Comparison

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Abstract. The possibility of analyzing the condition of bearing systems from the vibrations generated during their operation, by means of signal processing methods, has been of extensive research, over last few years. As, vibration signal is highly non-stationary, time as well as frequency domain features cannot designate its behavior well. Though, Spectrogram is a time-frequency domain feature extraction method, its analysis is tedious and maybe, subjective. In the proposed method, the spectrogram images of the normal vibration data is compared with that of the contextual vibration, using Peak Signal-To-Noise Ratio (PSNR). It has postulated that, the pattern similarity between the contextual spectrogram and baseline is little when the bearing is faulty. The PSNR between the spectrogram image of normal bearing vibration data and the baseline is different from those between the baseline and vibration data corresponding to Inner Race Failure (IRF), Roller Element Defect (RED) and Outer Race Failure (ORF). The PSNR analogous to the vibrations picked up from normal and faulty bearings vary with a P value of 4.58445x10⁻²⁰. The method can discriminate faulty bearings with, 96.77% sensitivity and 100% specificity.

1. Introduction

Bearings are the prominent components in most of the machines. They set up free rotational or linear movement, by lessening friction. Bearing may turn broken because of substantial stacking, lacking grease and inadequate fixing. A few investigations have expressed that the significant reason for failure of machines is because of bearing problem [1-2]. Sudden failure of the bearing may crush up different parts of the machines additionally and may raise downtime costs. Regular strategies for observing bearing wellbeing incorporate motor current analysis, wear debris analysis, noise monitoring, temperature monitoring, vibration monitoring, chemical analysis, Laser displacement measurement etc [3-4]. The misalignment of the bearing produces vibration and noise. Signal processing techniques are the most vital part of the systems intended for the automated analysis and interpretation of bearing vibration. Feature extraction techniques used in these automated systems generally belong to time domain, spectral domain [5-6] or Time-Frequency (TF) domain. Peak/peak to peak and Root Mean Square (RMS) amplitude of vibration, skewness, kurtosis, crest factor, measures of Central Tendency (CT) , impulse factor, shape factor and clearance factor[7] are few of such time domain features usually employed.

K. Czarnecki [8] suggested that energy density estimated via ordinary spectrogram or Instantaneous Frequency Rate Spectrogram (IFRS) is a reliable feature as far as mechanical vibrations are concerned. R. Klein [9] demonstrated that faults in turbofan engine can be detected from the spectrogram of its vibrations, computed via Wigner-Ville, wavelets or Short Time Fourier transform (STFT). A. Belsuk and J. Prezelj [10] used spectrogram of the vibrations produced in gear units for monitoring their condition. S. K. Yadav and P. K. Kalra [11], demonstrated that the spectrogram of vibration has the potential to detect faults in single cylinder four stroke IC engine. Griffaton et.al [12] suggested that damaged bearings in highly sophisticated systems like aircraft engines can be identified.
just via simple visual inspection of spectrograms of vibration data. Yu et al. [13] employed a modified version of the ordinary spectrogram, termed as ‘adaptive gaussian chirplet spectrogram’, for analyzing the vibrations in rolling bearings. In any case, manual understanding of spectrogram is repetitive as it relies upon the mastery of the onlooker. In addition, the subjectivity characteristic in its manual judgment is a mind boggling issue. Image processing methods can be employed for the automated evaluation and comparative interpretation of spectrograms. As a base to such efforts Li et al. [14], had used the images of spectrum of vibration data, for diagnosing faults in bearings. Hua et al. [15] used Quaternion invariable moment to account for color features of the vibration spectrograms. To interpret the spectrogram Klein et al. [16] solely utilized the ridge information.

In the spectrogram image, the variation of pseudo colors or grey levels in a particular column reflects how different the spectral power of a particular frequency component is, between distinct epochs. Thus, the variation of pseudo color or grey level in each column accounts for the variation of spectral power of a particular frequency component over time i.e. the non-stationarity of the signal. Similarly, the variation of pseudo color or grey level in each raw account for the relative distribution of spectral power over different frequency components within a single epoch itself. Quaternion invariable moment of the spectrogram image [15] does not seem to be sufficient to characterize the non-stationarity behavior of vibration data. Likewise, the ridges [16] alone cannot express continuous variation in the pseudo colors or grey levels in the spectrogram image which in turn reflects the time varying spectral features of the vibration data.

A method for condition monitoring and fault diagnosis of bearing system using pattern matching of spectrogram images is proposed in this paper. The spectrogram images of the baseline or reference vibration data which belongs to a normal bearing and contextual vibration data, whose fundamental bearing state is unknown, are compared for their mutual similarity as far as the variation in pseudo color or grey level with the help of Peak Signal To Noise Ratio (PSNR). It is postulated that when the bearing is not healthy, the grey level distribution of the spectrogram image of its vibration could be entirely diverse from that of the baseline image. In this context, the PSNR between them would be comparatively less. Rest of the paper is organized as follows. The details of vibration data used in the analysis and mathematical formulation of spectrogram images and PSNR are furnished in section 2. The statistical significance of PSNR between spectrogram images of base line and contextual vibration data to yield an accurate classification of faulty and normal bearings is analyzed in section 3.

2. Methodology

The method proposed in this paper, the spectrogram image of the contextual vibration has to be compared with a baseline spectrogram image of the vibration data from a healthy bearing, in terms of similarity in color or grey level distribution to identify whether the status of the bearing from which the contextual vibration is recorded is healthy or not. The bearing vibration data used for developing the automated method is availed from Prognostics Center of Excellence, National Aeronautics and Space Administration (NASA) [17].

The vibration information utilized in this paper comprises two conditions of bearing i.e; healthy and faulty. Three kinds of faults (healthy, Inner Race Failure (IRF), Roller Element Defect (RED) and Outer Race Failure (ORF).) are mainly considered. Every vibration sample is of one second span containing 20480 samples. The aggregate data collection contains 120 recordings, 30 recordings, from each fault group. That implies total data set comprises 30 recordings from healthy bearings and 90 recordings from faulty bearings.

To make the base line spectrogram image more consistent, the spectrograms of 8 consecutive vibrations, recorded at 10 minutes interval, from a healthy bearing, are averaged before color mapping. The spectrogram is converted to image or visual form through color or grey scale mapping. For a vibration signal ‘x(n)’ sampled at a rate of ‘fs’, split in to ‘Q’ segments of length ‘M’ samples each, given M<N [18], the STFT of a segment of length ‘M’,

\[ X_i(k) = \sum_{l=0}^{M-1} w(l)x(l)e^{-j2\pi kl/M}, 1 \leq i \leq Q \]  

(1)
where \( w(I) \) is the window function. The power spectrum of each segment,

\[
P_i(k) = \frac{1}{\sum_{k=0}^{N-1} |w(k)|^2} |X_i(k)|^2
\]  

(2)

Discrete spectrogram ‘S’ of the vibration data,

\[
S = \begin{bmatrix}
P_0(0) & P_0(1) & P_0(2) & \cdots & P_0(Q-1) \\
P_1(0) & P_1(1) & P_1(2) & \cdots & P_1(Q-1) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
P_{M-1}(0) & P_{M-1}(1) & P_{M-1}(2) & \cdots & P_{M-1}(Q-1)
\end{bmatrix}
\]  

(3)

As vibration data is highly non-stationary, Hamming window is used for computing the spectrogram in this paper. Number of samples in each segment is set to 4550 following the usual practice of setting \( M=N/4.5 \). The total number of samples, ‘\( N \)’ in each vibration recording is 20480 and the sampling frequency, \( F_s \) is equal to 20 KHz. The segments have 50% overlap. The similarity between the spectrogram image of the contextual vibration data and baseline spectrogram image is quantified using PSNR. The PSNR for an image of size \( M*N \) between the base line spectrogram image ‘X’ and the spectrogram image ‘Y’ of the contextual vibration data is computed as [19],

\[
\text{PSNR} = 10 \log_{10} \left( \frac{\text{Max}(X)}{M \cdot N \cdot \frac{1}{\Sigma_{i=0}^{M-1} \Sigma_{j=1}^{N-1} [X(i,j)-Y(i,j)]^2}} \right)
\]  

(4)

The computation of spectrogram, color mapping, comparative evaluation of the spectrogram images with PSNR and the statistical evaluation of the PSNR values are done in Matlab®. The statistical significance of PSNR between the spectrogram images of the contextual vibration data and baseline spectrogram image is verified for their capability to differentiate healthy, IRF, ORF and RED via Kruskal-Wallis. The flow diagram of the processes involved in the proposed method is illustrated in fig.1.

**Figure 1.** Block diagram of the processes involved in the proposed framework.
3. Results and Discussions

The baseline spectrogram image of the vibration data is shown in fig. 2 (a). Spectrogram images of the vibration data analogous to healthy, IRF, ORF and RED bearings are furnished in fig. 2 (b) – (e). The color distribution of the spectrogram images corresponding to the faulty bearings is completely different from the baseline in fig. 2 (a). It can be noted that the baseline spectrogram image (fig. 2 (a).) is similar to the spectrogram image of healthy class (fig. 2(b)) than the spectrogram image of the fault classes (fig. 2 (b) – (e)). This is a strong indication that the color distribution of spectrogram images is a trustworthy feature to distinguish normal and faulty bearings.

From table 1, the PSNR between spectrogram images of vibration data analogous to healthy, IRF, ORF and RED and the baseline are 39.38±2.52, 32.06±5.82, 30.40±2.45 and 23.87±0.95, respectively. It can be noted that, the PSNR between baseline and spectrogram images of vibration data corresponding to faulty bearings are significantly less than PSNR between baseline and spectrogram images of vibration data corresponding to healthy bearings. As far as numerical values of PSNR between baseline and spectrogram images of vibration data corresponding to ORF is concerned, they are confined to a narrow range compared to numerical values of the PSNR between baseline and spectrogram images of vibration data corresponding to other classes.

The ranges of the PSNR between the base line spectrogram image and a spectrogram image of the vibration data of different bearing states are as follows; healthy:32.10-46.16, IRF: 16.93 - 39.51, ORF: 21.18-25.32 and RED: 25.34-34.80, respectively. If the PSNR between the base line spectrogram image and a spectrogram image of the vibration data to be analysed is within the range of 25.34 to 32.10, it can be concluded that the bearing is either healthy or RED. For PSNR values between 34.80 and 39.51 then the bearing could be either healthy or of IRF. If the PSNR values lies between 21.18 and 25.32 then it would be either ORF or IRF. If the PSNR is specifically above 46.16, it is a clear sign that the bearing is healthy. This reveals that, from the PSNR values, faulty and healthy bearings can be distinguished easily.

The Box-Whisker plot of PSNR between spectrogram images of vibration data corresponding to four classes of bearings, healthy, IRF, ORF and RED and the baseline is illustrated in fig. 3. The box whisker plot states the assumptions made from the numerical values of PSNR. The box of PSNR between baseline and spectrogram images of vibration data corresponding to healthy bearings is lying sufficiently apart spatially from the boxes of PSNR between baseline and spectrogram images of vibration data corresponding to faulty bearings. Similarly the box of ORF is lying sufficiently apart spatially from the boxes of other class of vibration data.
Figure 3. Box-Whisker plot of PSNR between spectrogram images of vibration corresponding to healthy, IRF, ORF and RED and the base

Table 1. Numerical values of PSNR between spectrogram images of vibration data corresponding to four classes of bearings, healthy, IRF, ORF and RED and the baseline

| SI No. | Healthy | IRF  | RED  | ORF  |
|--------|---------|------|------|------|
| 1      | 39.41   | 38.59| 29.81| 24.28|
| 2      | 39.62   | 35.11| 29.71| 24.29|
| 3      | 39.95   | 36.36| 29.94| 23.28|
| 4      | 43.13   | 35.3 | 29.63| 24.29|
| 5      | 37.68   | 39.51| 30.33| 25.23|
| 6      | 38.68   | 38.28| 29.75| 24.32|
| 7      | 39.46   | 36.5 | 30.88| 22.32|
| 8      | 46.16   | 38.4 | 31.65| 24.31|
| 9      | 39.6    | 35.4 | 33.3 | 23.21|
| 10     | 38.3    | 36.58| 33.69| 23.18|
| 11     | 39.97   | 36.5 | 34.8 | 24.29|
| 12     | 43.17   | 35.66| 34.1 | 25.32|
| 13     | 39.02   | 35.83| 32.73| 24.28|
| 14     | 38.61   | 34.95| 32.11| 24.39|
| 15     | 38.82   | 34.45| 33.24| 24.48|
| 16     | 38.74   | 37.17| 33.68| 24.23|
| 17     | 38.87   | 34.67| 32.22| 24.18|
| 18     | 38.31   | 36.24| 31.73| 24.17|
| 19     | 44.53   | 29.51| 30.05| 24.21|
| 20     | 37.47   | 28.79| 29.22| 23.21|
| 21     | 38.18   | 27.03| 29.75| 23.18|
| 22     | 41.75   | 26.86| 29.54| 23.13|
| 23     | 32.1    | 25.62| 29.44| 23.11|
| 24     | 37.31   | 25.78| 29.53| 23.11|
| 25     | 38.74   | 25.39| 28.27| 25.13|
| 26     | 39.21   | 25.03| 27.67| 24.18|
| 27     | 40.21   | 25.43| 27.43| 24.42|
| 28     | 37.72   | 25.04| 26.21| 25.12|
| 29     | 38.73   | 25.02| 26.17| 22.14|
| 30     | 37.91   | 16.93| 25.34| 21.18|
The statistical significance of PSNR to distinguish healthy, IRF, ORF and RED is tested via Kruskal-Wallis. ANOVA table of the test is furnished in Table 2. The Chi-Square value (H) obtained from the Kruskal-Wallis test is 93.16, which is greater than the critical value 12.838. The Chi-Square is outside the critical region and it shows that the PSNR values corresponding to at least one of the bearing state could be different from others. From box whisker it has already been inferred that the class which differ from others in terms of PSNR is ORF. The PSNR corresponding to the vibrations acquire from normal and faulty bearings vary with a ‘P’ value of 4.58445x10^-20.

Table 2. Kruskal-Wallis ANOVA table

| Source   | Sum of Squares (SS) | Degree of Freedom (DF) | Mean Square (MS) | Chi-Square value (H) | Probability value (p) |
|----------|---------------------|------------------------|------------------|----------------------|-----------------------|
| Columns  | 112721.3            | 3                      | 37573.8          | 93.16                | 4.58445 x10^-20       |
| Error    | 31262.7             | 116                    | 269.5            |                      |                       |
| Total    | 112721.3            | 3                      | 37573.8          |                      |                       |

4. Conclusions
A signal processing method for the fault identification of bearing systems, based on pattern matching of spectrogram images of the contextual vibration data with spectrogram images of the baseline or reference vibration data which goes to a normal bearing by PSNR was proposed in this paper. It was observed that, if the PSNR between the spectrogram image of the contextual vibration and baseline is exclusively beyond 46.16, it is apparent that the bearing is healthy. The PSNR analogous to the vibrations attained from normal and faulty bearings vary with a ‘P’ value of 4.58445x10^-20. The suggested method is capable of detecting faulty bearing with 96.77% sensitivity and 100% specificity. Through the proposed method, subjectivity in analysis of spectrogram has been completely avoided.

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