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Bearing failure prediction using audio signal analysis based on SVM algorithms

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Abstract. Bearings are machine elements used in a wide variety of applications including transportation. The accurate prediction of a bearing failure is important to sensitive applications to secure its safety during the service life. Bearing failure prediction is useful both in bearing testing phase as well as in case of lifetime use. Real-time Audio signal analysis and advanced algorithms are able to identify the incipient failure, caused by defects, fatigue, overload or poor maintenance. Audio signal analysis and processing remains a domain where technique and algorithm needs to be developed. In this paper is presented a proof-of-concept technique and equipment developed to predict failure of bearings in case of testing phase. For this study, acoustic emission signals were measured and analyzed during life testing of bearing while other sound source are also recorded. Correlation between the acoustic emission patterns were identified in order to identify noise signal and identify the signal associated with bearing degradation. The developed solution to isolate other sounds signals means that the technique could be used while lifetime of the bearings. The results of this study provide evidence that accurate estimation of the failure of various bearings is possible by processing the vibration signal acquired from a single point, even in case of multiple sound sources are present and introduce noise in signal processing. The SVM classifier provides at least 92% mean accuracy. The influence of model on prediction accuracy has also been discussed in the work.

1. Introduction

Prognostics and health management (PHM) domain of study [1] is important and has proven the techniques highly effective in improving reliability. PHM refers to the techniques concerning condition monitoring, fault diagnostics and fault prognostics. Remaining useful life (RUL) prediction aims at assessing the degradation of bearings and to predict failure. Stimulating low maintenance costs, increasing plant availability, increasing productivity and safety have led to a growing interest in monitoring machine conditions.

Bearings are a common component of machines in industrial applications. This is the reason they have received tremendous importance from researchers in the field of PHM [2]. Different techniques are used to detect and diagnose bearing defects[3,4]. These could be classified as vibration and acoustic measurements, wear analysis and temperature measurement. Vibration monitoring and analysis in rotary machines is the most prevalent technique used to monitor, detect and analyze the state of the structure in real time or at predetermined time intervals due to rapid data collection and interpretation [5].

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Vibration signatures of the machine inform the operator to make decision for maintenance such as replacing the bearings [5]. Early detection of bearing defects is therefore essential to prevent damage to the alternate parts of a machine. The deformations of the bearing can be sorted as localized and distributed. Localized defects include bursts, cracks and pits caused by fatigue on tread surfaces. These defects could be caused by manufacturing errors and operating environments. Thus, monitoring the condition of bearings has been considered as a fundamental and basic part of any modern production facility [6]. Appropriate monitoring predicts the probability of a malfunction before it really happens. Several vibration monitoring methods and signal processing techniques have been explored to monitor conditions [7]. Bearing testing machine are important in confirming numerical simulation of bearings, that the bearings RUL prediction is correct.

The SVM [8] is an artificial intelligence algorithm able to identify and predict RUL based on trained data. In this paper, the SVM is used to predict the bearings degradation process. Different strategies have been applied to measure the vibrations and acoustic responses of faulty bearings; sound and sound pressure techniques, shock pulse method, time and frequency vibration measurements and acoustic emission technique [9,10]. Several statistical indicators that can be used as part of the real environment are the peak, the mean square root, standard deviation, peak factor, rebound factor, asymmetry, impulse factor, flattening, and shape factor [11]. It has been found that different statistical measures may indicate defective bearings. In order to test bearing materials, lubricants and bearing design the bearing manufacturer are using machine fatigue testing of bearing components [12]. The investigator compares theoretical life, measured in hours, resulted from design of bearing to the results outputted by testing machines.

2. Experimental details

In order to determine the occurrence of bearing surface defects, a real-time real time acoustic measurement system has been developed. The statistical parameters that are extracted from the acoustic signatures obtained from the bearing via the microphones are largely in the temporal domain. Correct analysis of signal time series can produce data measurements. Time domain statistics are used as irregular and trending parameters in an attempt to detect the presence of incipient bearing damage. In this paper, statistical and frequency analyzes of the acoustic signals for the detection of the defects of the bearing were performed. The bearing condition monitoring was implemented by analyzing the data of the captured acoustic signal. The functional information flow of the acoustic measurement system is shown in figure 1.

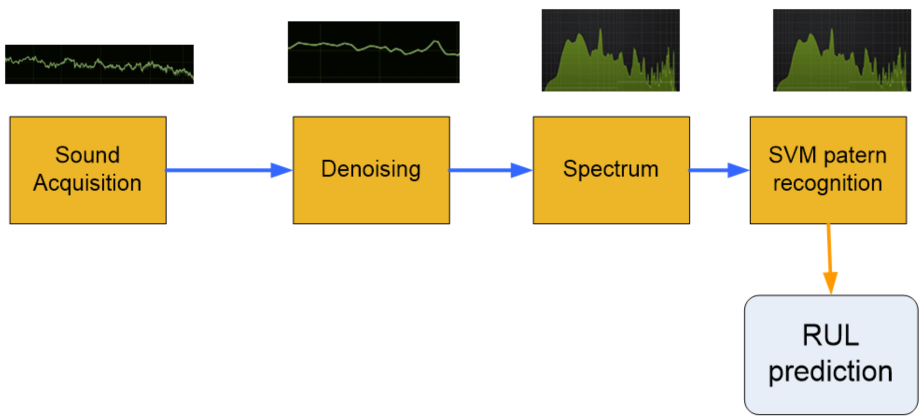

Figure 1. Architecture for bearing fault detection and prediction.

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A test device has been built to record the acoustic signals of good and defective bearings in the working environment. We have used the MA-910 bearings test machine, as shown in figure 2, a laptop, a microphone and 60 bearings. CAW33 type 22205 bearings were used for experimental work. Acoustic signals of good and defective bearings were recorded at 3700 rpm.

For this study, acoustic emission signals were measured and analyzed during life testing of bearing while other sound source are also recorded. Correlation between the acoustic emission patterns were identified in order to identify noise signal and identify the signal associated with bearing degradation.

The architecture describing flow of information is depicted in figure 1 with several steps: *i*) sound acquisition have been performed with a microphone on the testing machine; *ii*) denoising phase is very important in testing facilities as in the same room several testing machines might work in the same time; iii) spectrum analysis is the phase where spectrum is extracted from data and is described by 5 descriptors that we indicate bellow; *iv*) SVM pattern recognition of the sound pattern is able to predict remaining life time based on the 5 descriptors defining shape of spectra.

Figure 2. MA-910 Bearing Testing Machine.

A test device has been built to record the acoustic signals of good and defective bearings in the working environment. In order to securely mount the microphone a custom foam mount was fabricated. This 3D printed component ensures the microphone is unobstructed and allows for minimizing vibrations from testing machine. The cavity of the mount ensures no Helmholtz resonances can build up. A microphone was used to capture the acoustic signals from the bearings. It requires a maximum 3.6V supply and draws only 120µA and it is quoted as having a sensitivity of -38dB. Bearing acoustic signals under different conditions were recorded using MS Windows 7.0 Sound application. Furthermore, the audio converter is used to convert .wma files into .wav format to import them into FLSTUDIO using the wav-read function. The audio converter was also used to convert the sampling rate to 22.05 kHz. The statistical and frequency analysis techniques were then applied using the FLSTUDIO functions and tools.

Frequency spectra obtained for different bearings that have been categorized in frequency ranges based on power spectra. It has been found that the acoustic signals obtained from defective bearings have the highest power. The signals obtained from a good bearing had the lowest power.

The spectra for each case have exported as points coordinates defining the curves of spectra. As we notice in the figure 3 and figure 4, the comparing spectra shape for good condition bearing versus spectra shape for defective bearing, we noticed a distinct pattern. In figure 6 we can easily notice how the spectra shape for defective bearing assembles to each one, as well as spectra shape defining good condition bearings looks similarities.

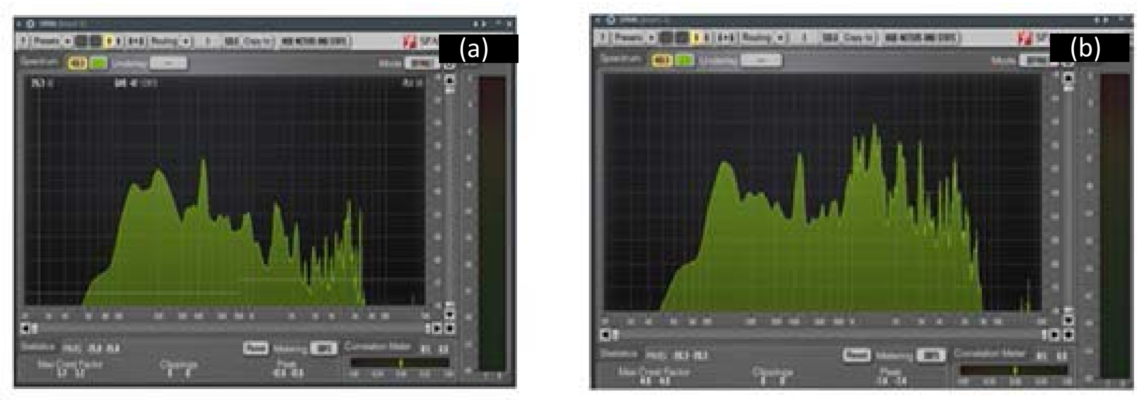

Figure 3. Spectra shape: (a) for good condition bearing and (b) for defective bearing.

To determine the sound frequency content of the good and defective bearings, the spectral power density of the captured sound signals was analyzed using the FLSTUDIO software.

The Fast Fourier Transform (FFT) method was used for spectral analysis for which a window function was selected to remove the captured signal heads to eliminate discontinuities.Since the acoustic signals are not deterministic in nature, the Welch method is able to compute the spectral power density of the acoustic signals. The spectral power density graphs of the acoustic signals of good and defective bearings obtained during experimentation are shown in figure 4.

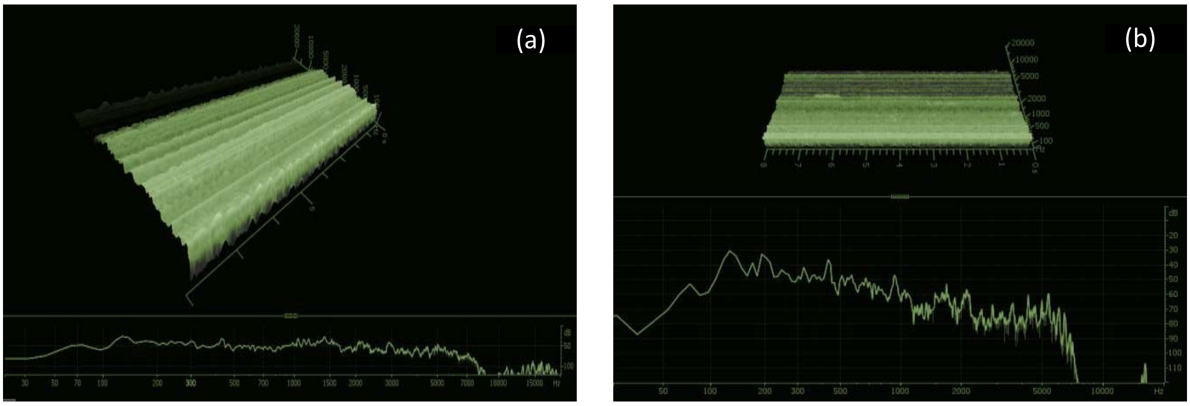

Figure 4. 3D representation of spectra for: (a) defective bearing and b) good condition bearing.

The acoustic bearings were recorded at a rotational speed of 3700 rpm. The experiment was performed several times, each of the acoustic signals for good condition and defective bearings were captured and used to calculate the parameters of the spectra. Acoustic signals of good and defective bearings are shown in figure 5.

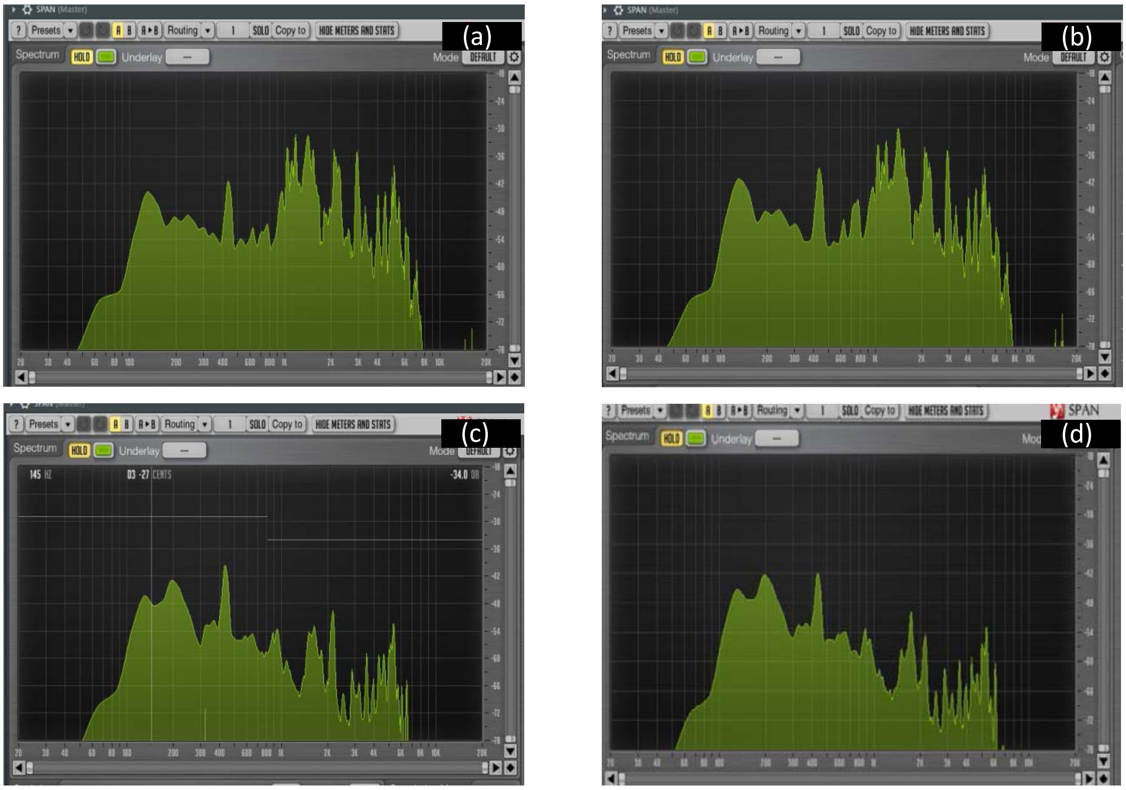

Figure 5. Acoustic signals of different bearing conditions at different speeds: (a) and (b) for good condition bearing spectra shape, (c) and (d) for defective bearing spectra.

SVM regression model was implemented using Rapidminer 5.0 software. The parameter evaluation technique is used to select five features that are used as predictors in multi-class support vector machine (SVM) classification. The same as we, humans describe shapes, we identifiy five parameters as inputs for SVM. SVM algorithm is concerning drawing a hyperplane between "good solutions" and "bad solutions", as depicted in figure 6.

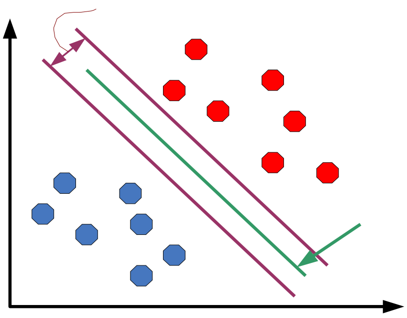

Figure 6. SVM Concept.

As described in figure 7, several parameters have been defined using spectra of the sound registered. P1 defines the angle of the first peek, P2 defines the length between first two peeks, P3 defines is the angle of the second peek, P4 the distance between second and third peek and P5 is the surface of the third peek.
By using this similitude that defines difference between sound patterns in the two cases, the SVM is trained for 50 known data sets of acoustic data.

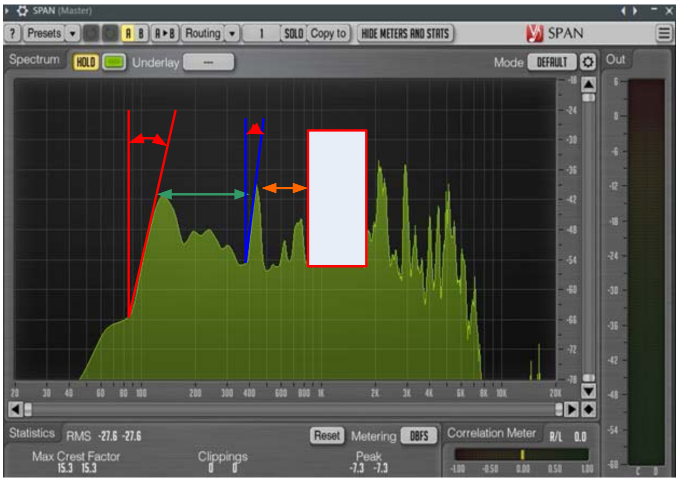

Figure 7. Parameters of the SVM algorithm defined by the spectra shape

3. Results

The diagnosis was performed with the help of Support Vector Machine using Rapidminer 5.0 software where parameters are those five defined above. Then the SVM model is trained using training data of 50 test and 20 test samples are used for testing the technique. The developed solution to isolate other sounds signals means that the technique could be used while lifetime of the bearings as well on bearing testing machines. In figure 9 is depicted the results using the technique described in this paper predicted versus real values. The results of this study provide evidence that accurate estimation of the failure of various bearings is possible by processing the vibration signal acquired from a single point, even in case of multiple sound sources are present and introduce noise in signal processing. The SVM classifier provides at least 89% mean accuracy, as shown in figure 8.

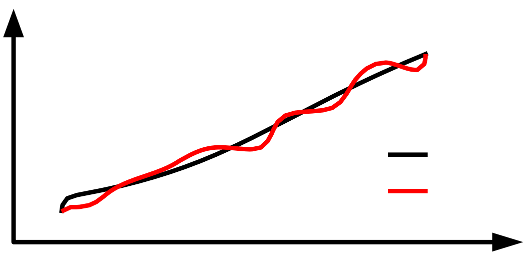

Figure 8. Actual vs predicted data for RUL

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4. Conclusions

Bearings are vital components in rotary machines that have received increased attention in the field of condition monitoring. This paper aimed at monitoring the condition of bearings on the basis of acoustic analysis based on SVM and predicting remaining useful life of bearings. Spectral shapes have clearly shown that bearings with different physical conditions emit acoustic signals with different spectral power densities. SVM algorithm using five defined parameters are able to describe spectra pattern and thus enabling to predict remaining useful life on bearing testing machine.

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