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BEARING FAULT DIAGNOSIS OF ELECTRICAL MACHINE BASE ON VIBRATION SIGNAL USING MULTI-CLASS SUPPORT VECTOR MACHINE

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ABSTRACT

In this paper, we propose a new bearing fault diagnosis system for electrical machines using multi-class support vector machine (MSVM). Firstly, we obtain the frequency spectrum of vibration signal using fast Fourier transform (FFT). Then the spectrum analysis of this signal for various bearing faults is presented. We show that the bearing faults result in some changes in the vibration signal spectrum. However, in some situations which these frequency components place in noisy domains or the fault is in the early stage, diagnosis of faults using spectrum analysis fails. Therefore, we employ this spectrum as the feature vectors in pattern recognition methods for faults identification. In this paper, each case of healthy or bearing fault (consisting of inner race, outer race, ball and cage faults) is considered as a separate class in a multi-class classification problem and the spectrum of the vibration signal is used as the feature vector. In order to evaluate our proposed method, a real world data set is employed. This data set is obtained from a set of experiments performed on an electrical machine to measure the vibration signal in each case of bearing faults and healthy condition. A multi-class classifier is designed using this data set. This classifier is able to identify the type of the bearing faults and our extensive experimental results demonstrate the effectiveness of the proposed method in bearing fault diagnosis of electrical machines.

KEYWORDS : Fault Diagnosis, Bearing Fault, Vibration Signal Analysis, Fast Fourier Transform, Multi-class Support Vector Machine.

Rotary machineries especially electrical motors show an important impact in the industry applications (Nandi, 2005). Therefore, monitoring and fault diagnosis of electrical machines have attracted the attention of many researchers in the recent years. Since the electrical motors encounter various stresses in working situations, prediction of their faults and preventing them will result in economic advantages. Each fault or defect which occurs in the rotary machinery will affect the vibrations of that machine. In this paper, we analyze these vibrations in order to detect the occurrence of the fault and even identify the type of the occurred fault. Generally, the vibrations of the motor under various loads and artificial faults are captured. The first step in repairs is fault detection and identification (Korbicz, 2004). So far, many works have been presented on monitoring both electrical and mechanical performances of electrical machines in the literature (Tavner, 2008, Bellini, 2008). These researches include two basic logics: 1) the fault detection and 2) the fault identification. The most well-known mechanical faults detection approach is based on analyzing the spectrum of vibration signal using signal processing methods. The spectrum of the vibration signal is computable, but if the faults are in the early stages, the frequency components will occur in the noisy region and therefore cannot be detected. On the other hand, the nonlinear behavior of electrical machines makes the fault identification difficult.

In the recent decade, the machine learning techniques such as neural network, fuzzy logic, genetic algorithm (Vas, 1999) and kernel based methods (Vapnik, 1998, Tipping 2001, Mohsenzadeh, 2013) are widely used for fault detection applications. Support vector machine is a statistical learning method with the state of the art performance in many classification applications (Vapnik, 1998). It can be claimed that the SVM classifier outperforms neural network classifiers in terms of generalization. Moreover, SVM is more interesting for the problem of electrical machines fault diagnosis, since the performance of SVM in not dependant on the number of extracted features. Inherently, SVM is a binary classifier and can discriminate two classes. We have been previously used SVM for the misalignment shaft fault diagnosis in (Estilaf, 2013). Considering that there are various types of bearing faults, in this paper we employ the multi class support vector machine for identifying these faults. In contrast to the previous works which use the strategies one-against-one or one-against-others (Peng, 2013) or semi-supervised learning methods (Xiukuan, 2009) to perform multi class discrimination using binary SVM classifier, we employed a MSVM which considers all classes simultaneously and performs multi class classification.

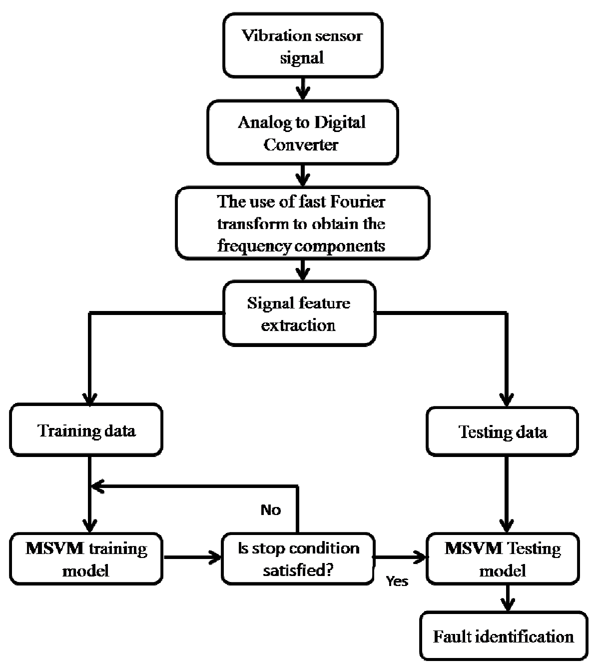

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Figure 1: The block diagram of the proposed system for bearing fault diagnosis

In this paper, we employed one of the pattern recognition methods for bearing fault diagnosis of electrical machines. Therefore, without involving any analyses of the frequency components of vibration signals, the type of the bearing fault is identified using MSVM. In our experiments, we consider six states including normal situation, ball fault, inner race fault and outer race fault (directed in the load zone (3 o'clock), directed orthogonal to the load zone (6 o'clock) and in the 12 o'clock). Figure 1 demonstrates the block diagram of the proposed system for bearing fault diagnosis based on MSVM. Our extensive experiments on the real world data indicate the efficiency of the proposed method.

Bearing Faults and Their Effects on the Vibration Signal

In this section, we introduce the main parts of the bearing and their possible defects. We also explain how these defects occur and how these defects affect the vibration signal. Then we present the frequency spectrum equations of the bearing faults.

Bearings are used to connect the rotating components to the fixed components of an electrical machine. The alloy defects cause the most of the bearing faults in the electrical machines. A bearing consists of four main parts: inner race, outer race, ball and cage which are placed in the space between rings and makes rotating possible for them (Immovilli, 2010). Generally, various defects in bearing occur in its main parts. Structure of a bearing and its dimensions are depicted in Figure 2.

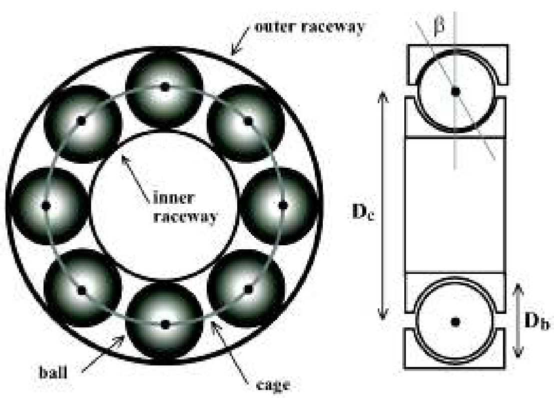

Figure 2: Structure of a rolling-element bearing

The bearing defects are typically local. Non-lubricating and acid or water corrosion may cause these defects. In normal operating conditions of a machine, small abrasion on the surfaces of bearing walls began to grow. When this process progresses, Ball began to produce a series of harmonic signals and make periodic impulse sequence that is detectable. Since the inner race defect is mostly produced by an outer factor, its vibration signal is weaker. Amplitude and period of the strike are determined by the rotation speed, fault location and dimensions of the bearing characteristics. The frequency components of each main parts of the bearing can be calculated in hertz. The frequency of ball defect is twice of the frequency of ball rotation which rotates around its own axis and is obtained as

$$F_B = \frac{D_c}{D_b} F_r \left[1 - \left(\frac{D_b \cos\beta}{D_c} \right)^2 \right], \tag{1}$$

and the cage frequency is

$$F_c = \frac{1}{2} F_r \left[1 - \frac{D_b \cos\beta}{D_c} \right]. \tag{2}$$

Also the frequencies of inner and outer race defects are as following

$$F_I = \frac{N_B}{2} F_r \left[1 + \frac{D_b \cos\beta}{D_c} \right] \tag{3}$$

$$F_o = \frac{N_B}{2} F_r \left[1 - \frac{D_b \cos\beta}{D_c} \right] \tag{4}$$

where D_c is the bearing pitch diameter, D_b is the ball diameter, F_r denotes the Supply frequency rotor f, β denotes the angle between the stator and the rotor and finally N_B is the number of balls.

Also the frequencies of inner and outer race defects can be obtained as

$$F_I = 0.4.N_B.F_r \tag{5}$$

$$F_O = 0.6.N_B.F_r. \tag{6}$$

Support Vector Machine Classifier

In this section, we review the support vector machine briefly. Then we explain the two common strategies for extending a binary classifier to a multi-class one. After that, we introduce MSVM and discuss the advantages and drawbacks of these approaches.

The support vector machine is introduced by Vapnik in 1998 (Vapnik, 1998). The SVM is a kernel based sparse learning method for discriminating two classes (Figure 4).

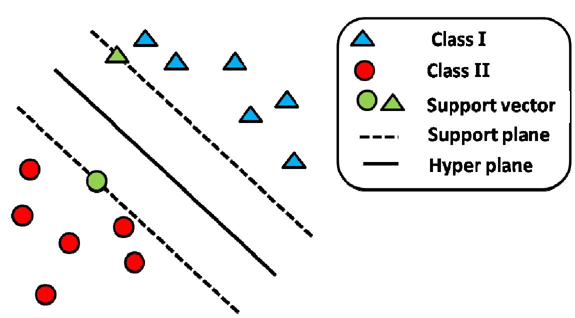

Figure3: Binary classification using SVM

The basic idea in the SVM is to map the data to a higher dimensional space in order to find a hyper-plane which can separate the two classes (Figure 3). In order to perform this mapping, SVM employs a kernel function. This kernel function can be a linear, polynomial or Gaussian function. The SVM is theoretically well established and has shown promising performance in many applications. In this section, we briefly review the theory of SVM.

Consider a given data set S of input points X_i for i=1,…,N. Each point X_i belongs to one of the classes with label $y_i \in \{1,-1\}$. Let φ be the kernel function which maps the data from the input space R^n to the feature space F. The hyper-plane wφ (x)+b discriminates the data in the feature space and the decision function is

$$f(x) = \text{sign}(w\phi(x)) + b \qquad (7)$$

There are many hyper-planes which can perform the discrimination task with minimum error. Therefore, the hyper-plane with minimum error and also the maximum margin is found as the optimum hyper-plane by the SVM. Margin is defined as the distance of the closest data point to the hyper-plane. To maximize the margin, the cost function ψ(w) =0.5(w×w) should be minimized subject to the constraint in Equation (7). Using Lagrange multiplier method, this constraint optimization problem is solved and the decision function is obtained as

$$y = \text{sign}\left[\sum_{i \in sv}^{\ell} \alpha_i \alpha_i^0 (\phi(x_i) \times \phi(x_j)) + b\right], \qquad (8)$$

where α is the result of the constrained optimization problem and SV denotes the support vectors.

Multi-class Support Vector Machine

The support vector machine is inherently a binary classifier which is designed to distinguish between two classes. There are two main strategies known as one-against-one and one-against-others for extending a binary classifier to be employed for a multi-class application. In one-against-one strategy, the multi-class problem with K classes is decomposed into K(K-1)/2 binary classification problems considering the data from one class against the data from another class as a binary classification task a K(K-1)/2 classifiers are designed for each problem. In one-against-others approach, K binary classifiers are designed considering the data of one class against all other remaining data from other classes as a binary classification problem. The one-against-one strategy has demonstrated a better performance in comparison with the one-against-others approach in many applications (Murphy, 2012). However, one-against-one approach (K(K-1)/2) needs to design more binary classifiers comparing with one-against-others (K). Both of these approaches require a post processing to combine the results of the designed binary classifier in testing stage, for example voting. Besides these two strategies, there is another approach which is inherently a multi-class classifier and is presented in (Liangli, 2006). In contrast to the two mentioned strategies (one-against-one and one-against-others), this method does not involve any post processing in the testing stage. In this paper, we employ this approach for identification of the bearing faults.

Experimental Results

In this section, we will evaluate the proposed system for the bearing fault diagnosis. First, we introduce the motor characteristics and the system configuration for the data measurement and acquisition. Then we will analyze the frequency components and finally we will present the experimental results of the proposed system on the mentioned data.

To evaluate our proposed method, we used the bearing test data from Case Western Reserve University. Figure 4 shows the system used for measuring the data. This system includes a 2 hp Reliance Electric motor (left), a torque transducer/encoder (center), a dynamometer (right) and control electronic (not shown). The data is collected from the 2 hp Reliance Electric motor and acceleration data is measured at different locations of bearings. An artificial defect about 0.007 inches in diameter is introduced to the inner raceway, ball and outer raceway. The faulted bearings are installed to the motor and the vibration signals are recorded through the accelerometer on the magnetic bases. The defect location with respect to the bearing load affects the vibration signals of the motor. Therefore three locations including 3 o'clock (in the load direction), 6 o'clock (orthogonal to the load direction) and 12 o' clock are used for the data measurements. The information from normal and faulted bearings is recorded with the rate of 48000 samples per second.

Figure4: The system configuration for data measurement

Spectrum Analysis of the Vibration Signal

A specific defect in the rotating equipments will cause vibrations with the specific spectrum (with the specific frequency, phase and amplitude). Therefore, we can analyze the spectrum of the vibration signal to detect and identify a defect in the electrical motor. In this paper, we use the Fast Fourier Transform (FFT) to calculate the spectrum of the vibration signal. Figures 5 and 6 depict the spectrum of the normal situation and the outer race fault in 3 o' clock, direction respectively. For clarity, these figures are shown in the frequency interval 0 to 120 Hz and the amplitude of the spectrum is normalized and plotted in dB scale. The mechanical frequency of rotor and its spectrum amplitude are marked in Figures 5 and 6. Comparison of curves in Figures 5 and 6 shows that the outer race fault

in 3 o'clock direction decreases the amplitude of the spectrum at the mechanical frequency of rotor. Therefore, we can employ these spectrums as the feature vectors for the MSVM classifier.

We also computed the amplitudes of side band frequency components of vibration signal for all the bearing faults cases and presented the results in Table 1. As can be seen in Table 1, we can compute the frequency spectrum of the vibration signal. But when the defects are in the early stages, the frequency components occur in noisy domains. Therefore they are not detectable by spectrum analyzing. In this paper we solve this problem by using the MSVM for detecting the bearing faults in these situations.

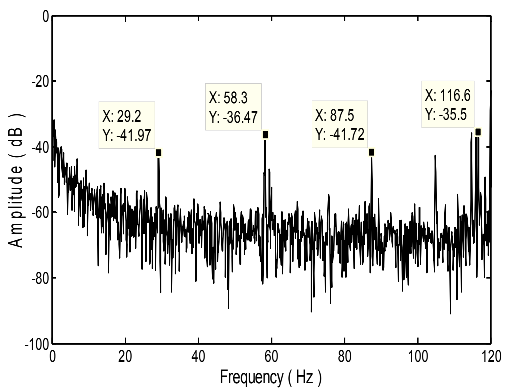

Figure5: The frequency spectrum of the vibration signal for the normal bearing

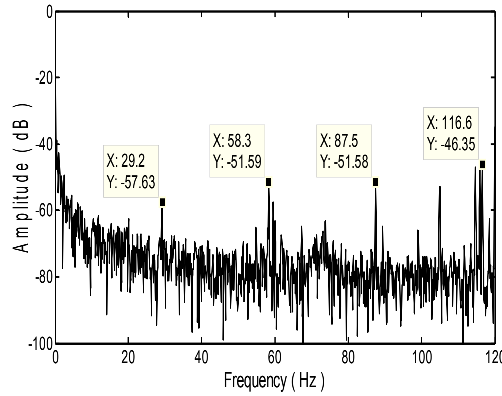

Figure6: The frequency spectrum of the vibration signal for the outer race fault (3 o'clock location)

Bearing Fault Diagnosis Using MSVM

In this section, we model the problem of bearing fault detection and identification as a multi-class discrimination problem. As illustrated in Table 2, the normal situation is considered as class 1 and the bearing faults are assigned to the classes 2 to 6. For the fault detection using MSVM, we construct the data base as follows:

Table 1: Comparing amplitudes of vibration signal spectrum for different ball bearing faults in rotor and side band frequencies

	Frequency (Hz)	Normal (dB)	Ball (dB)	Inner Race (dB)	Outer Race (3 o'clock) (dB)	Outer Race (6 o'clock) (dB)	Outer Race (12 o'clock) (dB)
F_r	29.2	-41.77	-52.25	-48.9	-57.63	-58.8	-48.36
$2F_r$	58.3	-36.47	-40.48	-38	-51.59	-60.26	-48.12
$3F_r$	87.5	-42.72	-55.36	-62.08	-51.58	-60.26	-67.82
$4F_r$	116.6	-35.5	-42.39	-54.99	-46.35	-52.57	-42.65

Table 2: Assigning class labels to ball bearing faults

Normal	Ball Fault	Inner Race Fault	Outer Race Fault (3 o'clock)	Outer Race Fault (6 o'clock)	Outer Race Fault (12 o'clock)
Class 1	Class 2	Class 3	Class 4	Class 5	Class 6

We use 960 measured vibration signals with length of 500. Then we calculate the FFT of these signals and consider the amplitude of them as the training samples. Therefore, we have 960 training samples with the length of 500 for each of the classes indicated in Table 2. In other words, there are 960×6=5760 samples in the data base. We employ 10 percent of data for training and 90 percent of data for testing.

Table 3 shows the accuracy of MSVM in fault identification, the number of support vectors and also the run-time of this method for different training set sizes. As can be seen, the accuracy of the proposed method for fault identification is very good even for small training set sizes. As shown in Table 3, the accuracy of fault diagnosis for 120 training samples is very good (99.91%). We also presented the detection accuracy for each kind of faults (ball fault, inner race fault and outer race fault (in 3, 6 or 12 o'clock directions)) and normal situation in Table 4 for 120 training samples. As shown, the accuracy of MSVM in the fault identification is very good (mostly 100%). In order to show the effectiveness of the proposed method in comparison to neural network (NN) methods, we compared the results of fault detection using our proposed method with a radial basis function (RBF) neural network in Table 5. Both methods (MSVM and RBF NN) are trained using 120 training samples and are tested over 1080 testing samples. The results in Table 5 indicate that the MSVM is superior to the RBF NN in terms of accuracy and run-time.

In order to design a neural network, the number of layers, the number of neurons in each layer and also the decision functions should be predetermined. In contrast, using SVM does not involve such structural problems.

CONCLUSION

In this paper we presented an effective method for identification of bearing fault in electrical machines. To this end, we first analyzed the frequency spectrum of vibration signal and showed that the ball bearing defects result in some changes in the vibration signal frequency spectrum. However

Table 3: Comparison of accuracy, sparsity (number of support vectors) and run-time of the MSVM in ball bearing fault diagnosis for different training set sizes

Number of training samples	Number of testing samples	Accuracy (%)	The number of support vectors	Time (s)
6	54	84.48	6	0.007
12	104	85.63	12	0.009
30	270	99.26	16	0.014
60	540	99.63	39	0.017
120	1080	99.91	58	0.043
240	2160	99.95	80	0.135
300	2700	99.88	89	0.201
576	5184	100	115	1.460

Table 4: Accuracy comparison of MSVM in identification of bearing faults for 120 training samples

Type of bearing fault	Class label	Number of training samples	Number of testing samples	Accuracy (%)
Normal	1	120	180	100
Ball	2	120	180	100
Inner Race	3	120	180	100
Outer Race (3 o'clock)	4	120	180	100
Outer Race (6 o'clock)	5	120	180	100
Outer Race (12 o'clock)	6	120	180	99.44

Table 5: Comparison of neural network and MSVM in terms of accuracy and speed

Classifier	Accuracy (%)	Time (s)

Multi -class Support Vector Machine	99.91	0.043
Artificial Neural Network	96.46	13.787

in some situations where the defects are in early stages and the frequency components are located in the noisy segments of the spectrum, the fault detection using spectrum analysis is hard. Therefore, in the proposed method, we used the spectrum as the feature vectors. These features are employed as the input of the multi-class support vector machine in order to identify the type of occurred fault. This method has been employed on the real world data and the results demonstrate the effectiveness of the proposed method in terms of accuracy and speed in comparison to neural networks. The high speed of the proposed method makes it suitable for on-line applications.

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