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Induction motors bearing fault detection using pattern recognition techniques

Jafar Zarei *

Department of Electrical and Electronics Engineering, Shiraz University of Technology, Shiraz, Iran

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ABSTRACT

This paper proposes a systematic procedure based on a pattern recognition technique for fault diagnosis of induction motors bearings through the artificial neural networks (ANNs). In this method, the use of time domain features as a proper alternative to frequency features is proposed to improve diagnosis ability. The features are obtained from direct processing of the signal segments using very simple calculation. Three different cases including, healthy, inner race defect and outer race defect are investigated using the proposed algorithm. The ANNs are trained with a subset of the experimental data for known machine conditions. Once the network is trained, efficiency of the proposed method is evaluated using the remaining set of data. The obtained results indicate that using time domain features can be effective in accurate diagnosis of various motor bearing faults with high precision and low computational burden.

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1. Introduction

Induction motors are a critical component of many industrial processes and are frequently integrated in commercially available equipment. Safety, reliability, efficiency, and performance are some of the major concerns of induction motor applications (Benbouzid, 1999). Although induction motors are reliable, they are subjected to some failures. Therefore, in the past two decades, there has been substantial amount of research to provide new condition monitoring techniques for induction motors mostly based on analyzing vibration signals, or other signals such as current, and hence a number of commercial tools are available in this area (Benbouzid, 2000; Benbouzid & Kliman, 2003; Lei, He, & Zi, 2009; Nandi, Toliyat, & Xiaodong, 2005; Schoen, Habetler, Kamran, & Bartfield, 1995; Singh & Ahmed Saleh Al Kazzaz, 2003; Tandon & Choudhury, 1999; Thomson, 1999). In some factories, very expensive scheduled maintenance is performed to prevent sudden motor failures. Therefore, there is a considerable demand to reduce maintenance costs and prevent unscheduled downtime for electrical drive systems, especially for induction motors (Singh & Ahmed Saleh Al Kazzaz, 2003). In spite of these tools, many industries are still faced with unexpected system failures which reduce motor lifetime (Benbouzid, 2000). The results of recent studies show that bearing problems account for 40% of all machine failures (Tandon & Choudhury, 1999). Therefore, this type of fault must be detected as soon as possible to avoid fatal breakdowns of machines that may lead to loss of production. Bearing defects may be categorized as "distributed" or "local" (Tandon & Choudhury, 1999). Distributed defects include surface roughness, waviness, misaligned races and off-size rolling elements. Localized defects include cracks, pits and spalls on the rolling surfaces. The dominant mode of failure in rolling element bearings is spalling of the races or the rolling elements. Localized defects generate a series of impact vibrations every time a running roller passes over the surface of a defect. The amplitude and period of this signal are related to position of the defect, speed and bearing dimensions. The vibration produced by defects is also modulated on the stator current. Since this signal can be easily measured for condition monitoring and control purposes, more recent studies on induction motors fault detection concentrate on monitoring of electrical signals such as stator current (Benbouzid, 1999, 2000; Nandi et al., 2005; Schoen et al., 1995; Singh & Ahmed Saleh Al Kazzaz, 2003; Tandon & Choudhury, 1999; Thomson, 1999; Zarei & Poshtan, 2009).

Although the stator current spectrum contains the components produced by bearing faults, other components such as characteristic harmonics that generated due to voltage supply distortion, air gap space, slotting or unbalanced load also exist in this signal. As a result, vibration analysis is still a conventional method for bearing fault detection (Benbouzid, 2000; Nandi et al., 2005; Schoen et al., 1995; Singh & Ahmed Saleh Al Kazzaz, 2003; Tandon & Choudhury, 1999; Thomson, 1999).

FFT is the simplest frequency domain analysis method. Bearing faults can be detected by analyzing the amplitude of characteristic defect harmonics using FFT, theoretically. However, the impact vibration generated by a bearing fault has relatively low energy, so it is often overwhelmed by noise with higher energy, and vibration generated from other macro-structural components. Therefore, it is difficult to identify the bearing faults in the spectra using conventional FFT methods. As a result, Fourier analysis makes it difficult to recognize faulty condition from the normal operating condition of the motor.

* Tel.: +98 711 7354500x2620; fax: +98 711 7353502.
E-mail address: zarei@sutech.ac.ir

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In order to overcome FFT problems and improve signal to noise ratio, advanced signal processing methods such as Short-Time-Fourier-Transform (STFT), Wavelet Transform (Benbouzid, 2000), and Wavelet Packet Transform (Nikolaou & Antoniadis, 2002; Zarei & Poshtan, 2007) have been recently exploited for the detection of bearing faults.

Besides computational efforts, these methods require an expert to decide about system conditions. In other words, an expert should infer whether the measured harmonics are produced by a defect or exist under normal conditions. Recently, great number of techniques has been proposed to automate condition monitoring, more generally for motors, based on the intelligent and/or expert systems (Lei et al., 2009; Xu, Xuan, Shi, Wu, & Hu, 2009; Yiakopoulos, Gryllias, & Antoniadis, 2011; Zhang, Xiong, Liu, Zou, & Guo, 2010). These methods include artificial neural networks (ANNs) (Ghate & Dudul, 2010; Li, Chow, Tipsuwan, & Hung, 2000), fuzzy logic (Xu et al., 2009), clustering approaches (Yiakopoulos et al., 2011), and support vector machines (SVM) (Widodo et al., 2009).

In (Li et al., 2000) both time and frequency domain features of the vibration signals are extracted to train a neural network. However, this method has a lot of computational burden to extract the features. Moreover, characteristic defect frequencies are dependent on the rotational shaft speed, so it is difficult to determine true features due to existence of side bands near to these frequencies. In contrast, time domain dimensionless features are robust against the load and speed variations.

Motivated by this consideration, to overcome these problems, and to make the diagnosis procedure intelligent, an approach based on pattern recognition using time domain features as a proper alternative to frequency domain features is proposed here for bearing fault detection. To evaluate the efficiency of the proposed method, time domain and frequency domain features are extracted based on analyzing experimental data of bearings. Three conditions, including healthy, inner race defect, and outer race defect are investigated. Then a neural network is rigorously trained using these features. Once the neural network is trained, it is used to classify the defects. The results show that using time domain features can be effective in accurate diagnosis of various motor bearing faults with low computational burden.

2. Characteristic defect frequency

Local defects or wear defects cause periodic impulses in vibration signals. Amplitude and period of these impulses are determined by shaft rotational speed, fault location, and bearing dimensions. The frequency of these impulses, considering different fault locations as in Fig. 1 are obtained by (1)–(4) (Tandon & Choudhury, 1999; Zarei & Poshtan, 2007).

Fundamental cage frequency is given by

$$f_c = \frac{f_s}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{1}$$

Ball defect frequency is two times the ball spin frequency and can be calculated as

$$f_{bd} = \frac{D}{d} f_s \left(1 - \frac{d^2}{D^2}\cos^2(\alpha)\right) \tag{2}$$

Inner race defect frequencies are given by

$$f_{id} = n_b(f_s - f_c) = \frac{n_b f_s}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{3}$$

Outer race defect frequencies are given by

$$f_{od} = n_b f_c = \frac{n_b f_s}{2d}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{4}$$

In these relations, f_s is the shaft rotation frequency, n_b is the number of rollers, d is the roller diameter, D is the pitch diameter of the bearing, and α is a contact angle as shown in Fig. 1.

A harmonic is made in the spectrum of vibration signal due to a defect in each part of the bearing. Since the impact of the defect is so minute in the early stages and hence the amplitude of new harmonics caused by an incipient defect is considerably less than the amplitude of noise and vibration caused by other components of the motor, defects cannot be easily detected using the conventional methods of analyzing the spectrum. Thus, advanced methods of signal processing besides an expert who decides which part is caused to generate that harmonic, are needed.

3. Multilayer perceptron neural networks

A multilayer neural network includes an input layer, an output layer, and one or more hidden layers. Each layer may include many neurons. A neuron in each layer of the network is connected to all the nodes or neurons in the previous layer (Haykin, 1999). An architectural graph of multilayer perceptron with one hidden layer is shown in Fig. 2. The input layer processing functions are all linear, but in the hidden layer nonlinear sigmoidal functions such as hyperbolic tangent, logistical function or any sigmoid function are usually used.

In the modeling of systems by multilayer neural network, after defining the structure, the neural network weights should be designed in a way that with applying the inputs, a very close output to the real output is achieved. This is called neural network training, which means setting the weights to decrease the errors between network output and real output. In order to increase the training speed, a linear function is usually selected for the output layer. In the following Levenberg–Marquardt training algorithm will be described briefly.

4. Levenberg–Marquardt training algorithm

While back propagation is based on the gradient descent algorithm, the Levenberg–Marquardt algorithm is an improvement to

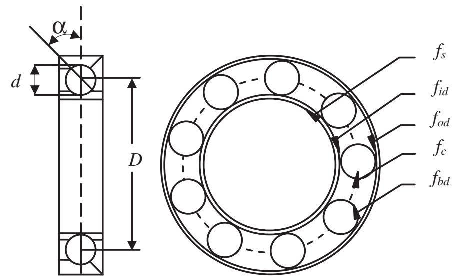

Fig. 1. Bearing dimension and characteristic defect frequencies.

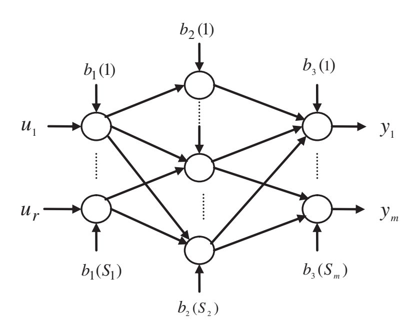

Fig. 2. General multilayer perceptron.

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