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Fault Diagnosis of Motor Bearing via Stochastic-Resonance-Based Adaptive Filter

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Abstract
The condition monitoring and fault diagnosis of a motor bearing is necessary to reduce breakdown loss and guarantee safe operation. A simple and easily implementing algorithm is proposed for fault diagnosis of motor bearing. The core part of the algorithm is a stochastic-resonance-based adaptive filter that can be realized signal denoising and adaptation of the filter coefficient. Processed by the filter, the period of the purified signal can is obtained, and then the fault type of the motor bearing can is identified. The proposed method has been distinct merits, such as low computational cost, contactless measurement, and availability for various speed motors. The proposed work is validated by a brushless dc motor and a brushed dc motor fabricating with defective/healthy support bearings.

Keywords: Acoustic signal processing, adaptive filters, brushless motors, dc motors, fault diagnosis, optimization methods, stochastic resonance (SR).

Introduction

Bearing is a vulnerable key component of a rotating motor that usually works in harsh environments, such as strong vibration, humidity, high temperature, and dust. A literature survey indicates that almost 40%–50% of motor failures are bearing related [6], [9]. Therefore, condition monitoring and fault diagnosis of a motor bearing is necessary to reduce breakdown loss and guarantee safe operation [5]. Condition monitoring can also be applied to improve operational consistency, decrease failure rate and improve the consumer service of electrical machines. In the past several decades, many techniques have been investigated to diagnose bearing faults. Several of the commonly used methods include motor current signature analysis [10], vibration monitoring [2], temperature measurement [7], and acoustic measurement [4]. These methods have successfully diagnosed/isolated different types of bearing in many kinds of motors, such as induction motor [11], permanent magnet synchronous motor, brushless dc motor (BLDCM), and brushed dc motor (DCM) [8].

However, several parameters need to be configured manually in the sophisticated procedures of the current filtering algorithms. For instance, a wavelet filter is used for denoising in bearing prognostic applications, but the optimum wavelet and threshold should be selected on the basis of a specific signal. An EMD-based filter is used to extract signatures from the defective signal, but the selection of the effective intrinsic mode functions (IMFs) needs priori knowledge. Correlation filtering method was introduced for transient modeling and parameter identification in the rotating machine fault diagnosis application, but the automatic selection of a suitable model still requires improvement.

The above mentioned methods uses filters, including finite impulse response (FIR), infinite impulse response (IIR), wavelet-based, EMD-based, and SR-based filters, are developed and implemented on a desktop platform that provides adequate computing resources for executing the complex operations, such as convolution, Fourier transform. The filtering algorithms used in above methods have several limitations.

Motivated by these limitations, Stochastic-Resonance-based adaptive filter is proposed for fault diagnosis of motor bearing. SR-based adaptive filter (SRAF) different from the traditional filters is use to adaptively purify noisy bearing signals that carry fault information. Once the filtered signal is obtained, the period of the fault-induced impulses can be estimated, and the fault type of the bearing can be identified. The proposed work has been distinct merits, such as low computational cost, contactless measurement, and availability for various speed motors. The proposed work can be provides a simple, flexible, and effective solution for conducting motor bearing diagnosis. The proposed algorithm can be validated by a brushless dc motor and a brushed dc motor fabricating with defective/healthy support bearings.

System Framework

The SRAF-based signal filtering method is proposed for fault detection of motor bearing. The method consists of four parts:

1. The Squaring and Low Pass Filtering Envelope (SLPFE) algorithm for demodulation of the acoustic bearing signal.
2. The SR algorithm for denoising and weak periodical signal enhancement.
3. The Advance and Retreat Optimization (ARO) algorithm for the adaptation of the SRAF parameter.
4. The signal period detection.

With the above steps, the fault-induced impulses that may be blurred by the background noise are purified, and the fault type of the bearing can be directly ascertained in accordance with the signal period.

The SRAF-based motor bearing fault detection scheme is shown in Fig.1

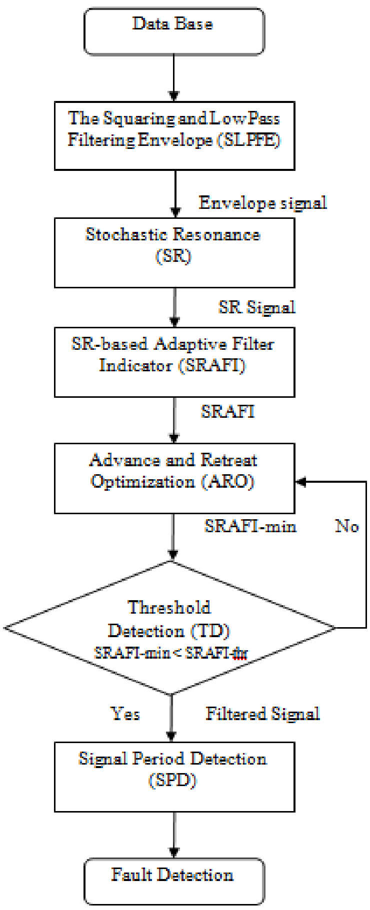

Fig.1. Flowchart of the SRAF-based motor bearing fault detection method

Implementation of system

Generally, when a fault appears in a bearing, the collision among the outer raceway, the inner raceway, the rolling element, and the cage induces the periodic impulses that can be detected in the acquired vibration or acoustic signal.

We have taken the data bases, which is nothing but acquired signal captured near the bearing of motor. The acquired signal consists of fault-induced impulses corrupted by the background noise. These data bases are read and plot using MATLAB code. The plot of acquired signal is shown below:

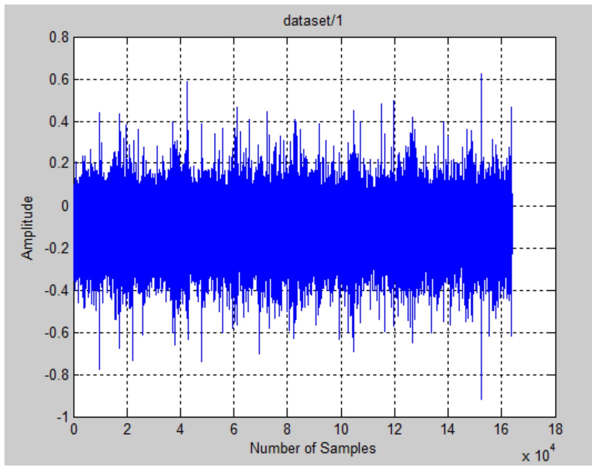

Fig.2. Plots of data bases (Acquired signals)

The machine vibration frequency is modulated by the fault-induced impulse signal. Therefore, demodulation or enveloping is applied to the acquired signal to better reveal the periodicity of the impulses. Therefore, an enveloping method called the squaring and low-pass filtering envelope (SLPFE) method is used to demodulate the acquired signal. The illustration of the SLPEF algorithm is shown below:

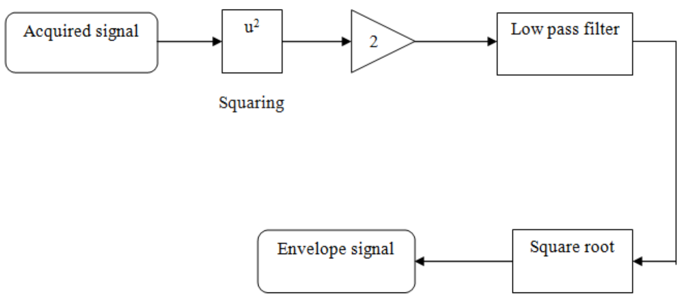

Fig.3. Illustration of the SLPEF algorithm

The squaring and low-pass filtering envelope (SLPFE) method is used to demodulate the acquired signal, as introduce as follows.

First, a standard modulated signal $U(t)$, which is the product of a low-frequency signal $U_l(t)$ and a high-frequency carrier signal $U_h(t)$, is expressed as

$$U(t)=U_l(t)\times U_h(t)=[A_l\cos(\omega_l t)+C]\times A_h\cos(\omega_h t) \qquad (1)$$

Where C is dc bias voltage that guarantees $A_l \cos(\omega_l t)+C > 0$. A_l and A_h represent the amplitudes of the low and the high frequency signals, and ω_l and ω_h represent the corresponding frequencies, respectively.
After squaring and filtering, finally the square root of the filtered signal is computed, and the envelope signal is achieved as

$$U_e(t) = A_h(A_l \cos(\omega_l t) + C) \qquad (2)$$

After processing SLPEF algorithm on acquired signal using MATLAB code is shown below:

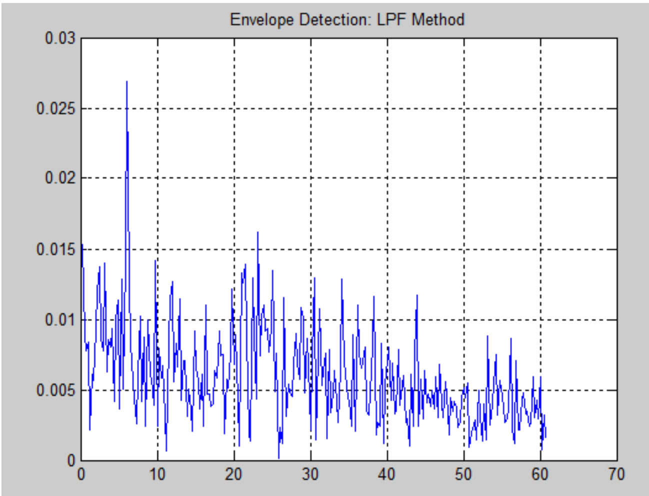

Fig.4. Envelope signal

Conclusion

An SRAF-based signal filtering method is proposed for fault detection of motor bearing. The method consists of four parts: 1) the SLPFE algorithm for demodulation of the acoustic bearing signal; 2) the SR algorithm for denoising and weak periodical signal enhancement; 3) the ARO algorithm for the adaptation of the SRAF parameter; and 4) the zero crossing detection algorithm for directly measuring the signal period. With the above steps, the fault-induced impulses that may be blurred by the background noise are demodulated and purified, and the fault type of the bearing can be directly ascertained in accordance with the signal period.
Compared with the established filters used in the motor bearing fault diagnosis, the proposed method has several distinct merits, such as low computational cost, contactless measurement, and availability for motors with various speeds. In this regard, the principle of the method may also be suitable for detection/isolation of a periodical fault in the gearbox, rotor system, or other rotating machines. Additionally, the algorithm framework is clear and simple.

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