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Application of multi-class fuzzy support vector machine classifier for fault diagnosis of wind turbine

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Abstract

This paper presents an approach for fault diagnosis of wind turbine (WT) based on multi-class fuzzy support vector machine (FSVM) classifier. In this method, empirical mode decomposition is adopted to extract fault feature vectors from vibration signals. FSVM is used for solving classification problem with outliers or noises, where kernel fuzzy *c*-means clustering algorithm and particle swarm optimization algorithm are applied to calculate fuzzy membership and optimize the parameters of kernel function of FSVM, respectively. In addition, to study the performance of the proposed approach, another two widely used methods, named back propagation neural network and standard support vector machine, are studied and compared. Discrete wavelet transform is also used to extract fault feature vectors. To validate the proposed approach, a direct-drive WT test rig is constructed and the experiments are carried out. The experimental results show that the proposed approach is an effective fault diagnosis method for WT, which has a better performance and can achieve higher diagnostic accuracy.

Keywords: Fault detection and diagnosis; Pattern recognition; Fuzzy support vector machine; Particle swarm optimization; Empirical mode decomposition; Wind turbine

1. Introduction

Wind turbine (WT) is often located in remote areas and easily subjected to extreme environment. This not only increases operation and maintenance (O&M) cost, but also reduces availability of wind power due to downtime of WT. In recent years, how to reduce the O&M cost and improve the availability of wind power becomes a critical issue. One effective way is applying fault diagnosis [1].

With the development of the computer technology, artificial intelligence technology has been widely applied for fault diagnosis in many fields [2–9]. For fault diagnosis of WT, several artificial intelligence technologies have been used, such as artificial neural network (ANN) [6,7] and support vector machine (SVM) [8,9]. ANN is based on traditional empirical risk minimization. It may suffer from several shortcomings, such as slow convergence velocity,

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over-fitting and easily relapsing into local extremum [10,11]. Therefore, it is difficult for ANN to establish global optimal model and acquire generalization capability. SVM is based on structural risk minimization principle [8], and it has some advantages, such as minimizing the empirical risk of training samples, ensuring the generalization capability and overcoming the shortcomings of ANN [8,10,11]. Nevertheless, SVM algorithm considers all training samples uniformly, and it is sensitive to outliers or noises in the training samples. Fuzzy support vector machine (FSVM) is a variant of SVM, which can effectively deal with outliers or noises in the training samples [9–15]. Hence, FSVM is adopted for fault diagnosis of WT in this paper.

Feature extraction of signal is an initial step for fault diagnosis with artificial intelligence technology. The signals of WT used for fault diagnosis are particle concentration in lubrication oil [1], vibration [6–9] and temperature [16], and vibration signal is the most commonly used. As the faults occur in the WT, the measured vibration signal is usually non-stationary signal with time-varying distribution. Hence, the traditional signal processing method is unsuitable for analyzing the non-stationary signal. Several methods based on wavelet transform have been reported in [17–20]. However, the wavelet transform has some inevitable shortcomings, such as border distortion, interference terms, energy leakage and choice of wavelet basis. The piecewise nonlinear decomposition can be used to process the non-stationary signal. Nevertheless, it is difficult to select the piecewise points and determine the number of the decomposition approximation. Recently, a new signal processing method, named empirical mode decomposition (EMD), is a powerful self-adaptive processing method for the non-stationary signal. EMD is able to decompose a complicated signal into a set of intrinsic mode functions (IMFs) automatically [21], and then the fault feature extracted from the IMFs is more distinct than those extracted from the original signal [22,23].

The objective of this paper is to present an approach for fault diagnosis of WT using multi-class FSVM classifier. In this approach, EMD is adopted to extract fault feature vectors from vibration signals. A multi-FSVM classifier is used to solve classification problem with outliers or noises, where the multi-class FSVM classifier is constructed by one-against-other method, and kernel fuzzy c-means (KFCM) clustering algorithm and particle swarm optimization (PSO) algorithm are applied to calculate fuzzy membership and optimize the parameters of kernel function of FSVM, respectively. The remainder of this paper is organized as follows: Section 2 illustrates feature extraction. Section 3 discusses FSVM. Section 4 proposes fault diagnosis steps. Section 5 validates the proposed approach with a direct-drive WT test rig. Finally, conclusions are drawn in Section 6.

2. Feature extraction

2.1. Empirical mode decomposition

As EMD is used, each signal is decomposed into a finite set of IMFs, where each IMF must satisfy the following conditions [21].

(1) In the whole dataset, the number of extrema and the number of the zero crossings must either be equal or differ at most by one.

(2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

An IMF represents a simple oscillatory model embedded in the signal. Hence, the signal $x(t)$ is decomposed as

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

where $c_i(t)$ is the ith IMF, and $r_n(t)$ is the mean trend of $x(t)$. The IMFs $c_1(t), c_2(t), \ldots, c_n(t)$ include different frequency bandwidths ranging from high to low. The frequency components contained in each frequency band are different and they can change with the variation trend of $x(t)$. Additionally, the detailed procedure for decomposition process of EMD is described in [21].

2.2. Feature extraction

EMD decomposes an original signal into a number of IMFs, and each IMF component involves local characteristic of the signal. As WT operates with different faults, amplitude energy of each IMF is different. Hence, fault feature