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Condition multi-classification and evaluation of system degradation process using an improved support vector machine

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ABSTRACT

Degradation process is a non-negligible phenomenon in system condition monitoring and reliability practices. Traditional binary-state characterization (i.e., normal and failure) on system health condition may not provide accurate information for maintenance scheduling, and the multi-state classification for degradation process is a necessary step to realize cost-effective condition based maintenance. Support vector machine (SVM) is a useful technique for system condition monitoring and fault diagnosis. However, the SVM classification accuracy of deteriorating system is usually poor, because characteristics of different degradation states may not be very distinctive. This paper presented an improved support vector machine for system degradation classification and evaluation. The core of the proposed method can be summarized as: an improved voting scheme in one-against-one SVM, and an optimization of classification process by utilizing inherent physical property of system state transition. A case study of cooling fan bearing accelerated life time test is conducted to obtain the experimental data, and a comparison before and after optimization shows that the proposed method improves the classification accuracy.

1. Introduction

With the growth of system structural and functional complexity, reliability becomes a critical concern in modern industry. This leads to the development of various condition monitoring and health assessment techniques so as to guarantee product reliability and availability [1–4]. In condition monitoring and reliability practices, reliability technicians want to know whether a system operates properly, so that appropriate maintenance actions can be taken accordingly. However, system performance usually demonstrates deteriorating trend before it reaches final functional failure, and this phenomenon refers to system degradation process. Under such circumstance, the implementation of cost-effective maintenance for deteriorating system is a challenging issue due to complicated system degradation characteristics.

Condition based maintenance (CBM) is an enabling technology for the realization of cost-effective maintenance strategy. The advantages of CBM over time-based preventive maintenance (i.e., the planned maintenance) can be summarized as: improved system operational reliability, and reduced maintenance costs. For example, Al-Najjar [5] conducted a comparison case study with real maintenance implementations in several companies, and developed the steps for establishing and running cost-effective condition-based maintenance. Tian et al. [6] investigated the condition-based maintenance optimization for wind power generation system, and their work focused on the CBM optimization (to reduce maintenance cost) for multi-unit and multi-system cases existing in wind farm operation. Castanier et al. [7] analyzed the CBM policy for a two-unit deteriorating system under sequential non-periodic inspections, and proposed a parametric maintenance decision framework to minimize the system long-run maintenance cost. In summary, the above research mainly concentrates on the maintenance cost-effectiveness analysis.

Due to the performance deterioration existing in most systems, the binary-state characterization (i.e., normal and failure) on system health condition may not provide accurate information for cost-effective maintenance scheduling, and the multi-state deterioration process modeling is a necessary step in CBM. Moghaddass and Zuo [8] developed the multi-state deterioration model and the corresponding unsupervised parameter estimation method for a condition-monitored device with incomplete information through condition monitoring. Tan et al. [9] utilized a Gamma process to model a deteriorating system, and the impact of imperfect maintenance actions on system reliability was considered in their research. Zhang et al. [10] proposed a sequential failure limit maintenance policy for multi-state repairable system. Shu et al. [11] investigated the multi-state degradation problem in machine tool reliability and performance evaluation, and proposed a non-homogeneous continuous-time Markov process model for tool degradation.

In CBM, system health state is evaluated through various measures collected by condition monitoring technology [12,13]. In order to

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implement cost-effective condition based maintenance for deteriorating systems, the multi-state condition classification methods should be investigated to obtain precise health condition. In general, this is a pattern classification problem, and a lot of artificial intelligence techniques have been investigated in machinery condition monitoring and fault diagnosis, which include artificial neural network (ANN) [14], hidden Markov model [15], fuzzy logic system [16], support vector machine (SVM) [17,18,19], etc. Compared with ANN and other artificial intelligence methods, SVM has the following advantages:

(1) It is based on structural risk minimization principle which improves the applicability even under the conditions of limited samples [20–21] and avoids over-fitting on account of good parameter adjustment.
(2) Nonlinear kernels are employed in SVM to implement the separation of nonlinearly separable sets.
(3) The state classification methods based on SVM have a simpler model compared with traditional approaches.

Therefore, in this paper, SVM is adopted to classify and assess the degradation trend of machinery.

As a promising pattern classification technique, SVM has been widely used in mechanical system fault diagnosis, and a review conducted by Widodo and Yang [22] provided a comprehensive survey on recent research and development of SVM in machinery condition monitoring and fault diagnosis. However, less research has been done on the use of SVM in mechanical equipment degradation trend classification. Here are some examples: Pan et al. [23] conducted bearing performance degradation assessment using a hybrid model of support vector data description and fuzzy c-means. Sotiris et al. [24] utilized SVM to realize system anomaly detection in the absence of failure information. Shen et al. [25] proposed a monotonic degradation assessment index of roll bearing with fuzzy support vector data description and running time.

It should be noted that the current challenge in this research is the multi-state condition classification, and the multi-state classification (multi-classification) SVM should be considered in this paper. Hsu and Lin [26] conducted a comparison study on the performance of a variety of multi-class SVMs, and the one-against-one SVM (OAOSVM) was proved to be more suitable in practice. The classification accuracy of deteriorating system based on OAOSVMs can be further improved, because the degradation trend of a multi-state deteriorating system is progressive and irreversible and the correlation with adjacent health states should be considered in the application of multi-class SVM. The process of degradation can be seen as a hidden semi-Markov model (HSMM), which is an extension of hidden Markov model (HMM) [27]. In HSMM, the unobservable process is semi-Markov rather than Markov, which means that the probability of hidden state change is decided by the length of time since entry into the current state, while in HMM, the probability is constant.

This paper proposes an improved OAOSVM based condition multi-classification and evaluation method for deteriorating system, with an HSMM being utilized to depict system degradation process. By analyzing the characteristics of system degradation, a state transition matrix can be obtained. The results obtained from OAOSVMs can be optimized by taking OAOSVM results and the state transition matrix into a formula proposed in this research. The final results show that this approach can improve the condition multi-classification accuracy of system degradation process.

The rest of this paper is organized as follows. Section 2 briefly introduces the principle of SVM and multi-class SVM. Section 3 details the principle and concept of the improved SVM based condition multi-classification method. Section 4 describes a cooling fan bearing accelerated life test rig where the test data come from, and gives the classification results after using the optimization method. A comparison analysis between the results before and after the optimization is presented. Conclusions are given in Section 5.

2. Principle of support vector machine

Support vector machine is a statistical learning theory based machine learning method [22], which uses structural risk minimization principle to minimize an upper bound on the expected risk. The basic idea of SVM based classification can be summarized as follows: (1) map input vectors in low-dimensional space into a high-dimensional feature space in which the classification problem can be processed linearly by using the support vector kernel function; (2) construct a hyperplane (an optimized linear division) in feature space which can separate two classes. This binary classification approach can be extended to multi-classification problems which are more common in real world.

2.1. Binary-class SVM

For a given training sample group $G=\{(\mathbf{x}_i,y_i),i=1,2,\ldots,l\}$, where $\mathbf{x}_i\in R^n$ is a training sample, and $y_i\in\{+1,-1\}$ represents the classification label of $\mathbf{x}_i$. $\mathbf{x}_i$ belongs to class one if $y_i=+1$; conversely, $\mathbf{x}_i$ belongs to class two if $y_i=-1$. The purpose of SVM is to find a decision function which can correctly classify the testing samples.

The binary-class schematic diagram shown in Fig. 1 ($\mathbf{x}_i\in R^2$, in case of two dimensions) can illustrate the concept of SVM. "*" represents the samples belonging to class one, and "¤" represents the samples belonging to class two. When G is linearly separable, a line "H" which can correctly classify these two types of samples can be found. "H_1" and "H_2" are lines passing the sample points which are nearest and parallel to H at the same time. The separating distance between them is the classification margin of the two types of samples. H is considered as the optimal classification line when it can minimize the empirical risk and confidence interval. That is to say, it can not only correctly classify the samples, but also make the margin maximum. In the situation of high-dimensional space, the optimal classification line is named as optimal separating plane or hyperplane [22].

Assume that all samples $\mathbf{x}_i\in R^n$ in training sample group $G=\{(\mathbf{x}_i,y_i),i=1,2,\ldots,l\}$ are separable. The hyperplane that separates the set of data $\mathbf{x}$ can be described by the following equation [22]:

$$\mathbf{w}^T\cdot\mathbf{x}+b=0, \tag{1}$$

where $\mathbf{w}\in R^n$ and b are the weight vector and the scalar, respectively, and they are the factors determining the position of hyperplane.

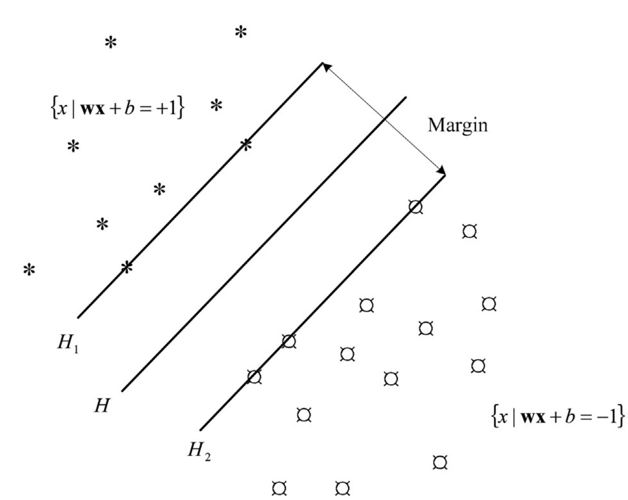

Fig. 1. Sketch map of SVM.

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