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Multiclass fault diagnosis in gears using support vector machine algorithms based on frequency domain data

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ABSTRACT

As a dominant machine learning method, the support vector machine is known to have good generalization capability in its application of the multiclass machine–fault classification utility. In this paper, an application of the SVM in multiclass gear–fault diagnosis has been studied when the gear vibration data in frequency domain averaged over a large number of samples is used. It is established that the SVM classifier has excellent multiclass classification accuracy when the training data and testing data are at identical angular speeds. However, this method relies on the availability of both the training and testing data at that particular angular speed of the gear operation. But the training data may not always be available at all angular speeds of the gear. Hence, two novel techniques, namely the interpolation and the extrapolation methods, have been proposed; these techniques that help the SVM classifier perform multiclass gear fault diagnosis with noticeable accuracy, even in the absence of the training data at the testing angular speed. This method is based on interpolating and extrapolating the training data at angular speeds near the speeds of the test data. In this study effects of choice over different kernels and parameters of SVM on its overall classification accuracy has been studied and optimum values for these are suggested. Finally, the effect on length of training data and data density on the SVM accuracy is also presented.

1. Introduction

The physical condition monitoring of machines is very important from the point of view of the long life of machines along with their availability, safety and reliability. Successfully implementing a condition monitoring programs, allows the machine to operate to its full capacity without stoppage of the machine at fixed periods for inspections. Traditional health monitoring techniques, though effective, have their own disadvantages as they cannot be implemented when the machine is running, and hence the machine has to be shut-down for inspection, leading to loss of production time and even untimely replacement of machine elements.

Among various techniques, condition monitoring through the use of vibration analysis is an established technique for detecting the loss of mechanical integrity of components of machinery. The vibration analysis of machine components returns a wide range of information regarding the operational conditions of the machinery. When one or more components turn faulty, this is reflected in the vibration signature, the most common being the increased amplitude, shifting of the natural frequency and a host of other not easily identifiable features. Numerous techniques, like artificial neural networks (ANN), genetic programming (GP), support vector machine (SVM) algorithms, etc. (see [1,2]) have now been finding applications in the condition monitoring. Most of these techniques are based on artificial intelligence models that implement feature extraction and optimization.

Widodo and Yang [2] reported the potential advantage of the machine condition monitoring and fault diagnosis

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to be gained from reduced maintenance cost, improved productivity and increased machine availability. An attempt was made to summarize and review the recent research and development of SVM in machine condition monitoring and diagnosis. The application of expert system (ES) as a branch of the artificial intelligence (AI) in the maintenance is suggested and SVMs based on statistical learning theory can serve as an ES. The SVM is based on Vapnik–Chervonenkis theory (VC-theory [3,4]). SVMs have gained popularity in the machine learning community because of the excellence of generalization ability as compared to traditional methods such as the ANN and found applications initially in the field of handwriting recognition, face detection, etc.

Hsu et al. [5] reported a logical and simplified methodology of operation of the SVM, targeted generally at beginners, providing a general overview of the subject and thereafter providing guidelines to obtain acceptable results. Samanta [6,7] reported a comparison of the performance of two different classifiers namely ANNs and SVMs for gear and bearing fault diagnosis. Time domain vibration signals of defective and normal bearings were processed for feature extraction. Also input features and classifier parameters to be selected were optimized using genetic algorithms (GA). They also reported feature extraction from the time-domain signal, those features mainly being the mean, root mean square (rms), variance, skewness, kurtosis and normalized higher order central moments.

Tax et al. [8] employed a feature based procedure from the power spectrum, envelope spectrum, autoregressive modeling and classical spectrum for failure detection of a small submersible pump. They tried to find the best representation of data features such that the target class that can best be distinguished from the outlier class (distinguish between normal to abnormal class). The support vector data description (SVDD) was proposed to accomplish their work for finding the smallest sphere containing all target data. Jack and Nandi [9] performed fault detection of roller bearing using SVM and ANN. They used vibration data taken from a small test rig and simulated the bearing condition, which had four faults: faults of the inner race, outer race, rolling element, and cage. They defined and calculated statistical features based on moments and cumulants, and selected the optimal features using GA. In the classification process, they employed SVM using RBF kernel with constant kernel parameter. Tiwari et al. [1,10] applied SVM algorithm to induction motor and gear faults, respectively; for the binary classification, however, the performance for the multi-classification were not good.

The aim of the present work is to investigate SVM based multiclass fault diagnosis for different angular speeds of a gear-pair ranging from low to high values. Secondly, the works aims at finding how the training data from nearby angular speeds can be used to train the SVM classifier when it could not be trained at the angular speed of the test data. The multiclass prediction accuracy is first presented for faults in gears using the SVM algorithm for all angular speeds ranging from 600 rpm to 1800 rpm at intervals of 150 rpm. In the first part, the SVM was first trained with the vibration data in frequency domain at these speeds and then the classification ability of the SVM was tested for the testing data at the same speed. In the next part of the paper two novel techniques have been proposed, namely the interpolation and the extrapolation techniques, that help carry out multiclass classification using the SVM, even when the training data is not available for a particular testing angular speed of gears. The analysis is carried over a variety of kernels in the SVM and the best kernel for SVM classifier is noted. The effect of changes in some of the key SVM parameters on overall accuracy is also studied and an optimum value for different cases is presented. Finally, the effects of selection of training data and data density on the accuracy of SVM classifier are also presented.

2. Support vector machines

SVMs are a set of related supervised learning methods that analyze data and recognize patterns, and are used for classification and regression analyses. The basic SVM deals with two-class problems—in which the data are separated by a *hyper plane* defined by a number of *support vectors* [3,4]. The standard SVM takes a set of input data, and predicts, for each given input, which of two possible classes the input is a member of, which makes the SVM *a non-probabilistic binary linear classifier*. Since the SVM is a classifier, then given a set of training examples, each marked as belonging to one of two categories, the SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, the SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible (Fig. 1). Here we use the two support vectors, C-support vector and ν-support vector, for classifications.

C–Support Vector Classification (C–SVC): Given training vector $x_i \in R^n$, $i = 1, 2, \ldots, l$, in two classes, l is the number of training data, R^n is the real number set and an indicator vector $y \in R^l$ such that $y_i \in \{1, -1\}$, C–SVC (Boser et al. [11]; Cortes and Vapnik [12]) formulated the following primal optimization problem

$$\min_{w,b,\xi} \quad \frac{1}{2}w^T w + C\sum_{i=1}^{l}\xi_i$$
$$\text{Subject to } y_i\{w^T\phi(x_i) + b\} \geqslant 1 - \xi_i \text{ with } \xi_i \geqslant 0, \quad i = 1, 2, \ldots, l; \tag{1}$$

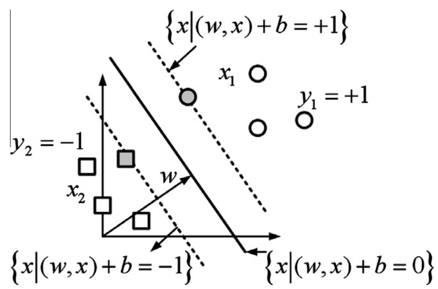

Fig. 1. The classification of data by the SVM.