Measurement 55 (2014) 1–14

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

# Support vector machine based optimization of multi-fault classification of gears with evolutionary algorithms from time–frequency vibration data

D.J. Bordoloi, Rajiv Tiwari *

*Department of Mechanical Engineering, Indian Institute of Technology Guwahati, Guwahati 781039, India*

ARTICLE INFO

*Article history:*
Received 1 March 2013
Received in revised form 17 December 2013
Accepted 23 April 2014
Available online 5 May 2014

*Keywords:*
Support vector machine
Optimization
Multi-fault classification
Wavelets
Interpolation and extrapolation

ABSTRACT

A multi-fault classification of gears has been attempted by support vector machine (SVM) learning techniques with the help of time–frequency (wavelet) vibration data. A suitable exploitation of SVM is based on the selection of SVM parameters. The main focus of the present paper is to study the performance of the multiclass capability of SVM techniques. Different optimization methods (i.e., the grid-search method (GSM), the genetic algorithm (GA) and the artificial bee colony algorithm (ABCA)) have been performed for optimizing SVM parameters. Four fault conditions of gears have been considered. The continuous wavelet transform (CWT) and wavelet packet transform (WPT) are estimated from time domain signals, and a set of statistical features are extracted from the wavelet transform. The prediction of fault classification has been attempted at the same angular speed as the measured data as well as innovatively at the intermediate and extrapolated angular speed conditions, since it is not feasible to have measurement of vibration data at continuous speeds of interest. The classification ability is noted and compared with predictions when purely time domain data is used, and it shows an excellent prediction performance.



## 1. Introduction

In rotating machinery, among various machine elements, gears are one of the critical components. The premature detection of its failures and diagnostics has become vital for undisrupted operation of machineries and protection of skilled human resources. Time domain, frequency domain and time–frequency domain procedures have been extensively practiced on vibration based measurements by maintenance personnel and scholars for the detection and diagnosis of gear faults [1–3].

Vibration signals measured by sensors from machines need to be processed and classified through modern machine learning tools (such as the artificial neural network (ANN), support vector machines (SVM), fuzzy logic systems (FLS), etc.) for its important diagnostics of the state of faults [4]. Wavelet transforms are well recognized methods of time–frequency analysis. These methods are superior in processing of signals of transient characters than the fast Fourier transform (FFT) or the Hilbert transform. Hence, features extracted from wavelet coefficients of vibrational signals for gear-box faults diagnosis have an immense prospect. A review of the wavelet transform applications in gearbox vibration analysis, as early as 1993, was documented by Peng and Chu [5]. For a decade or so, the support vector machine (SVM) has been used widely in condition monitoring and fault diagnosis of machinery for the binary-fault classification of machine elements. Widodo and Yang [6] reviewed the SVM as a tool for the condition monitoring of machinery and discussed

* Corresponding author. Tel.: +91 0361 258 2667; fax: +91 0361 258 2699.

*E-mail address:* rtiwari@iitg.ernet.in (R. Tiwari).

http://dx.doi.org/10.1016/j.measurement.2014.04.024
0263-2241/

about the effectiveness of SVM. They also indicated that among numerous methods available in faults classifications the application of SVM is still uncommon.

Wang and Mcfadden [7] utilized the wavelet transform to represent all possible types of transients in vibration signals generated by faults in a gearbox. Jack and Nandi [8] examined the performance of SVM and ANN classifiers in the binary class (i.e., fault/no-fault recognitions) and attempted to improve the overall generalization performance of both techniques through the use of GA based feature selection process. Samanta [9] presented the detection of gear condition using the ANN and the SVM with the GA based attribute collection from vibration data. He used the GA for the attribute collection and optimizing radial basis function (RBF) kernel parameters in the binary classification. Xuan et al. [10] used the power spectral density (PSD) of vibration signals of gearbox casing to construct spectral features. The GA was used to reduce the feature dimension from the original signal. The classifier was based on support vector machines with the multi-class classification ability. Liu et al. [11] proposed a weighted SVM with the GA based parameter selection for the binary SVM parameter selection. They showed through experimental data the effectiveness of method. Rajas and Fernandez-Reyes [12] described a GA methodology for regulating multiple parameters in SVM kernels with weighted RBF kernels using the HAT (Hospital Medical School, London, UK) proteomic dataset. Huang and Wang [13] optimized *C*-SVC parameters and feature subset simultaneously, without degrading the SVM classification accuracy with the GA based method. It performs attribute selection and parameters setting in an evolutionary way.

Saravanan et al. [14] performed a comparative analysis of proximal support vector machine (PSVM) and SVM by using the Morlet wavelet attribute of bevel gearbox. Cheng et al. [15] used the intrinsic mode function autoregressive (IMF–AR) model and the SVM for classification of gear faults in the case of smaller number of samples. Tiwari et al. [16] presented an approach based on the SVM technique to detect and classify multiple gear-fault conditions using frequency domain vibration signals. The overall classification efficiency of the SVM was compared with the reported efficiency. Saravanan et al. [17] extracted statistical features from vibration signals of a gearbox, which were selected using the decision tree (DT). A fuzzy classifier was built and tested with representative data. Ali et al. [18] extracted statistical features from vibration signals of the time, frequency, and time–frequency domains. To remove the redundant information and to reduce the burden of classification module, the Euclidian distance was used to select prominent features.

Gao et al. [19] used the wavelet lifting, together with SVMs and rule-based reasoning fault diagnosis methods. They concluded that the SVM was suitable for the pattern recognition of problems with small sample sizes. Zamanian and Ohadi [20] used the exact wavelet analysis to minimize effects of overlapping and distortion in the case of gearbox faults. The SVM with radial basis function (RBF) was used to extract features from the exact wavelet analysis for fault classifications. Samadzadegan et al. [21] indicated the prospect of artificial intelligence methods for the optimization of *C*-SVC parameters (a GA-based approach). They evaluated and compared with classic methods of the parameter tuning, i.e. the grid search, using the RBF kernel. Bordoloi and Tiwari [22,23] optimized the SVM parameters by GA and ABCA by utilizing statistical features (standard deviation, kurtosis and skewness) of time and frequency domain data, respectively. Four fault conditions of a gear box were considered. The faults were classified at the same speed at which vibration data were used for training but also at the intermediate and extrapolated speeds.

Based on available *literatures,* it could be summarized that the SVM has still an immense prospect and very little efforts have been performed for the multi-fault classification for gears. Looking into tremendous information contained in wavelets an attempt in conjunction with the SVM and the optimization of SVM parameters for the multi-fault classification would be a worth effort, which is lacking in available literatures. Moreover, for the fault prediction at the extrapolation and interpolation rotational speeds in gears by training SVMs at dissimilar rotational speed scarcely any effort has been made.

The present work analyses the multi-fault classification of a gear box based on time–frequency domain vibration data through the SVM. The chipped tooth (CT), the missing tooth (MT), the worn tooth (WT) and the normal gear (or no defect i.e., ND) fault situations have been implemented. The optimization of SVM parameters has been performed by the GSM, GA and ABCA techniques before final training and testing of the classifier. A group of statistical features like the kurtosis, the standard deviation and the skewness have been extracted from the wavelet transform data. Initially, the training and testing data have been selected for the same rotational speed for a range of rotational speeds. Subsequently, the training and the testing were performed at rotational speeds other than at measured ones, i.e. at the intermediate and extrapolated rotational speeds. This has a practical advantage in that it is not feasible to have measured data at all speed of interest. Predictions are excellent and the results are compared with results of purely time domain features of previous published work [22].

## 2. Experimental studies

Experiments were conducted on a Machinery Fault Simulator™ (MFS) and a schematic drawing of it is depicted in Fig. 1. This setup could be considered for the replication of a variety of machine faults, for example in the gearbox, shaft misalignments, rolling element bearing damages, resonances, reciprocating mechanism effects, motor faults, pump faults, etc. In the MFS, a 3-phase induction motor was connected to a rotor that in turn was coupled to the gear box through a pulley and belt device. The gear box and its assemblage are illustrated in Fig. 2. In the analysis of faults in gears, three different types of faulty pinion gears to be precise the ND, CT, MT and WT were considered and are depicted in Fig. 3. The online data in time domain were captured with a tri-axial accelerometer (with a sensitivity of 100.3 mV/g in the *x*-axis direction, 100.7 mV/g in the *y*-axis direction and 101.4 mV/g in the *z*-axis direction)