Available online at www.elixirpublishers.com (Elixir International Journal)

Control Engineering

Elixir Control Engg. 43 (2012) 6974-6977

ISSN: 2229-712X

Fault diagnosis and classification of planetary gearbox of MF285 tractor final drive using Fast Fourier Transform (FFT), Stepwise Backward Selection and support vector machine (SVM) classifier

M. Khazaee, H. Ahmadi, M. Omid and A.Moosavian

Department of Mechanical Engineering of Agricultural machinery, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran.

ARTICLE INFO

Article history:

Received: 4 January 2012;
Received in revised form: 6 February 2012;
Accepted: 17 February 2012;

Keywords

Condition monitoring,
Fault diagnosis,
Planetary gearbox,
Support vector machine,
Stepwise backward selection.

ABSTRACT

Gearboxes are widely applied in power transmission lines, so their health monitoring has a great impact in industrial applications. In this study we present fault diagnosis and classification method for intelligence condition monitoring of MF285 final drive. Broken and worn tooth face of ring gear of gearbox as two common faults of gears are studied. The vibration signal was collected by an accelerometer type VMI102 from the experimental setup that was built for this the research. Each class had 150 samples that divided in two parts. 105and 45 samples for training and test data were considered. These signals were processed by Fast Fourier Transform (FFT) signal processor for made better decomposition to feed the feature extraction and feature selection method. 30 features were extracted from frequency domain of vibration signals. Stepwise Backward Selection was employed as feature selection technique for select the better features for the best fault detection result and increases the accuracy degree of fault detection and classification. 9 features selected were used as input to Support Vector Machine (SVM) for fault classification. Least Square Support Vector Machine (LS-SVM) was applied for SVM. Results showed that the accuracy for train and test data was about 99.05% and 95.56% that greater than 85% so that's acceptable. Also results show the ability and high quality of this procedure for planter gearbox health monitoring.

Introduction

Reliability has always been an important aspect in the assessment of industrial products[1]. With the increase in production capabilities of modern manufacturing systems, plants are expected to run continuously for extended hours. Therefore, the condition monitoring of machines, especially early fault diagnosis, is proved to be necessary and has been received wide attentions in this decade[2]. By development of technology, cost of time-based preventive maintenance increased thus, new approaches in maintenance such as condition-based maintenance (CBM) developed[3, 4]. The development of fault detection and diagnostic schemes for gear transmission systems has been an active area of research in recent years, due to the need for many manufacturing companies to reduce unplanned production capacity loss caused by gear transmission systems failure and to improve equipment reliability through condition monitoring and failure prevention[5].

Rotating machineries are used considerably utilized in the manufacturing of industrial products. Gearboxes as a key rotating motion transmission component, plays a critical role in industrial applications[3].Condition monitoring of rotating machinery is important in terms of system maintenance and process automation[6]. Planetary gearboxes are widely used in transferring power, changing the amount of torque or rotating velocity due to wide range of gear ratios, taking low volume in designing the power trains, low sound noise and at last smoother working than simple gearboxes. Because of these advantages they used in helicopters and tractors widely[7]. Planetary gears have tree main part Ring gear, Sun gear, and planet gears that shown in Fig1. The final drive of MF285 tractor is a type of planetary gearboxes that has three planet gears and the ring gear of that is stationary.

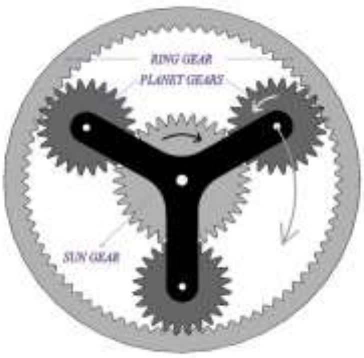

Fig1. The planetary gearboxes structure

In this work we focus on the detection and classification of two common faults of final drive namely, broken tooth and worn tooth face of ring gear. We use the vibration signals for the research because the vibration signals of rotating machinery usually contain a lot of useful information[6]. In most machine fault diagnosis and prognosis systems, the vibration of the rotating machine is directly measured by an accelerometer[8, 9].

In recent articles, advanced non-parametric approaches have been considered for signal processing such as wavelets, Fast

Tele:
E-mail addresses: khazaee.meghdad@ut.ac.ir

Fourier transform (FFT), short time Fourier transform (STFT)[5,10]. Each class has 150 samples that divided in two parts: 105 samplesassumed for training the classifier and45 samples for testing the system. Every velocity signal was analyzed with FFT signal processor by MATLAB software and after 30 statistical and vibration parameters of frequency domain signals was extractedsuch as average, maximum, minimum, range, standard deviation and etc. the selected features was employed to feed the SVM classifier for fault detection and classification.

Experimental setup

For this work, at first a test bed was built to mount the final drive and electromotor on it. The 3KW electromotor was used to drive power to the gearbox using a coupling power transmission. The input shaft of final drive was drove by the electromotor in 300RPM and its speed was controlled by an inverter. The experiment setup is shown in Fig2.

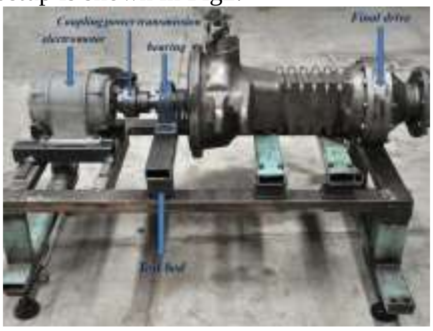

Fig 2. The experimental setup

Three classes are studied in this work, namely, healthy gearbox, broken tooth and tooth worn face of ring gear, that each class included the common fault of gearboxes. These classes are shown in Fig3.

(i)Tooth worn face (ii) Broken gear

Fig3. Two common faults of gears

Then the velocity signals werecollected by an accelerometer type VMI102 that set vertically on the surface of final drive. Also the Easy-viber was usedas data accusation with sampling rate of 8192 Hz.

Signal processing

Many signal processing techniques are presented in recent years for processing the vibration signal aim to have a better feature extraction and selection. In this study the Fast Fourier transform (FFT) was used as signal processor technique that suitable for the steady conditions and constant speed. The velocity time signals were transferred into frequency domain by FFT.This process is done for every sample. The MATLAB software was used for the signal processing.

Feature extraction and selection

The statistical parameters and frequency domain functions were applied to extracting features. 30 features was extracted by MATLAB software such as maximum, minimum, average, root mean square(RMS), standard deviation (Stdv), variance (Var), 5th Momentum (5th M), sixth momentum (6thM), crest Factor, skewness, kurtosis, etc. the extracted features was used to feed the support vector machine (SVM) classifier.

Stepwise Backward Selection

Stepwise selection is a method that allows moves in direction, dropping or adding variables at the various stages. Backward stepwise selection involves starting off in a backward procedure and then potentially adding back variables if they later appear to be substantial. The process is one of alternation between choosing the least substantial variable to drop and then re-considering all dropped variables for re-introduction into the model.This means that starting with all the variables set, stepwise backward selection eliminates the variable which leads to the smallest increase in prediction error. Variable removal stops when the new candidate model substantially increases the prediction error. Significance is computed by a partial F-test. The value of p (significance level) is 0.0001 with linear model. In this step 9 features are selected[11].

Support vector machine (SVM)

The Support Vector Machines (SVM) have been developed by Vapnikand are gaining popularity due to many appealing features, and promising empirical performance.SVM, based on statistical learning theory, is a proper technique for solving a variety of learning and function assessment problems.SVM was originally designed for binary (2-classes) classification[12].Fig 3 shows the classification of binary SVM. Also, SVM has been recently applied to solve multi-class problems. Many researches have been done on developing 2-class SVM into multi-class SVM.

Currently there are two types of methods for multi-class SVM. One builds a multi-class SVM by combining several 2-class SVMs, including 'one-against-all', 'one-against-one'. The other one considers all classes at once, including 'all-together' [13].

Suppose label the training data $\{x_i, y_i\}, i = 1,...,l$, $y_i \in \{-1,1\}, x_i \in R^d$. There are some hyperplane that separates the positive (class +1) from the negative (class -1) examples. The vector x which lie on the separating hyperplane satisfy $w.x + b = 0$, where w is normal to the hyperplane. In the separable case, all data satisfy the following constraints:

$w.x_i + b \geq +1,\ \ y_i = +1$ (1)

$w.x_i + b \leq -1\ ,\ \ y_i = -1$ (2)

These can be combined into the following inequalities:

$y_i(\ w.x_i + b\ ) - 1 \geq 0, for\ \forall i$ (3)

$d_+(d_-)$ is the shortest distance from the separating hyperplane to the closest positive (negative) training data. The margin of a separating hyperplaneis defined to be $d_+ + d_-$. By constraints Eq.(1) and Eq.(2) , $d_+ = d_- = 1/\|w\|^2$ and the margin is simply $2/\|w\|^2$. Thus we can find the separating hyperplane which gives the maximum margin by minimizing $\|w\|^2$, subject to constraints Eq.(4). Using the Lagrange multiplier technique, a positive Lagrange multipliers $\alpha_i, i = 1,...,l$, one for each of the inequality constraints Eq.(4) is determined. This gives Lagrangian:

$$\min l_{\,p} = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i.w + b) + \sum_{i=1}^{l} \alpha_i$$

$\alpha_i \geq 0$ (4)

In order to deal properly with nonlinear SVM, l_p is transformed into dual problem:

$$\max l_p = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j (x_i.x_j)$$

$$\alpha_i \geq 0 \ \sum_{i=1}^{l}\alpha_i y_i \geq 0 \ (5)$$

In the case where the data cannot be separated by hyperplane without errors, Vapnikpropose that introducing positive slack variables $\xi_i, i = 1,\ldots,l$,the constraints become:

$$w.x_i + b \geq +1 - \xi_i \text{ for } y_i = +1 \ (6)$$

$$w.x_i + b \leq -1 + \xi_i \text{ for } y_i = -1 \ (7)$$

$$\xi_i \geq 0 \ (8)$$

The goal is to buildhyper plane that makes the smallest number of errors. Hence the objection function becomes Minimize:

$$\|w\|^2 / 2 + C(\sum_i \xi_i) \ (9)$$

where C is penalty parameter, a larger C corresponding to assigning a higher penalty to errors. The C must be chosen by the user. The optimization problem becomes:

$$\max l_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j (x_i.x_j) \ (10)$$

$$0 \leq \alpha_i \leq C \ \sum_i \alpha_i y_i \geq 0$$

Suppose that the data is mapped to a higher dimension space (feature space), using a mapping which is called ϕ

$$\phi : R^d \rightarrow F \ (11)$$

Then the training algorithm would only depend on the data through dot products in F , i.e. on functions of the from $\phi(x_i).\phi(x_j)$. Kernel function is the significant concept of SVM, The definition of kernel is:

$$k(x_i.x_j) = \phi(x_i).\phi(x_j) \ (12)$$

In below, the formulation of three kernels is given:

Linear: $k(x_i.x_j) = x_i.x_j$

Polynomial:

$$k(x_i.x_j) = (\gamma x_i.x_j + 1)^d \quad , \quad \gamma > 0 \quad (13)$$

GaussianRBF:

$$k(x_i.x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)$$

So the optimization problem of nonlinear SVM is:

$$\max l_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j k(x_i.x_j)$$

$$0 \leq \alpha_i \leq C, \sum_i \alpha_i y_i \geq 0 \ (14)$$

After solving this optimization problem, those points for which $\alpha_i > 0$ are called ‘support vectors’. Then they determine w by Eq.(15). And b can be found by KKT ‘complementarily’ condition Eq.(16), where s_j are support vectors and N_s is the number of support vectors.

$$w = \sum_j^{N_s}\alpha_j y_j \phi(s_j) \ (15)$$

$$\alpha_i(y_j(w.\phi(s_j) + b) - 1) = 0 \ (16)$$

Finally, the class of x is:

$$sign(w.x + b) = sign\left(\sum_j^{N_s}\alpha_j y_j k(s_j, x) + b\right) (17)$$

Least Square SVM

Least Square Support Vector Machine (LS-SVM) is reformulations of SVM which lead to solving linear KKT systems. LS-SVMis closely related to regularization networks [14]and Gaussian processes. For huge scale problems LS-SVM is proposed, based on the Nyström approximation with active selection of support vectors and calculation in the primal space.The methods with primal-dual representations have also been extended for kernel spectral clustering, data visualizationand dimensionalityreduction and survival analysis [15].In the present work, LS-SVM is used.

Results

The vibration signals of gearbox were transferred to frequency domain by FFT signal processor. Fig4 shows the time signal and FFT signal of one sample of each class that was studied in this research.

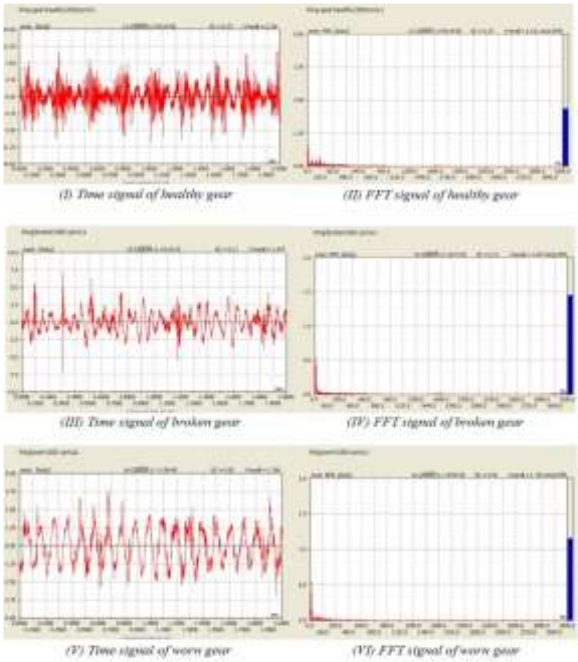

Fig4. The time signal & frequency signal of classes that made by MATLAB software

30 features were extracted from the frequency domain signals for three conditions of the gear. Dataset foreach class were divided into two parts, training andtest dataset. The layout of all data set was shown in Table1.

The Stepwise Backward Selection technique with p=0.0001 and linear model was applied for select the best features. Finally, LS-SVM generated by trainingwith train dataset and simultaneously simulated bytest dataset.

The target values were specified as 1, 2 and 3, respectively, representing healthy gear box, ring gear with a cracked tooth and planet gear with tooth face worn. The one-against-one method was applied for multi-class problem. Also, the RBF kernel was used with square kernel width (σ) of 0.1 and 10-fold cross validation.

This work was implemented on all features and 4 selected features for training and test data. The performance of LS-SVM in all features for training and test data was 98.78% and 95.56%, respectively. Also, the train and test success of LS-SVM with 9 selected features was 99.05% and 95.56%. It is obvious that the performance of LS-SVMwith feature selection was relatively better. Also, computation time was a much lower for 9 features. It can be found that the stepwise backward selection is a proper technique for feature selection in fault diagnosis of machine. By attention to the results, it be seen that the LS-SVM classifies the different faults of planter gears perfectly. It's due to the unique ability in classification problems.

Conclusions

This paper includes an intelligent fault detection and classification method of planetary gears of MF285 final drive, based on FFT as a signal processing technique, Stepwise Backward Selection as a feature selection and LS-SVM as a powerful classifier for fault classification. The accuracy rateon training and test data was 99.05% and 95.56% with 9 selected features that shows the power and quality of presented diagnostic model for fault detection and classification.

References

1. B. Bagheri, H. Ahmadi and R. Labbafi, Implementing discrete wavelet transform and artificial neural networks for acoustic condition monitoring of gearbox, *Elixir Mech. Engg. 35 (2011) 2909-2911*

2. G. Niu, A. Widodo, J. D. Son and B.S. Yang, Decision-level fusion based on wavelet decomposition for induction motor fault diagnosis using transient current signal, Expert Systems with Applications 35 (2008) 918–928

3. B. Bagheri, H. Ahmadi, and R. Labbafi, Application of Data Mining and Feature Extraction on Intelligent Fault Diagnosis by Artificial Neural Network and k-Nearest Neighbor, ICEM 2010, Rome, Italy, 2010, pp. 7.

4. H. Ahmadi, and K. Mollazade, A practical approach to electromotor fault diagnosis of Imam Khomaynei silo by vibration condition monitoring. African Journal of Agricultural Research 4 (2008) 383-388.

5. M. Yang and V. Makis; ARX model-based gearbox fault detection and localization under varying load conditions; Journal of Sound and Vibration 329 (2010) 5209–5221

6. R. R. Schoen, T. G.Habetler, F. Kamran and R. G.Bartheld, 'Motor bearing damage detection using stator current monitoring', IEEE Transactions on Industrial Applications, Vol 31, No 6, pp 1274-1279, 1995

7. R. Labbafi, H. Ahmadi, B. Bagheri, S.S. Mohtasebi, A. Rajabipour and M. Khazaee, fault classification of planetary gears based on decision tree and regression model.3rdEuropean Conference on Tribology, June 7-9, 2011; Vienna, Austria

8. Z K Peng and F L Chu, 'Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography', Mechanical Systems and Signal Processing, Vol 18, pp 199-221, 2004.

9. H. Ahmadi and K. Mollazade, 'Fault diagnosis of an electro-pump in a marine ship using vibration condition monitoring', Insight, Vol 51, No 8, pp 431-438, August 2009.

10. M. Omid, Design of an expert system for sorting pistachio nuts through decision tree and fuzzy logic classifier. Expert Systems With Applications (2010) 1-9. 11. A. Widodo, and B.S. Yang, Wavelet

11. The LOGISTIC Procedure, Chapter 39, Overview, SAS OnlineDocä: Version 8, pp 1903-2040.

12. C. Cortes and V.Vapnik, 'Support-vector network, Machine Learning', 20: pp 273-297, 1995.

13. J. N. Wang, S. M.Guu and S. T. Chou, 'On multiclass support vector machines: One-Against-Half approach', International journal of operations research, Vol. 6, No. 1, pp 24-32, 2009.

14. T. Evgeniou, M. Pontil and T. Poggio, 2000, Regularization networks and support vectormachines, Advances in Computational Mathematics, 13(1), 1–50.

15. De Brabanter, K et al, 2011, LS-SVMlab Toolbox User's Guide version 1.8, ESAT-SISTA Technical Report 10-14.

Table1. Descriptions of data sets in each condition

Class	Train	Test	Total
Healthy	105	45	150
Broken gear	105	45	150
Worn tooth face	105	45	150
Total	315	135	450