An Appropriate Approach for Condition Monitoring of Planetary Gearbox Based on Fast Fourier Transform and Least-Square Support Vector Machine

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***Abstract*— Planetary gearboxes play a significant role in industrial applications and the necessity of condition monitoring with non-destructive tests is increasing. In this paper we presented an intelligent method for fault detection and classification of this gearbox using vibration signals. This method focuses on the worn gears detection; therefore three classes were defined, namely, healthy gears, ring gear with worn tooth face and planetary gear with worn tooth face. Each class has 60 samples that divided in two parts: 45 samples for training data and 15 samples for testing system. The time signals were transferred to frequency domain by Fast Fourier Transform (FFT). Then 24 statistical features of frequency signals were extracted. The extracted feature was used to feed SVM for fault classification. Using these techniques together, 95.6% and 92.3% classification accuracy is gained for train and test data which show the quality and high ability of generated fault diagnosis system.**

***Keywords*— Fault Detection, Condition Monitoring, Support Vector Machine (SVM), Fast Fourier Transform (FFT) and Planetary Gearboxes**

I. INTRODUCTION

Due to the importance of monitoring the health of system without stopping, the uses of non-destructive tests are widely improved. Condition monitoring is a conventional method for preventing machineries from failure and breakage.

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The use of conditional monitoring allows Maintenance to be scheduled or other actions to be taken to avoid the consequences of failure, before it occurs. The condition monitoring and fault detection schemes improve gear transmission systems Reliability and reduce their failure occurrence [1]. Automation, as another significant stage in industries commonly implemented to reduce the cost of production, quality control and maintenance. Based on these theories several methods are developed to automate the condition monitoring and quality control of systems.

The undeniable abilities of artificial intelligence on this way, persuades researches to use different methods of AI in their fields of study. Fuzzy Logic, Neuro-Fuzzy systems, Artificial Neural networks and Support Vector Machine algorithm are the most usual algorithms for implementing artificial Intelligence [2]. Beside these techniques, acoustic signals and signal processing are commonly used for non-destructive tests in fault diagnosis systems. Both vibration and acoustic signals carry rich and useful information about the condition of the system and it has been very popular for condition monitoring and early fault detection of gearboxes [1].

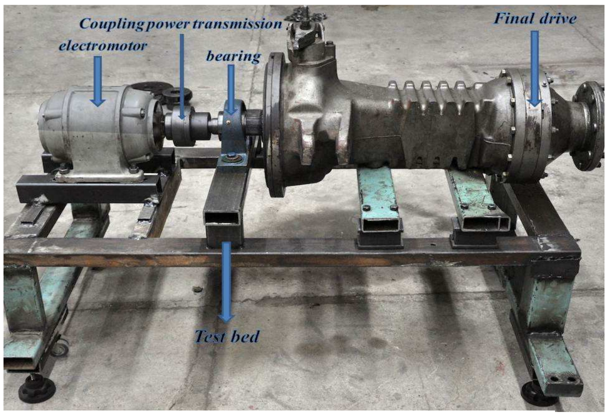
Rotating machineries are used considerably utilized in the manufacturing of industrial products. Gearboxes as a key rotating motion transmission component, plays a critical role in industrial applications [3]. Therefore, attracts research interests in condition monitoring and fault diagnosis of this equipment. Importance of gears and bearings in condition monitoring of the machine is undeniable, thus, processing and analysis of acoustic and vibration signals of the gearbox gears is the common way of extracting reliable representative of the gearbox condition [4], [5].

Planetary gear boxes are one of the most common types of gearboxes that Because of their wide gear ratios, especially in a heavy industrial machines and helicopter are considered. It is composed of three main components that consist of: i) ring gear, ii) planets gears, iii) sun gear. Their main advantage is low weight and occupies less space on transmission lines. The final drive of MF285 tractor that was used in this research is a type of planetary gearbox and it is *one of the main components of this tractor's* power transmission line. So There recognition and classification of its defects is an important step in maintaining the power transmission lines.

II. EXPRIMENTAL 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 200RPM and its speed was controlled by an inverter. The experiment setup is shown in Fig. 1.

Three classes were classified in this work, namely, healthy gearbox, tooth worn face of planetary gears and tooth worn face of ring gear, that each class consider a type of worn fault as a most common fault of gearboxes. These classes are shown in Fig. 2.



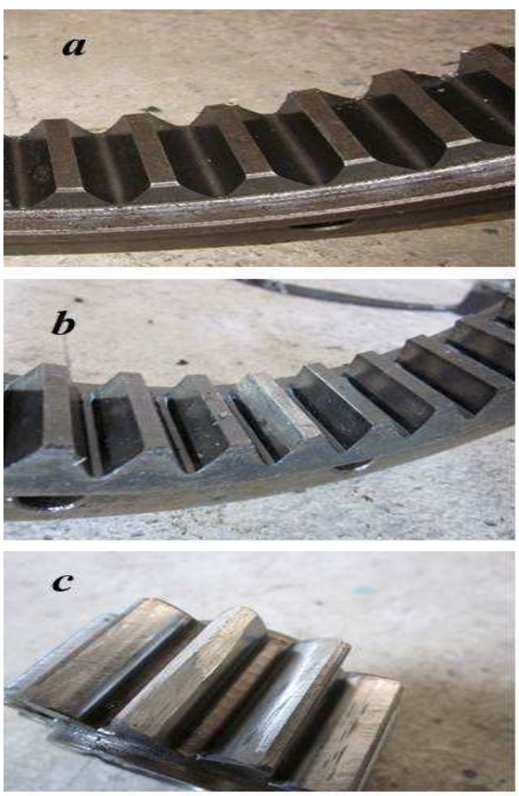


Fig. 2. The different defect of gears: a) Healthy b) worn tooth face Ring gear c) worn tooth face planet gear

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

III. SIGNAL PEOCESSING AND FEATURE EXTRACTION

In recent articles, advanced non-parametric approaches have been considered for signal processing such as wavelets, Fast Fourier Transform (FFT), short time Fourier transform (STFT) [1], [6]. Most noise and vibration-acoustic analysis instruments utilize a Fast Fourier Transform (FFT) which is a special case of the generalized Discrete Fourier Transform. It converts the vibration signal from time domain representation to its equivalent frequency domain representation. In this study FFT signal processing technique was employed to transfer the vibration signals from time domain to frequency domain. Fig. 3 shows the time signal and Fig. 4 shows the FFT signal of one sample of each class that was studied in this research.

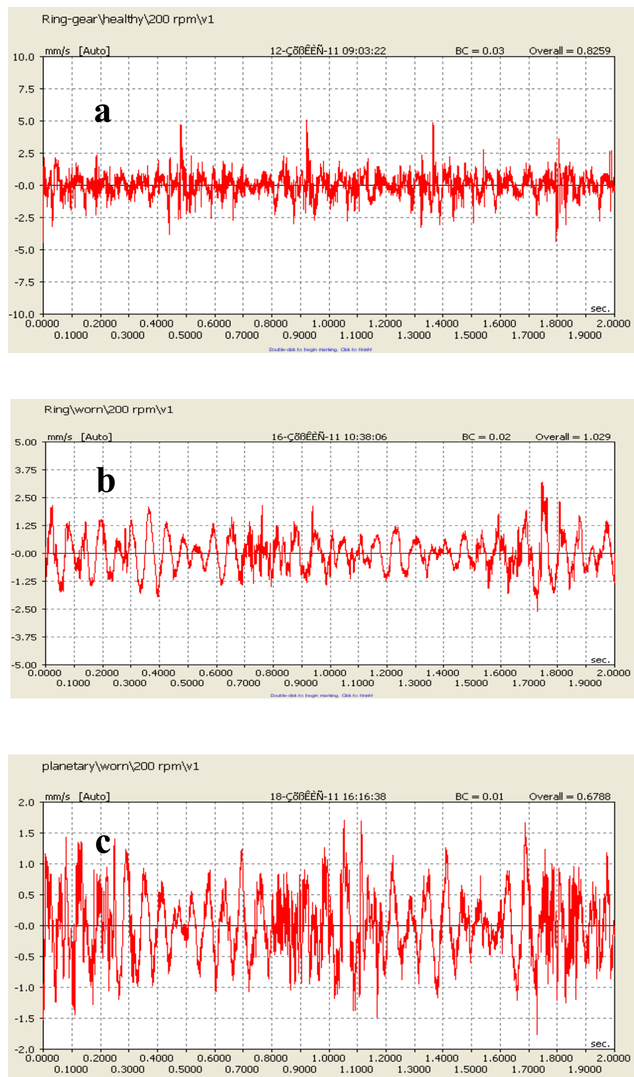


Fig. 3. The time signal of classes: a) Healthy b) worn tooth face Ring gear c) worn tooth face planet gear

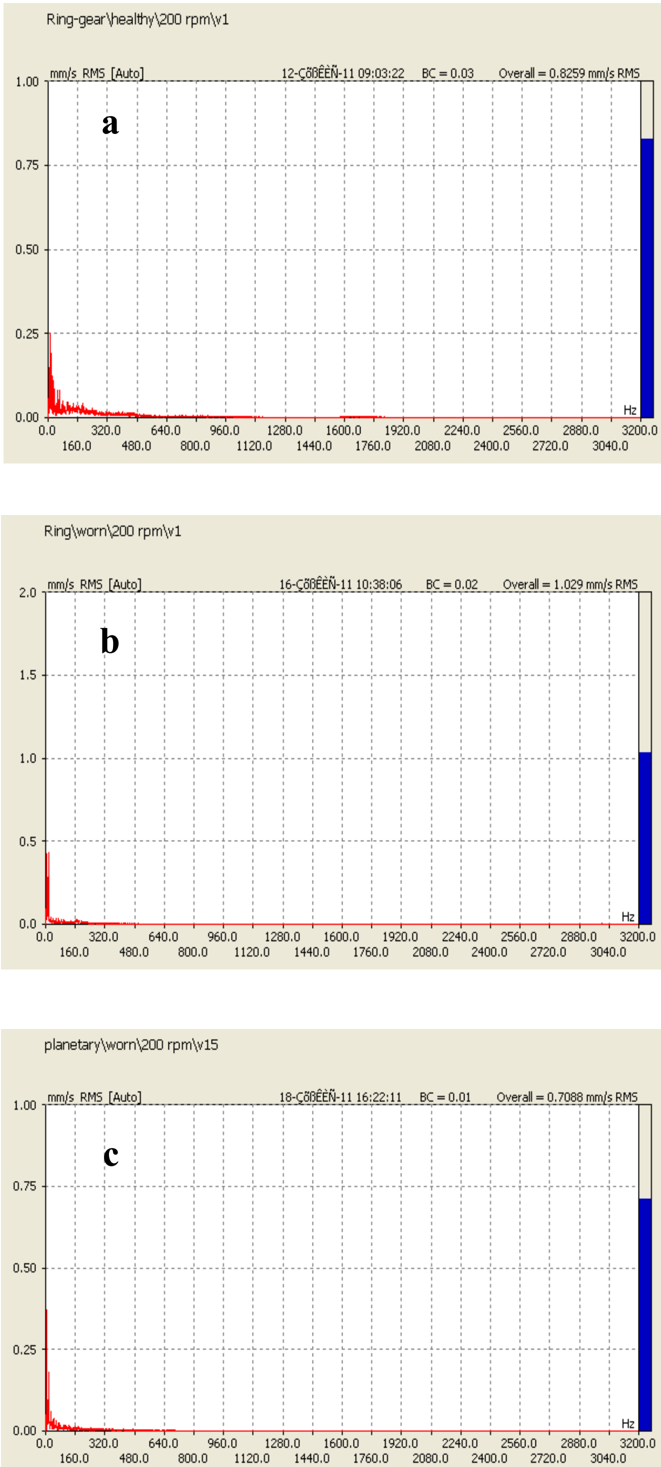


Fig. 4. The frequency signal of classes: a) Healthy b) worn tooth face Ring gear c) worn tooth face planet gear

Every velocity signal was analyzed with FFT signal processor by MATLAB software and after 24 statistical and vibration parameters of frequency domain signals was extracted such as average, maximum, minimum, range, standard deviation and etc. the selected features was employed to feed the SVM classifier for fault detection and classification.

IV. SUPPORT VECTOR MACHINE

Support vector machine (SVM) has become an increasingly popular technique for machine learning activities including classification, regression, and outlier detection. Detailed reviews on SVM are available elsewhere [7], [8]. The idea of using SVM for separating two classes is to find support vectors (i.e., representative training data points) to define the bounding planes, in which the margin between the both planes is maximized.

A. SVM Mathematics

Given a training set of N data points $\{y_k, x_k\}_{k=1}^{N}$, where $x_k=R^n$ is the k th inputpattern and $y_k=R^n$ is the k th output pattern, the support vector method approachaims at constructing a classifier of the form:

$$y(x)=sign\left[\sum_{k=1}^{N}\alpha_k y_k \psi(x,x_k)+b\right] \quad (1)$$

Where α_k are positive real constants and $b$is a real constant. For $\psi(.,.)$ one typically has the following choices: $\psi(x,x_k)=x_k^T x$ (linear SVM); $\psi(x,x_k)=(x_k^T x+1)^d$ (polynomial SVM of degree d); $\psi(x,x_k)=\exp\left\{-\|x-x_k\|^2/2\sigma^2\right\}$ (RBF SVM); $\psi(x,x_k)=\tanh[\kappa x_k^T x+\theta]$ (two layer neural SVM), where σ, κ and θ are constants.

The classifier is constructed as follows. One assumes that

$$w^T\varphi(x_k)+b\geq 1 \text{ if } y_k=+1 \quad (2)$$

$$w^T\varphi(x_k)+b\leq -1 \text{ if } y_k=-1$$

Which is equivalent to

$$y_k[w^T\varphi(x_k)+b]\geq 1,\ k=1,\dots,N \quad (3)$$

Where $\varphi(.)$ is a nonlinear function which maps the input space into a higher dimensional space. However, this function is not explicitly constructed. In order to have the possibility to violate (3), in case a separating hyperplane in this higher dimensional space does not exist, variables ξ_k are introduced such that:

$$y_k[w^T\varphi(x_k)+b]\geq 1-\xi_k \quad , \quad k=1,\dots,N \quad (4)$$

$$\xi_k\geq 0 \quad , \quad k=1,\dots,N$$

According to the structural risk minimization principle, the risk bound is minimized by formulating the optimization problem

$$\min_{w,\xi_k}\partial_1(w,\xi_k)=\frac{1}{2}w^T w+c\sum_{k=1}^{N}\xi_k \quad (5)$$

subject to (4). Therefore, one constructs the Lagrangian

$$\ell_1(w,b,\xi_k;\alpha_k,\upsilon_k)=\partial(w,\xi_k)-\sum_{k=1}^{N}\alpha_k\{y_k[w^T\varphi(x_k)+b] -\frac{n!}{r!(n-r)!}-1+\xi_k\}-\sum_{k=1}^{N}\upsilon_k\xi_k \quad (6)$$

by introducing Lagrange multipliers $\alpha_k \geq 0$, $\upsilon_k \geq 0$ ($k=1,\ldots,N$) The solution is given by the saddle point of the Lagrangian by computing

$$\max_{\alpha_k,\upsilon_k}\min_{w,b,\xi_k}\ell_1(w,b,\xi_k;\alpha_k,\upsilon_k) \quad (7)$$

One obtains

$$\frac{\partial\ell_1}{\partial w}=0\rightarrow w=\sum_{k=1}^{N}\alpha_k y_k\varphi(x_k)$$
$$\frac{\partial\ell_1}{\partial b}=0\rightarrow \sum_{k=1}^{N}\alpha_k y_k=0$$
(8)
$$\frac{\partial\ell_1}{\partial \xi_k}=0\rightarrow 0\leq\alpha_k\leq c \quad , \quad k=1,\ldots,N$$

which leads to the solution of the following quadratic programming problem

$$\max_{\alpha_k}Q_1(\alpha_k;\varphi(x_k))=-\frac{1}{2}\sum_{k,l=1}^{N}y_k y_l\varphi(x_k)^T\varphi(x_l)\alpha_k\alpha_l+\sum_{k=1}^{N}\alpha_k$$
(9)

Such that

$$\sum_{k=1}^{N}\alpha_k y_k=0 \quad , \quad 0\leq\alpha_k\leq c \quad , \quad k=1,\ldots,N$$

The function $\varphi(x_k)$ in (9) is related then to $\psi(x,x_k)$ by imposing

$$\varphi(x)^T\varphi(x_k)=\psi(x,x_k) \quad (10)$$

Which is motivated by Mercer's Theorem. Note that for the two layer neural SVM, Mercer's condition only holds for certain parameter values of κ and θ.

The classifier (1) is designed by solving

$$\max_{\alpha_k}Q_1(\alpha_k;\psi(x_k,x_l))=-\frac{1}{2}\sum_{k,l=1}^{N}y_k y_l\psi(x_k,x_l)\alpha_k\alpha_l+\sum_{k=1}^{N}\alpha_k \quad (11)$$

subject to the constraints in (9). One does not have to calculate w nor $\varphi(x_k)$ in order to determine the decision surface. Because the matrix associated with this quadratic programming problem is not indefinite, the solution to (11) will be global [9].

Furthermore, one can show that hyperplanes (3) satisfying the constraint $\|w\|/2\leq a$ have a VC-dimension h which is bounded by

$$h\leq\min([r^2a^2],n)+1 \quad (12)$$

where [.] denotes the integer part and r is the radius of the smallest ball containing the points $\varphi(x_1),\ldots,\varphi(x_N)$. Finding this ball is done by defining the Lagrangian

$$\ell_2(r,q,\lambda_k)=r^2-\sum_{k=1}^{N}\lambda_k(r^2-\|\varphi(x_k)-q\|^2/2) \quad (13)$$

where q is the center of the ball and λ_k are positive Lagrange multipliers. In a similar way as for (5) one finds that the center is equal to $q=\sum_k\lambda_k\varphi(x_k)$, where the Lagrange multipliers follow from

$$\max_{\alpha_k}Q_2(\lambda_k;\varphi(x_k))-\sum_{k,l=1}^{N}\varphi(x_k)^T\varphi(x_l)\lambda_k\lambda_l+\sum_{k=1}^{N}\lambda_k\varphi(x_k)^T\varphi(x_k) \quad (14)$$

such that

$$\sum_{k=1}^{N}\lambda_k=1 \quad , \quad \lambda_k\geq 0 \quad , \quad k=1,\ldots,N$$

Based on (10), Q_2 can also be expressed in terms of $\psi(x_k,x_l)$. Finally, one selects a support vector machine with minimal VC dimension by solving (11) and computing (12) from (14) [10].

B. Least square SVM

In this section we introduce a least squares version to the SVM classifier by formulating the classification problem as

$$\min_{w,b,e}\partial_3(w,b,e)=\frac{1}{2}w^Tw+\gamma\frac{1}{2}\sum_{k=1}^{N}e_k^{\,2} \quad (15)$$

Subject to the equality constraints

$$y_k[w^T\varphi(x_k)+b]=1-e_k \quad , \quad k=1,\ldots,N \quad (16)$$

One defines the Lagrangian

$$\ell_3(w,b,e;\alpha)=\partial_3(w,b,e)-\sum_{k=1}^{N}\alpha_k\{y_k[w^T\varphi(x_k)+b]-1+e_k\} \quad (17)$$

Where α_k are Lagrange multipliers (which can be either positive or negative now due to the equality constraints as follows from the Kuhn-Tucker conditions. The conditions for optimality

$$\frac{\partial\ell_3}{\partial w}=0\rightarrow w=\sum_{k=1}^{N}\alpha_k y_k\varphi(x_k)$$
$$\frac{\partial\ell_3}{\partial b}=0\rightarrow \sum_{k=1}^{N}\alpha_k y_k=0$$
$$\frac{\partial\ell_3}{\partial e_k}=0\rightarrow \alpha_k=\gamma e_k \quad , \quad k=1,\ldots,N \quad (18)$$

$$\frac{\partial \ell_3}{\partial \alpha_k} = 0 \rightarrow y_k[w^T \varphi(x_k) + b] - 1 + e_k = 0 \quad , \quad k = 1, \ldots, N$$

Can be written immediately as the solution to the following set of linear equations

$$\begin{bmatrix} I & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -Y^T \\ 0 & 0 & \gamma I & -I \\ Z & Y & I & 0 \end{bmatrix} \begin{bmatrix} w \\ b \\ e \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vec{1} \end{bmatrix} \qquad (19)$$

where $Z = [\varphi(x_1)^T y_1; \ldots; \varphi(x_N)^T y_N]$, $Y = [y_1; \ldots; y_N]$, $\vec{1} = [1; \ldots; 1]$, $e = [e_1; \ldots; e_N]$, $\alpha = [\alpha_1; \ldots; \alpha_N]$. The solution is also given by:

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + \gamma^{-1} I \end{bmatrix}, \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \qquad (20)$$

Mercer's condition can be applied again to the matrix $\Omega = ZZ^T$, where

$$\Omega_{kl} = y_k y_l \varphi(x_k)^T \varphi(x_1) = y_k y_l \psi(x_k, x_1) \qquad (21)$$

Hence, the classifier (1) is found by solving the linear set of Equations (20)–(21) instead of quadratic programming. The parameters of the kernels such as σ for the RBF kernel can be optimally chosen according to (12). The support values α_k are proportional to the errors at the data points (18), while in the case of (14) most values are equal to zero [11].

We have implemented this method by using LS-SVM Toolbox. The software is available at http://www.esat.kuleuven.ac.be/sista/lssvmlab

V. SIMULATION RESULTS

In this research, three classes were defined for classification. Each class has 60 samples that divided in two parts: i) 45 samples for training SVM classifier ii) 15 samples for testing data.

This work was implemented on all 24 features training and test data. The performance of LS-SVM in all features for training and test data was 95.6% and 91.3%, respectively. This accuracy shows the ability and quality of presented system for fault diagnosis and classification of planetary gearbox.

VI. CONSLUSIONS

In this paper consider an intelligent system for fault detection and classification of MF285 tractor`s final drive planetary gearbox, based on vibration signals, FFT signal processor and SVM classifier. The accuracy of train and test data was 95.6% and 91.3% that great than 85% so acceptable. The results show that the LS-SVM is appropriate classifier for planetary gearbox fault diagnosis. Also the results showed the ability of this procedure in planetary gearbox condition monitoring.

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