Faults Classification of Tractor Gearbox Using Linear Regression Model

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Abstract
Vibration signals acquired from a gearbox usually are complex, and it is difficult to detect the symptoms of an inherent fault in a gearbox. In this paper, an intelligent diagnosis method with the parameters in frequency domain based on the fast Fourier transform and regression model for the fault diagnosis of MF-240 Tractor gearbox is developed. Vibratonal signals was analyzed with FFT by MATLAB software and after that 11 features of FFT values of vibration signal were extracted using descriptive statistical parameters. J48 algorithm is used as a feature selection procedure to select pertinent features from data set. WEKA program was implemented on train data to build the decision tree. The linear regression models were developed using MATLAB. Totally 3 faults in MF-240 Tractor gearbox were considered in the developed model. Accuracy for the linear regression model was gained equal with 88.33%.

Keywords**:** Fault Classification, Decision Tree, Regression, MF-240 Tractor Gearbox

Introduction
In gearboxes and power drive trains in general, gear damage detection is often very critical and can lead to increased safety in aviation and in industry as well (Loutas et al, 2009). Gears are the most efficient and compact devices used to transmit torques and change the angular velocities. They are widely applied in many machines, such as mining machines, automobiles, helicopters, and aircraft turbine engines. Gearbox vibration data carries a lot of useful information and it has been very popular for condition monitoring and early fault detection of gearboxes. The condition monitoring and fault detection schemes improve gear transmission systems reliability and reduce their failure occurrence. 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 (Yang and Makis, 2010). The publications in the field of condition monitoring via vibrations are quite versatile. Fault detection is achieved by comparing the signals of gearbox running under normal and faulty conditions. The faults considered in this study are broken gear, worn gear and faulty bearing. In conventional condition monitoring, the commonly used method is vibration analysis in frequency domain through Fast Fourier Transform (FFT). In most machine fault diagnosis and prognosis systems, the vibration of the rotating machine is directly measured by an accelerometer (Labbafi et al, 2011). The level of vibration can be compared with historical baseline value to assess the severity. Interpreting the vibration signal is a complex process that requires specialized training and experience. Commonly used technique is to examine the individual frequencies present in the signal. These frequencies correspond to certain mechanical component or certain malfunction. By examining these frequencies and their harmonics, the analyst can identify the location, type of problem and the root cause as well (Cempel, 1988). After processing the signals the next step is feature extraction. Some statistical or vibration indexes are using in this step. In this paper tree fault of gearbox was classified by M5P that is a reconstruction of Quinlan's M5 algorithm for inducing trees of regression models. Selecting a few and focusing on advanced signal processing techniques the works of Wang and McFadden (Wang and Mcfadden, 1993a;Wang and Mcfadden, 1993b) must be mentioned, that utilized time-frequency analysis techniques and showed that the spectrogram has advantages over Wigner–Ville distribution for the analysis of vibration signals for the early detection of damage in gears. Baydar and Ball (Baydar and Ball, 2000; Baydar

et al, 2003) have proposed the instantaneous power spectrum and have shown that it is capable in detecting local tooth faults in standard industrial helical gearboxes. The propagation of local faults was identified by monitoring variations in the features of the power spectrum distribution. The same authors have also applied the Wigner–Ville distribution (Baydar and Ball, 2001) as well as the wavelet transform (Baydar and Ball, 2003) on vibration and acoustic signals for the same purpose. Zhan and Makis (Zhan and Makis, 2006) presented an adaptive Kalman filter-based AR model with varying coefficients fitted to the gear motion residual signal in the healthy state of the gear of interest considering several load conditions. The compromised model order was determined using several criteria. Liu and Makis (Liu and Makis, 2008) proposed a gear failure diagnosis method based on vector autoregressive (VAR) modeling of the vibration signals, dimensionality reduction applying dynamic principal component analysis and condition monitoring using a multivariate Q control chart.

Material and Method

A gearbox that was mounted on an agricultural tractor as a main part of its power transmition system was used to perform the experiments. The main objective of the study is to find whether the MF-240 Tractor gearbox is in good condition or in faulty condition. If the gearbox is in faulty condition then the aim is to segregate the faults into broken gear, worn gear and faulty bearing. Vibration data of the gearbox in the good condition (healthy) was used for comparison between healthy and faulty conditions of gearbox. Considered faults were healthy gearbox, with faulty bearing, worn gear and broken gear, as shown in Figure 1. Broken gears, worn gears and faulty bearings supplied from the workshops of tractor. Table 1 shows the description of fault conditions.

Figure 1- Gearbox faults

Table 1- The description of faulty gearbox

Fault Condition	Fault Description
Broken Gear	Number Of Broken Teethes: 1
Worn Gear	Decrease Of Teeth Thickness: 2.3%
Faulty Bearing	Decrease Of Roller Diameter: 4.8%

A piezoelectric accelerometer, type VMI 102 (VMI Ltd, Sweden), was mounted on the gearbox body in the vertical direction. Accelerometer specification is provided in Table 2. The sensor was connected to the signal-conditioning unit (Easy-Viber FFT analyzer), where the signal goes through a charged amplifier and an analogue-to digital converter (ADC). The vibration signal in digital form was saved on computer through a USB port for further analyses. The software SpectraPro4 that accompanies the signal conditioning unit was used for recording the signals directly in the computer's secondary memory.

Table 2- Accelerometer specification

Accelerometer type	VMI-102
Sensitivity	100mv/g
Frequency response (+/-3db)	0.7-15000Hz
Resonant frequency	30000Hz
Temperature range	-50ºC … +120ºC

In this paper three fault of MF-240 Tractor gearbox was classified. Test-bed was designed and constructed to install gearbox. One of method for reducing unwanted vibrations is isolation the system from ambient. For reducing unwanted vibrations and noise, four shock absorbers installed under bases of the test bed. Then vibration signal of each class (healthy, broken gear, worn gear and faulty bearing) was captured. Many signal processing techniques are presented for processing the signals aim to have a better feature extraction and selection. In recent articles, advanced nonparametric approaches have been considered for signal processing such as wavelets, fast fourier transform (FFT), short time fourier transform (STFT) (Schoen et al, 1995). In this study the fast fourier transform was used as signal processor technique that suitable for the steady conditions and stationary behaviors. The velocity time signals were transferred into frequency domain by FFT(Figure. 2. This process is done for every sample. The FFT toolbox in MATLAB software was used for the signal processing. Each class has 100 samples that divided in two parts: 70 samples assumed for training the classifier and 30 samples for testing the system. after proccessing signals, 11 features from the coefficient of FFT was extracted such as average (**Ave**), maximum(**Max**), minimum(**Min**), standard deviation (**Std**), energy (**En**), skewness (**Sk**), Kurtosis (**Ku**), slippage (**Sl**), root mean square (**RMS**), moment4 (**M4**) and moment5 (**M5**) . Then the input space divided in two part train set and test set. Train matrix with 12 column and 280 rows was fed to WEKA program to build a model. Last column of train matrix was the label of classes for example label 1 was considered for class healthy. The rows of train matrix were the replications. After constructing the model the test data was fed to model to evaluate the accuracy of the model.

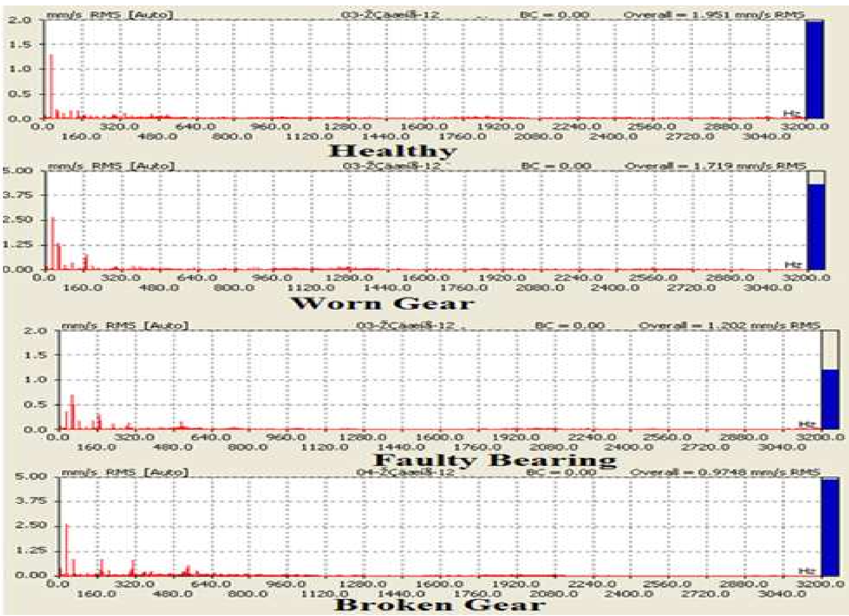

Figure 2-Vibration signals of MF-240 Tractor gearbox in different states.

Results And Discussion

In Figure 3 the decision tree on train data was shown. At the last of every branch a linear regression model constructs to predict the class of data.

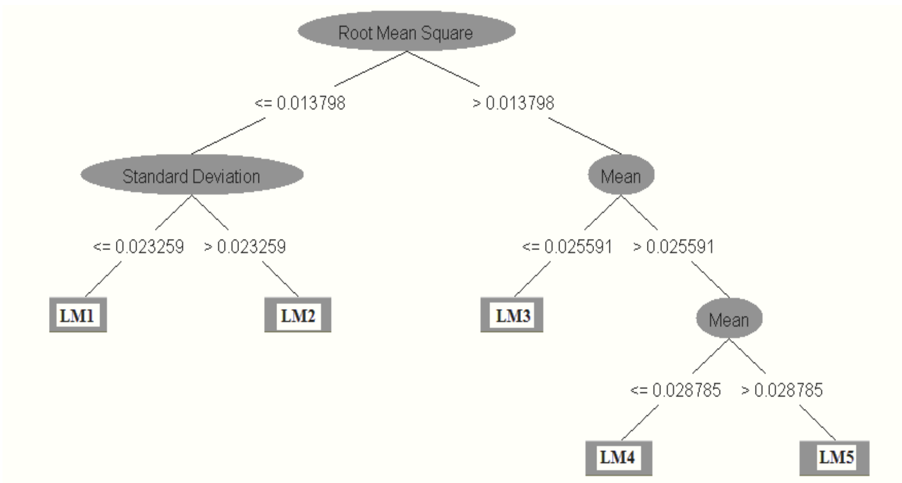

Figure 3- Decision tree and regression model

Equation (1) shows the regression model for different state of MF-240 Tractor gearbox. Different coefficients a, b, c and Constant was shown in the Table 3. Each of the regression models represents a state of MF-240 Tractor gearbox (LM1: Broken Gear, LM2: Faulty Bearing, LM3: Broken Gear, LM4: Healthy, LM5: Worn Gear).

$$LM = a \times RMS + b \times Std + c \times Ave + d \qquad (1)$$

Table 3- Coefficients of linear models

Regression Model	a	b	c	Constant	State Of The Gearbox
LM1	0.8965	1.9143	0.7613	2.342	Broken Gear
LM2	0.8965	2.1075	0.7613	2.845	Faulty Bearing
LM3	-1.321	6.413	-0.7632	0.413	Broken Gear
LM4	-1.321	6.413	-0.3214	1.719	Healthy
LM5	-1.321	6.413	0.4711	5.954	Worn Gear

The classification results are calculated by using of the regression model evaluation, where the data set to be evaluated is randomly partitioned so that in each condition 70 samples are used for training the J48 algorithm for making the tree decision and 30 samples are used for testing the regression model. The confusion matrix for each condition is given in Table 4.

Table 4- Confusion matrix for gearbox condition

Condition	Healthy	Faulty Bearing	Worn Gear	Broken Gear
Healthy	26	0	1	3
Faulty Bearing	1	28	0	1
Worn Gear	0	0	28	2

Broken Gear	3	2	1	24

The performance of the classifier can be checked by computing the statistical parameters such as sensitivity, specificity and total classification accuracy defined by

- ✓ **Sensitivity:** number of true positive decisions/number of actually positive cases.
- ✓ **Specificity:** number of true negative decisions/number of actually negative cases.
- ✓ **Total classification accuracy:** number of correct decisions/total number of cases.

The values of statistical parameters are given in Table 5. Results show that the total classification accuracy is 88.33%. Correct classification rate of four gearbox condition output healthy, faulty bearing, worn gear and broken gear were found to be 86.67%, 93.33%, 93.33% and 80% , respectively.

Table 5- The value of statistical parameters

Data Sets Label	Sensitivity(%)	Specificity (%)	Total classification accuracy (%)
Healthy	86.67	95.56	
Faulty Bearing	93.33	97.78	88.33
Worn Gear	93.33	97.78	
Broken Gear	80	93.33	

Conclusions

In this paper an intelligent system for fault classification of MF-240 Tractor gearbox was proposed. The vibration features of these signals of gearbox were employed for this work. In order to effectively diagnose faults, every velocity signal was analysed with fast fourier transform and after that 10 features from the FFT was extracted such as average, maximum, minimum, range, standard deviation, moment1, moment2 and etc. The linear regression models were developed using MATLAB. Totally four faults in gearbox were considered in the developed model. As it was shown in Table 4, accuracy for the linear regression model was gained as 88.33%.

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طبقه بندی عیوب گیربکس تراکتور توسط رگرسیون خطی

چکیده

سیگنال‌های ارتعاشی به دست آمده از گیربکس پیچیده هستند و معمولا تشخیص علائم عیب و خرابی از روی آنها دشوار است. در این مقاله، یک روش هوشمند برای تشخیص عیب در گیربکس تراکتور مسی فرگوسن ۲٤۰ با استفاده از پارامترهای حوزه فرکانس براساس تبدیل فوریه سریع و مدل رگرسیون توسعه داده شد. سیگنال‌های ارتعاشی توسط تبدیل فوریه سریع در نرم افزار متلب تجزیه و تحلیل شدند و سپس ۱۱ ویژگی آماری از مقادیر تبدیل فوریه سریع استخراج شدند. از الگوریتم J48 برای انتخاب ویژگی‌های برتر و از برنامه WEKA برای ساخت درخت تصمیم استفاده شد. سپس مدل‌های رگرسیون خطی در متلب ایجاد شدند. جمعا سه حالت خرابی در گیربکس تور مسی فرگوسن ۲٤۰ در نظر گرفته شد که دقت مدل رگرسیون خطی برای تشخیص حالت عیب ٪٪۸۸/۳۳ بود

کلمات کلیدی: طبقه بندی عیب، درخت تصمیم، رگرسیون، گیربکس تراکتور مسی فرگوسن ۲٤۰