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Vibration based real time brake health monitoring system – A machine learning approach

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Abstract. In an automobile, the brake system is the most important control component which ensures the safety of both passengers and vehicles. The continuous application of the brake causes the system gets faulty due to reasons like wear, mechanical fade, oil leak, etc., These faults or failures need to be monitored using proper monitoring techniques in order to avoid the incidents that may lead to accidents. Thus, the continuous monitoring of the brake system is very much essential for the safety of the vehicle. In this study, an experimental investigation was carried out for monitoring the brake system using vibration signals. An experimental setup which resembles the brake system was fabricated. The vibration signals were acquired under various brake condition such as good and faulty. From the acquired vibration signals, the features were extracted using statistical feature extraction techniques and feature selection was carried out. The selected features were then classifieds using a set of tree family classifiers such as random forest, random tree, LMT and decision tree. The classification accuracy of all the algorithms was compared and discussed.

1. Introduction

In an automobile, the brake system is one of the vital control element which is responsible for reducing the vehicle speed and also to stopping distance. Any failure in the brake system makes an adverse effect on vehicle stability and the traveler's safety. The National Motor Vehicle Causation Survey (NMVCCS) indicated 22 percentages of crashes were occurred because of brake related failure [1]. In 2007, Bayerische Motoren Werke (BMW), recalled over 1, 60,000 SUVs, due to the brake fluid failures. Chrysler took back 60,000 vehicles which were sold out in 2007 because of brake failure [2]. Monitoring of such system for faults will reduce the number of accidents and increase the degree of safety. There is no specific approach for monitoring the failure of the brake system. Hence it is necessary to develop an approach to monitor the brake related faults. The hydraulic brake system may get faulty due to reasons like mechanical fade, pad wear, the insufficient fluid pressure in the master cylinder, oil leak, etc. If these faults were gone unnoticed, the accidents will occur. Hence, the preventive maintenance of the brake system is suggested in order to avoid damage. This is achieved through the continuous Condition Monitoring (CM) process. CM emphases on numerous parameters in which the substantive changes indicating the development of a fault [3,4]. Fault detection is a subfield of condition monitoring which anxieties itself with observing a framework, identifying when a fault has emerged and seen the sort of fault. Fault detection techniques are mainly classified into two types namely signal processing based fault detection (SPBFD) and model-based approach (MBA). In this study SPBFD approach has been focused on the fault diagnosis of hydraulic brake study. In recent years, the vibration signal has been focused on many fault diagnostic study. The hydraulic brake system is producing the

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vibration under different operating conditions. The produced vibration signatures are directly related with the fault conditions. Hence, the vibration signal under various fault conditions has been considered for the learning process in this study.

The statistical feature analysis has been studied for many applications. The features can be extracted from the raw signals using various techniques like visual basic code, LabVIEW graphical program, and MATLAB. In this study, a novel LabVIEW graphical program was used for quarrying the features. Feature selection is required so as to diminish the computational unpredictability. The selection of feature was done with the new approach called Incremental Wrapper-based Subset Selection (IWSS). In this selection method first, the ranking was done with the filter method followed by a wrapper approach [5]. The suggested features were then used for feature classification. Classification is a feature based supervised learning. Many learning algorithms such as decision tree (Gearbox fault diagnosis) [6], best first tree (Brake fault diagnosis) [7], Random Forest (Engine) [8], K Star (Brake fault diagnosis and tool condition monitoring) [9,10], Fuzzy (Centrifugal pump) [11], Logit Boost (Brake fault diagnosis) [12] were reported for many fault diagnosis applications including brake failures. In these studies, the possibility of implementing in real time with real-time experiments is a huge challenge for the researchers. In this study, a real time brake health monitoring has been initiated for monitoring the brake conditions. Figure 1 shows the methodology for monitoring the condition of the brake.

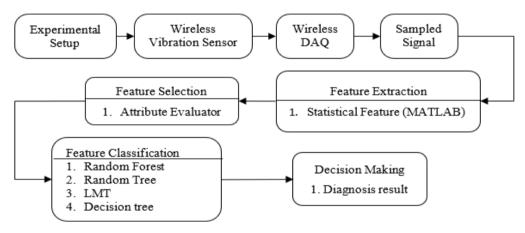


Figure 1. Flow Chart – Brake fault diagnosis procedure

2. Experimental Study

A commercial passenger vehicle (Maruti Zen) brake system was considered for the experimental study (Figure. 2). The real vehicle was used for the test. A fabricated setup with a free roller was used to drive the wheel. The drive shafts were allowed to run at a constant speed (331 rpm) over the free wheel on the test setup. Piezoelectric type shear uniaxial accelerometer (500 g range, 10.26 mV/g sensitivity) was used for acquiring the vibration signals and a wireless data acquisition hardware (DAQ - Model NI 9234, 4 channel, 51.2 kilo Samples /sec) through a LabVIEW graphical program. The following frequently occurring faults namely, Disc Brake Pad Wear Even Inner (DBPEI), Disc Brake Pad Wear Even Inner and Outer (DBPEIO), Disc Brake Pad Wear Uneven Inner (DBPUEI), Disc Break Pad Wear Uneven Inner and Outer (DBPUEIO), Reservoir Leak (RL), Brake Oil Spill on the Disc (BOS) and a Brake without any fault (GOOD) were considered for the simulation. Once the faults were simulated, the vibration signals were captured from the LMV brake system with the following settings:

- 1) Sample length: 12000 chosen arbitrarily
- 2) Observation frequency: 25 kHz (As per Nyquist sampling theorem)
- 3) Number of samples: 65

4) Wheel speed: 331 rpm

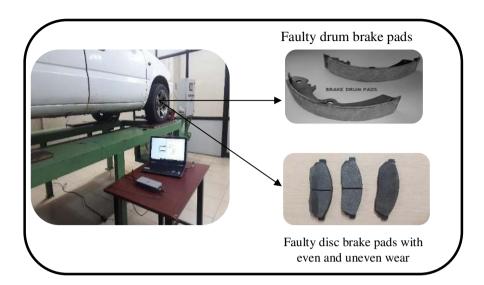


Figure. 2. Experimental Setup – Hydraulic Brake system

3. Result and Discussion

The vibration signal was acquired under different fault condition from the experimental test setup. The acquired vibration signals were extracted using various statistical feature extraction techniques. Table 1 shows the extracted sampled statistical features from the acquired vibration signal. After the feature extraction, the IWSS attribute evaluator and ranker search feature selection method was carried out. And the selected features were classified using different classification techniques such as random forest, random tree, LMT and decision tree.

Table 1. Sampled extract	ed statistical fea	iture from the acquire	d vibration signal
Feature	Values	Feature	Values
Mean	0.05223	Maximum	0.141155
Standard Deviation	0.412191	Minimum	1.836311
Variance	0.169901	Range	-1.39755
Kurtosis	3.233003	RMS	3.233864
Median	0.046706	Impulse factor	0.41547
Mode	0.138532	Shape factor	35.15817
Skewness	0.05223	K factor	7.954618
Standard Error	0.762931	Total	12000
Sum	626.7599		

Table 1. Sampled extracted statistical feature from the acquired vibration signal

3.1. Classification using Random Forest

By using the random forest, the selected statistical features were classified. A random forest is a collaborative approach for structure an expansive number of decision trees at the preparation time and yielding a strategy for ordering the individual tree. The random forest starts with a standard machine learning method, a decision tree in which information is entered. As the information brings down, this tree gets assigned to smaller and smaller subsets. The overall classification accuracy of the random forest algorithm is 93.19%.

Misclassification details are presented as misperception matrix. Table 2 demonstrates the misperception matrix for the random forest. In the misperception matrix, the primary line first component (A) speaks to the absolute number of data points relating toward "GOOD(GD)" condition

of the brake system. The primary component in the first column (A) speaks how many are effectively classified as 'A' condition. Among the 65 data points, 56 are effectively classified. Nine data point was misclassified as "Disc Pad Wear Even Inner (DBPEI)" belongs to 'B' condition. Similarly, the third element in the third column (C) represents "Disc Pad Wear Even Inner & Outer (DBPEIO)" condition. Among the 65 data, all are effectively classified and there are no misclassified condition data points. Similarly, the other elements in the third row represent the miss-classification details. In the third row other than the third element, all other values are zero so there is no misclassification. The same way the classification accuracy can be calculated.

Table 2. Misperception Matrix for random forest

Table 3. Misperception Matrix for random tree

Category	a	b	c	d	e	f	g	_	Category	а	b	c	d	e	f	g
a	56	9	0	0	0	0	0		a	51	14	0	0	0	0	0
b	9	56	0	0	0	0	0		\boldsymbol{b}	11	54	0	0	0	0	0
\boldsymbol{c}	0	0	65	0	0	0	0		\boldsymbol{c}	0	0	65	0	0	0	0
d	0	0	0	57	0	6	2		d	0	0	0	58	0	5	2
\boldsymbol{e}	0	0	0	0	64	0	1		\boldsymbol{e}	0	0	0	0	65	0	0
f	0	0	0	2	0	63	0		f	0	0	0	8	0	57	0
\boldsymbol{g}	0	0	0	2	0	0	63		g	0	0	0	1	0	0	64

a - GOOD; b- DBPEI; c – DBPEIO; d – DBPUEI; e – DBPUEIO; f – BOS; g - RL.

3.2. Classification using Random tree

The random tree algorithm can manage both arrangement and regression issues. The random tree is an accumulation (outfit) of tree indicators that is called a forest. Using feature selection method all the sixteen contributing features were selected for the random tree classification. The selected features were classified using a random tree. Table 3 shows the misperception matrix of a random tree. The maximum classification accuracy of a random tree is 90.99%.

3.3. Classification using Logistic Model tree (LMT)

Logistic Model tree (LMT) is a well-known tree induction and linear logistic regression approach for classification. LMT made up of the target variables (both binary and multiclass), Missing and numeric values. The outcome of LMT in the form of a tree which encompass with binary leaves on numerical attributes. Using feature selection method top eleven features were contributed for the LMT classification. The selected features were classified using LMT. Table 4 shows the misperception matrix of LMT. The LMT produces the maximum classification accuracy of 93.85 %.

3.4. Classification using Decision tree

A decision tree is a tree-based knowledge structure used to select features through the classification rules. J48 is an classification algorithm used to generate a decision tree. Using feature selection method top nine features were contributed for the decision tree classification. The selected features were classified using a decision tree. Table 5 shows the misperception matrix of the decision tree. The decision tree produces the maximum classification accuracy of 92.09 %.

Table 4. Misperception Matrix for LMT.

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Category	а	b	c	d	e	f	g
a	58	7	0	0	0	0	0
b	10	55	0	0	0	0	0
\boldsymbol{c}	0	0	65	0	0	0	0
d	0	0	0	58	0	5	2
\boldsymbol{e}	0	0	0	0	64	0	1
f	0	0	0	1	0	64	0
g	0	0	0	2	0	0	63

Table 5. Misperception Matrix for Decision tree

Category	а	b	с	d	e	f	g
a	56	9	0	0	0	0	0
\boldsymbol{b}	8	57	0	0	0	0	0
\boldsymbol{c}	0	1	64	0	0	0	0
d	0	0	0	57	0	6	2
e	0	0	0	0	64	0	1
f	0	0	1	4	0	59	1
g	0	0	0	3	0	0	62

4. Comparative study

In this study, the acquired vibration signals were extracted using the statistical technique. The extracted features were classified using different classifier such as a Random Tree, Random Forest, LMT and Decision Tree classification algorithm. Figure 3 shows the overall classification accuracy of various feature classifiers. The comparative study also reveals the maximum classification accuracy among the considered classifiers. The LMT produced the maximum accuracy of 93.85% (427 out of 455 data points) in just 0.07 seconds. The random forest produced the accuracy of 93.19% (424 out of 455 data points) in 0.09 seconds. The decision tree produced classification accuracy as 92.088% (419out of 455) and the random tree produced classification accuracy as 90.99 % (414out of 455). The computational time of best first tree and the random forest is high compare to LMT. The LMT produced maximum classification accuracy as 93.85%.

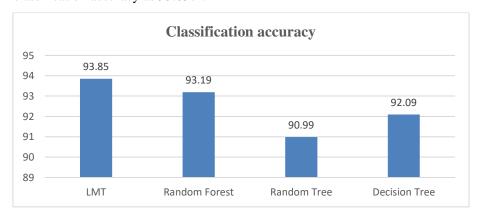


Figure. 3. Overall classification accuracy

5. Conclusion

In the paper, the statistical feature extraction techniques were discussed for the hydraulic brake fault diagnosis study through the vibration signal. Random forest, random tree, LMT and decision tree classifiers were used for classifying the faults. In this study, six fault conditions along with the good condition of a brake system were considered. The vibration signals occurred under all simulated conditions was acquired using a piezoelectric type accelerometer. Using statistical feature extraction techniques the acquired vibration signals were extracted. The attribute evaluator and effect of number of features methods used for feature selection. Then the selected features were classified using Random forest, random tree, LMT and decision tree classifiers. The experimental study shows that the LMT produced better classification accuracy of 93.85% compare to the other classifiers. This study can be extended on a real road condition for monitoring the health status of the hydraulic brake system. This detailed investigation will also provide a pathway for making and on-board diagnostic (OBD) module for finding the brake related faults well in advance.

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