Application of Meta family Classifiers for monitoring hydraulic brake system using vibration based statistical learning approach

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Abstract. In the modern days, use of vehicles is increasing rapidly. It is very essential that the vehicle must have a good control mechanism which ensures the safety of the vehicle. The brake system in automobile is one of the important control element which needs to be monitored. The unconditional brake leads to catastrophic failures. Hence, the brake system should be monitored regularly. An experimental study is proposed for the brake system monitoring using vibration signals. The vibration signals are captured under all possible brake conditions. The hidden information in the vibration are extracted as statistical features. We carry out the feature selection. Classification using the selected features is the final step in machine learning (ML). Meta family classifiers are used for the study. Among the considered classifiers, Bagging algorithm produced 80.8 % accuracy for monitoring the brake condition.

1. Introduction

The brake is one of control element which helps to avoid accidents by controlling the vehicle. The brake components such as brake calliper, brake pads, ad discs are hided inside and is very difficult to monitor during operation. The only possible way is to inspect using the trusted repair facility under idle condition of the vehicle. However, there is a huge scope for the online monitoring system using which the system malfunction can be identified through advanced technological development. Many researchers are performing the monitoring study on the brakes. A recent study highlighted the frequency of accidents survey. Referring Figure 1, among the total accidents, brake related failures occupy 17%. This motivates us for developing a study for monitoring the brake condition.

In this study vibration signatures captured under all fault conditions are used for the analysis. The captured vibration signatures are time domain in nature. It is processed using the feature based learning. In this study, the hidden information is extracted using the visual basic code. The extracted information is segregated based on its contribution. The selected features can be classified using supervised learning techniques, such as, decision tree [2], best first tree [3], Random Forest [4], Bayes and Naïve Bayes [5], Support Vector Machine [6, 7, 8], Fuzzy [9], Logit Boost [10], Sequential minimal optimization (SMO) and Multi-layer perceptron (MLP) [11] were reported for many fault diagnosis applications including brake failures.
In this study, real time brake health monitoring has been initiated for monitoring the brake conditions. Vibration based health monitoring through various machine learning algorithms such as bagging tree, Iterative classifier optimizer, logit boost, filtered classifier and random committee is carried out. The Figure 2 shows the methodology followed in this study.

![Flow Chart – Brake fault diagnosis procedure](image)

2. Experimental Study

A Light Motor Vehicle (Maruti Zen) is allowed to run on an fabricated road simulator setup which consists a free roller test setup with free roller is considered for the study (Fig. 3).
The drive wheel is allowed to run at (30 kmph) [1]. An uniaxial accelerometer (with 10.26 mV/g sensitivity) was used to assimilate the signal through a wireless data acquisition hardware (NI 9234). The vibration is acquired under the frequently occurring faults namely, Inner and outer brake pad wear, uneven pad wear in inner and outer brake pad, reservoir leak, oil spill on the disc with the following settings: Observation frequency: 25 kHz; Wheel speed: 331 rpm.

### 3. Feature Extraction and selection

The process of extracting the hidden information in the vibration signals is feature extraction. The visual basic code is used for extracting the hidden information as features. A set of twelve features were extracted from the raw signals (Table 1). The contributing features alone essential for the classification process. Hence, a ranker search feature selection method is proposed.

| Feature               | Value     |
|-----------------------|-----------|
| Mean                  | 0.007105  |
| Standard Error        | 0.003026  |
| Median                | 0.003994  |
| Mode                  | 0.035336  |
| Standard Deviation    | 0.331472  |
| Sample Variance       | 0.109874  |
| Kurtosis              | -0.09342  |
| Skewness              | 0.048353  |
| Range                 | 2.46823   |
| Minimum               | -1.29315  |
| Maximum               | 1.175077  |
| Sum                   | 85.26126  |
| Count                 | 12000     |

### 4. Results and Discussion

The selected features were classified using different Meta Family classifiers such as Bagging, Iterative Classifier Optimizer, Classification via Regression, Logit Boost, Random Committee, Filtered Classifier.
4.1. Feature Classification using Bagging tree

A Bagging classifier is an ensemble meta-estimator that fits base classifiers each on random subsets of the original dataset and then sum up their individual predictions to form a final prediction [10]. The data is trained through bootstrap sampling and the tree is constructed. The selected features were classified using the Bagging tree. The classification details have been given as misperception matrix as shown in Table 2. Table 3 shows the overall classification accuracy.

In the misperception matrix, the first-row represents the number of data points corresponding to ‘BOS (Brake Oil Spill)’ condition. The first element in the first column refers the data points that are correctly classified as ‘BOS’ condition. Among the 80 data points, 57 are correctly classified as BOS. Non diagonal elements in each column represent miscategorised data. The five data points are miscategorised as “DBPEI (Disc Pad Wear Even Inner)” , three data points are miscategorised as “DBPUEI (Disk Brake Pad Wear (Uneven) Inner)”, twelve data points are misclassified as “RL (Reservoir Leak)” and 1 data point is miscategorised as “DBPEIO (Disk Brake Pad Wear (Even) Inner &Outer)”. The same way the classification details and the classification accuracy is presented. Among the 560 data points, 107 data points were misclassified. Hence the overall classification accuracy is 80.89 %.

Table 2. Misperception Matrix for Bagging classifier (Statistical)

| BOS | DBPEI | GOOD | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|-----|-------|------|--------|---------|----|---------|--------------|
| 57  | 5     | 0    | 3      | 2       | 12 | 1       | BOS          |
| 0   | 79    | 0    | 1      | 0       | 0  | 0       | DBPEI        |
| 0   | 0     | 80   | 0      | 0       | 0  | 0       | GOOD         |
| 3   | 1     | 0    | 47     | 0       | 13 | 16      | DBPUEI       |
| 0   | 0     | 0    | 0      | 78      | 2  | 0       | DBPUEIO      |
| 18  | 0     | 0    | 10     | 6       | 43 | 3       | RL           |
| 5   | 0     | 0    | 5      | 0       | 1  | 69      | DBPEIO       |

BOS (Brake Oil Spill); DBPEI ( Disc Pad Wear (Even) Inner ); GOOD ( Brake without any Fault); DBPUEI ( Disk Brake Pad Wear (Uneven) Inner ); DBPUEIO ( Disk Brake Pad Wear (Even) Inner & Outer ); RL ( Reservoir Leak); DBPEIO (Disk Brake Pad Wear (Even) Inner &Outer).

Table 3. Classification accuracy

| Correctly Classified Instances | 453 | 80.89 % |
|--------------------------------|-----|---------|
| Incorrectly Classified Instances | 107 | 19.11 % |

4.2. Classification using Iterative Classifier Optimizer

This method chooses the best number of iterations for an Iterative Classifier such as Logit Boost using a percentage split evaluation through optimization [11]. The classification accuracy and the Misperception Matrix is shown in Table 4 and Table 5 respectively. Iterative classifier categorizes 450 data points correctly with accuracy 80.36 %.

Table 4. Classification accuracy

| Correctly Classified Instances | 450 | 80.36 % |
|--------------------------------|-----|---------|
| Incorrectly Classified Instances | 110 | 19.64 % |
Table 5. Misperception Matrix for Iterative Classifier Optimizer (Statistical)

| BOS  | DBPEI | GOOD  | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|------|-------|-------|--------|---------|----|--------|---------------|
| 58   | 1     | 0     | 6      | 1       | 11 | 3      | BOS           |
| 0    | 78    | 0     | 1      | 0       | 0  | 1      | DBPEI         |
| 0    | 0     | 80    | 0      | 0       | 0  | 0      | GOOD          |
| 5    | 1     | 0     | 46     | 0       | 14 | 14     | DBPUEI        |
| 1    | 0     | 0     | 0      | 76      | 3  | 0      | DBPUEIO       |
| 14   | 0     | 0     | 11     | 6       | 48 | 1      | RL            |
| 5    | 0     | 0     | 9      | 0       | 2  | 64     | DBPEIO        |

4.3. Feature Classification via Regression

The classification is done using a regression model for each class [12]. The classification accuracy is found as 79.82 % (447 data is correctly categorized out of 560 data). The correctly categorized data is shown in Table 6 and the misperception matrix is shown in Table 7.

Table 6. Classification accuracy

| Correctly Categorized data | 447 | 79.82 % |
|----------------------------|-----|---------|
| Incorrectly Categorized data | 113 | 20.18 % |

Table 7. Misperception Matrix for Classification via Regression (Statistical)

| BOS  | DBPEI | GOOD  | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|------|-------|-------|--------|---------|----|--------|---------------|
| 56   | 3     | 0     | 3      | 1       | 15 | 2      | BOS           |
| 0    | 79    | 0     | 1      | 0       | 0  | 0      | DBPEI         |
| 1    | 0     | 79    | 0      | 0       | 0  | 0      | GOOD          |
| 3    | 1     | 0     | 47     | 0       | 11 | 18     | DBPUEI        |
| 1    | 0     | 0     | 1      | 76      | 2  | 0      | DBPUEIO       |
| 15   | 0     | 0     | 15     | 5       | 40 | 5      | RL            |
| 1    | 0     | 0     | 7      | 0       | 2  | 70     | DBPEIO        |

4.4. Feature classification using LogitBoost

LogitBoost classifies the data using additive logistic regression as multi-class problems [9]. The logit boost algorithm is able to categorize 445 data with 79.46 % accuracy. The classification accuracy and the misperception matrix is given in Table 8 and Table 9 respectively.

Table 8. Classification accuracy

| Correctly Categorized data | 445 | 79.46 % |
|----------------------------|-----|---------|
| Incorrectly Categorized data | 115 | 20.54 % |

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| BOS | DBPEI | GOOD | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|-----|-------|------|--------|---------|----|--------|---------------|
| 58  | 2     | 0    | 6      | 1       | 11 | 2      | BOS           |
| 0   | 78    | 0    | 1      | 0       | 0  | 1      | DBPEI         |
| 0   | 0     | 80   | 0      | 0       | 0  | 0      | GOOD          |
| 5   | 1     | 0    | 44     | 0       | 14 | 16     | DBPUEI        |
| 1   | 0     | 0    | 0      | 76      | 3  | 0      | DBPUEIO       |
| 14  | 0     | 0    | 11     | 6       | 46 | 3      | RL            |
| 5   | 0     | 0    | 10     | 0       | 2  | 63     | DBPEIO        |

### Table 9. Misperception Matrix for LogitBoost

| BOS | DBPEI | GOOD | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|-----|-------|------|--------|---------|----|--------|---------------|
| 57  | 2     | 0    | 4      | 2       | 14 | 1      | BOS           |
| 0   | 79    | 0    | 1      | 0       | 0  | 0      | DBPEI         |
| 0   | 0     | 80   | 0      | 0       | 0  | 0      | GOOD          |
| 4   | 1     | 0    | 48     | 1       | 12 | 14     | DBPUEI        |
| 0   | 0     | 0    | 2      | 76      | 2  | 0      | DBPUEIO       |
| 19  | 0     | 0    | 13     | 5       | 41 | 2      | RL            |
| 4   | 0     | 0    | 17     | 0       | 1  | 58     | DBPEIO        |

### 4.5. Feature Classification using Random Committee

Random Committee is an ensemble of randomizable base classifiers which are built using the different random number seed. The average predictions of all the individual base classifiers will be the final prediction. The final accuracy is presented in the form of misperception matrix as shown in Table 10 and the detailed accuracy is shown in Table 11.

#### Table 10. Classification accuracy

| Incorrectly Categorized data | 439 | 78.39 % |
|-----------------------------|-----|---------|
| Incorrectly Categorized data | 121 | 21.61 % |

| BOS | DBPEI | GOOD | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|-----|-------|------|--------|---------|----|--------|---------------|
| 57  | 2     | 0    | 4      | 2       | 14 | 1      | BOS           |
| 0   | 79    | 0    | 1      | 0       | 0  | 0      | DBPEI         |
| 0   | 0     | 80   | 0      | 0       | 0  | 0      | GOOD          |
| 4   | 1     | 0    | 48     | 1       | 12 | 14     | DBPUEI        |
| 0   | 0     | 0    | 2      | 76      | 2  | 0      | DBPUEIO       |
| 19  | 0     | 0    | 13     | 5       | 41 | 2      | RL            |
| 4   | 0     | 0    | 17     | 0       | 1  | 58     | DBPEIO        |

#### Table 11. Misperception Matrix for Random Committee

4.6. Feature Classification using Filtered Classifier

In this classifier, an arbitrary filter is used to process the data. The filter is decided based on the training and testing instances. The classification accuracy is processed with the filter without changing its original structure [13]. The filtered classifier produced the classification the maximum accuracy as 77.32 %. Table 12 shows the classification summary where as Table 13 shows the misperception matrix for filtered classifiers.
Table 12. Classification accuracy

| Classified Instances          |     |
|-------------------------------|-----|
| Correctly Classified Instances| 443 |
| Incorrectly Classified Instances| 127 |

Table 13. Misperception Matrix for Filtered Classifier

|     | BOS  | DBPEI | GOOD | DBPUEI | DBPUEIO | RL | DBPEIO | classified as |
|-----|------|-------|------|--------|----------|----|--------|---------------|
| 60  | 5    | 0     | 4    | 2      | 8        | 1  | 2      | BOS           |
| 0   | 78   | 0     | 0    | 0      | 0        | 2  | 0      | DBPEI         |
| 0   | 0    | 80    | 0    | 0      | 0        | 0  | 1      | GOOD          |
| 6   | 1    | 32    | 0    | 0      | 10       | 31 | 0      | DBPUEI        |
| 0   | 0    | 0     | 0    | 77     | 3        | 0  | 0      | DBPUEIO       |
| 23  | 0    | 12    | 5    | 34     | 6        | 1  | 72     | RL            |
| 4   | 0    | 0     | 3    | 0      | 1        | 72 | 0      | DBPEIO        |

4.7. Comparative study

Among the considered six meta-family classifiers, the bagging classifier produced maximum accuracy. Table 14 shows the comparative results of all meta-family classifiers study shows the statistical feature with Bagging classifier, produced better classification accuracy 80.89% compared to the other classifiers. The obtained accuracy details can be validated using the detailed accuracy as shown in Table 15. True positive (TPR) rate and False positive (FPR) rate must be one and zero respectively. Referring Table 15, the average of TPR is 0.809 which is acceptable in the real time study.

Table 14. Comparative study with effect of speed with different Meta classifiers

| Name of the classifier         | Accuracy (%) |
|-------------------------------|--------------|
| Bagging                       | 80.89        |
| Iterative classifier optimizer| 80.36        |
| Classification via regression | 79.82        |
| Logit boost                   | 79.46        |
| Random committee              | 78.39        |
| Filtered classifier           | 77.32        |

Table 15. Detailed Accuracy by Class

|     | TP Rate | FP Rate | Precision |
|-----|---------|---------|-----------|
| 60  | 0.713   | 0.054   | 0.687     |
| 0   | 0.988   | 0.013   | 0.929     |
| 1.000| 0.000   | 0.000   | 1.000     |
| 0.588| 0.040   | 0.712   |
| 0.975| 0.017   | 0.907   |
| 0.538| 0.058   | 0.606   |
| 0.863| 0.042   | 0.775   |
| Wt. Avg | 0.809 | 0.032 | 0.802 |
5. Conclusion

In this study, the required information is extracted from the captured vibration signals using visual basic code. The best first search method was used for selecting features. Various meta-family classifiers were used for the classification. The observed experimental study shows that the Bagging tree produced the maximum classification accuracy as 80.89 % compared to the other meta-family classifiers. This study can be extended on a real road condition under various operating speed for monitoring the health condition of the brake system. This detailed investigation helps to develop an on-board diagnostic (OBD) module for finding the brake related faults well in advance in vehicles.

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