Fault Identification and Classification in Motorcycle Engine Using Acoustic Emission Signal and Machine Learning Techniques

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Abstract. When the engine of a motor-cycle goes into its defective stage, it affects the performance of the motorcycle and hence decreases its efficiency. Therefore, for the smooth running of the motorcycle, the health monitoring of its engine is very essential which increases its life and efficiency. Acoustic emission signature from the motorcycle engine is a measuring parameter to identify the faults in the engine. During its healthy stage, the motor vehicle engines generate a specific acoustic emission signature. But when the engine goes into the defective stage then a significant change in these acoustic emission signature occurs. This change can be used to diagnose the defects in motor engines. The objective of this work is to diagnose the faults in the motorcycle engine using statistical and time-frequency analysis of the acoustic emission signal and then classify the faults using machine learning classifiers. In this experimental work, an instrumentation system is used to acquire the acoustic emission signal from the engines under different conditions. Then the statistical parameters from the acoustic signatures are computed and compared to identify the faults. The wavelet analysis of the acquired acoustic emission signal is also done to diagnose the faults. The classifiers are used to classify the faults by using the statistical parameters as its input. At first stage, the experimental set-up is developed to acquire acoustic emission signatures from the healthy and defective engines. In second stage, signal analysis using statistical and wavelet signal processing technique is done to identify the faults in the engine and in the third stage, the faults in the engine are classified using the machine learning techniques. The result of the proposed work shows that the classification accuracy of the random forest classifier is better than the decision tree classifier. The novelty of the proposed work is that the wavelet analysis along with machine learning technique is used to diagnose the faults in the engine

Keywords: Motorcycle engine, condition monitoring, acoustic emission, statistical analysis, wavelet transform, machine learning classifier.

1. Introduction
The continuous monitoring of engine health of two- wheelers is very essential to maintain its performance, less fuel consumption and long life. Acoustic and vibration signatures generated by engines are the two measuring parameters for the fault identification in the motorcycle engine. The comparison of the acoustic emission signals generated by the healthy and defective engines under test can be compared to detect the faults. Acoustic emission signal monitoring is one of the popular technique used in many cases for condition monitoring of machine faults [1,2]. The time or statistical signal processing technique can be used for engine fault diagnosis. In this technique the statistical parameters from the measured signals are compared and analyzed for fault diagnosis [3]. Other than time analysis,
the frequency and time-frequency signal processing technique can be used to diagnose the faults in machines or motor engines. Anami B.S. et al. have explained in their research the utilization of wavelet analysis for condition monitoring [4]. In some literature, the time and frequency analysis of vibration signal is deployed for fault detection [5]. The wavelet transform analysis may be continuous or discrete. P.K. Kankar et al. have explained the utilization of continuous wavelet transform (CWT) scalograms to detect the faults [6]. The principle, technique and application of wavelet transform can be found in details in some literature [7]. B. Li and his team have explained how gear faults can be diagnosed with the usage of multi scale morphological filters [8]. The application of neural network is another good option which can be used for machine fault diagnosis. The use of neural network and artificial neural network for machine fault diagnosis has been found in many past works [9], [10], [11]. In current scenario, the machine learning techniques are widely used for the purpose of classification. In many literatures the machine learning techniques have been employed for the machine fault monitoring and classification [12], [13], [14], [15].

To carry the proposed experiment, three motor-cycle engines under different conditions are used. For this purpose, one healthy engine and two defective engines are used. The proposed experiment is employed in three phases. In first phase, the statistical analysis is done to identify the faults. In second phase, the wavelet analysis is done to identify the faults more precisely. In third phase, machine learning techniques are employed to diagnose the faults. These machine learning techniques are used to classify the faults in motorcycle engine.

2. Experimental work

The experiment is done using the Honda Activa 3G motorcycle engine. Three different engines of same make and model is used for this purpose. The details about the engine type and specification is tabulated in Table 1. One defect-free good condition engine (GE) and two faulty engines FE-I (Travelled distance is 35025 KM) and FE-II (Travelled distance is 20156 KM) are used for the experiment. A hand-held sound level meter, B & K 2270 is used to collect the acoustic emission from the engines. The data is acquired at the sampling rate of 52 KHz. The experimental set-up with the motorcycle and hand-held sound level meter is shown in Figure 1. The bore and piston of the engine used in the proposed work are shown in Figure 2. The acquired acoustic signal and its PSD from the good condition engine (GE), Faulty vehicle engine (FE-I) and faulty vehicle engine (FE-II) are appeared in Figure 3, Figure 4 and Figure 5 respectively. The data acquisition is done at the workshop in a very quiet environment where there is no other sound interference. The hand-held sound meter is placed properly with a holding stand. The instrument is properly calibrated and installed before its use to take the readings of the measurement.

Figure 1. Experiment set-up with motorcycle and hand-held sound meter
Figure 2. The bore and piston of the motorcycle engine.

Table 1. Engine specification.

| Sl. No | Specification | Details            |
|--------|---------------|--------------------|
| 1      | Make          | Honda Activa 3G    |
| 2      | Engine type   | Air-Cooled, 4 stroke, SI Engine |
| 3      | Bore          | 50 mm              |
| 4      | Stroke        | 55.6 mm            |
| 5      | Displacement  | 109.6 cc           |

Figure 3. The acoustic emission signal acquired from the good condition engine (GE); (a) time scale, (b) Power spectral density.
Figure 4. The acoustic emission signal acquired from the faulty engine (FE-I); (a) time scale, (b) Power spectral density.

Figure 5. The acoustic emission signal acquired from the faulty engine (FE-II); (a) time scale, (b) Power spectral density.

Figure 6. Continuous wavelet transform scalograms; (a) good condition engine (GE), (b) faulty engine (FE-I), (c) faulty engine (FE-II).
3. Results and Discussion

Initially the statistical signal processing technique is deployed on the acoustic emission signals collected from the engines under test. The statistical parameters of the acoustic emission signals are computed by using the mathematical formulas given in equation 1 to equation 11 as given below and then the computed statistical parameters have been compared.

\[
\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (X_i - \mu)^2}
\]  

(1)

\[
\text{Mean} = \mu = \frac{1}{N} \sum_{i=1}^{n} X_i
\]  

(2)

\[
\text{Peak Level} = P_v = \frac{1}{N} [\text{Max}(X_i) - \text{Min}(X_i)]
\]  

(3)

\[
\text{Crest Factor} = C = \frac{P_v}{\text{RMS}}
\]  

(4)

\[
\text{Skewness} = S = \frac{1}{N} \sum_{i=1}^{n} \left( \frac{X_i - \mu}{\text{RMS}} \right)^3
\]  

(5)

\[
\text{Kurtosis} = K = \frac{1}{N} \sum_{i=1}^{n} \left( \frac{X_i - \mu}{\text{RMS}} \right)^4
\]  

(6)

\[
\text{variance} = \sigma^2 = \frac{1}{N} \sum_{i=1}^{n} (X_i - \mu)^2
\]  

(7)

\[
\text{Standard Deviation} = \sigma = \left( \frac{1}{N-1} \sum_{i=1}^{n} (X_i - \mu)^2 \right)^{\frac{1}{2}}
\]  

(8)

\[
\text{Clearance Factor} = \text{CI}_f = \frac{P_v}{\frac{1}{N} \sum_{i=1}^{n} |X_i|}
\]  

(9)

\[
\text{Impulse Factor} = \text{I}_f = \frac{P_v}{\frac{1}{N} \sum_{i=1}^{n} |X_i|}
\]  

(10)

\[
\text{Shape Factor} = \text{S}_f = \frac{1}{\text{RMS}} \frac{1}{\frac{1}{N} \sum_{i=1}^{n} |X_i|}
\]  

(11)

Table 2 has projected the statistical parameter values which are computed from the acoustic emission signals, collected from the engines under test. The statistical parameter values for the healthy and faulty engines are compared. From the table, it is clearly observed the change in statistical parameter data of the faulty engines in comparison to the healthy engine. For example, the kurtosis for the healthy vehicle (GE) is 3.85 but for the FE-I it is 9.04 and for FE-II it is 5.75. Similarly, the RMS value for the GE is 0.01 and for the FE-I and FE-II, it is 0.03 and 0.02 respectively. Similarly, there are changes in the other statistical values in faulty engines as compared to the good condition engine. These changes in values indicate the presence of the faults in the faulty engines under test.

These statistical parameter values are used in the fault classification techniques later in this work. Though statistical analysis clearly indicates about the fault present in engines but the wavelet analysis is more informative about the defects. Therefore, the wavelet analysis is done on the acquired acoustic emission signals. It is a time-frequency analysis. In this signal processing technique, Morlet wavelet is used. From the scalograms of the wavelet transform it is observed that the clear prominent and periodical strips appeared in the case of defective vehicle engines as compared to the healthy engine. The change in pattern is clearly observed in the scalograms. The wavelet scalograms for the acoustic signals acquired from the good condition engine and faulty engines are shown in Figure 6.
Table 2. The Comparison of statistical data

| Sl. No. | Static Parameters | Good Condition Engine (GE) | Faulty Condition Engine (FE-I) | Faulty Condition Engine (FE-II) |
|---------|-------------------|-----------------------------|-------------------------------|-------------------------------|
| 1       | RMS               | 0.01                        | 0.03                          | 0.02                          |
| 2       | Peak Frequency    | 85.25                       | 74.12                         | 42.35                         |
| 3       | Peak Value        | 0.07                        | 0.17                          | 0.14                          |
| 4       | Crest factor      | 5.77                        | 6.64                          | 7.05                          |
| 5       | Skewness          | -0.005                      | -0.256                        | 0.122                         |
| 6       | Kurtosis          | 3.85                        | 9.04                          | 5.75                          |
| 7       | Standard Deviation| 0.013                       | 0.026                         | 0.020                         |
| 8       | Clearance Factor  | 716.03                      | 665.97                        | 624.78                        |
| 9       | Impulse Factor    | 7.43                        | 10.74                         | 9.45                          |
| 10      | Shape Factor      | 1.28                        | 1.61                          | 7.43                          |
| 11      | SNR               | 0.83                        | 0.78                          | 0.75                          |

Two machine learning techniques are used for the classification of motorcycle engine faults. The algorithms used for this purpose are Random forest and Decision tree. The statistical data, computed earlier are used as the inputs to the machine learning algorithms to find the type of faults in engines. The five statistical parameters are considered for the machine learning process. These parameters are kurtosis, skewness, peak frequency, RMS and crest factor. For this reason, 168 number of training samples considered for the machine learning process. 56 training samples for each that is for the healthy engine (GE), faulty engine (FE-I) and faulty engine (FE-II). The confusion matrix is evaluated for the used machine learning algorithms, that is for the Random forest and decision tree classifiers and are tabulated in Table 3 and Table 4 respectively.

From the confusion matrix of the Random forest, it is noticed that the classification is 100% for FE-I engine, but it is slightly misclassified for GE and FE-II engines. The classification accuracy is good. From the confusion matrix of the Decision tree, it is noticed that the accuracy is high for the FE-I engine, but the misclassification rate is higher as compare to Random forest for fault identification. Therefore, random forest classifier has been found better in comparison to decision tree classifier for this present experimental work.

Table 3. Confusion matrix for random forest classifier.

| Engine Class | GE  | FE-I | FE-II |
|--------------|-----|------|-------|
| GE           | 55  | 0    | 1     |
| FE-I         | 0   | 56   | 0     |
| FE-II        | 1   | 0    | 55    |
Table 4. Confusion matrix for decision tree classifier.

| Engine Class | GE  | FE-I | FE-II |
|--------------|-----|------|-------|
| GE           | 41  | 0    | 15    |
| FE-I         | 0   | 56   | 0     |
| FE-II        | 9   | 1    | 46    |

4. Conclusion

This paper shows the use of acoustic emission signal processing technique for the fault detection in motorcycle engine. Statistical parameter values of the acoustic signature alter significantly when a defect occurs in the vehicle engine. Though statistical analysis identifies the faults but the wavelet analysis is more informative to identify the faults in the motorcycle engines. The faults are classified successfully by using the machine learning techniques. The Random forest classifier has been found better as compare to the decision tree classifier for engine fault classification. The novelty of the proposed work is that the wavelet analysis along with machine learning technique is used to diagnose the faults in the engine. The proposed method can be extended to condition monitoring of any rotating machine. This idea provides lot of scopes for the under graduate (UG) and post graduate (PG) students. By using the proposed idea, the UG and PG students may carry out their research in the field of condition monitoring and fault diagnosis.

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