Knock is an undesirable event that causes most of the abnormal combustion in spark ignition (SI) engines. In this paper, a novel knock intensity diagnosis method for SI engines by vibration analysis based on the ensemble empirical mode decomposition (EEMD) is proposed. First, the vibration signal measured from the test SI engine cylinder head is decomposed by the EEMD. Because the EEMD can eliminate the mode mixing problem existing in the classic empirical mode decomposition (EMD), the EEMD method can provide an improved time-scale decomposition result with a clearly physical meaning for the individual IMFs. Second, a series of temporal and frequency statistical characteristics are calculated from the IMF component in which the knock characteristics appear including peak value, standard deviation, shape factor, kurtosis, crest factor, etc. Finally, the obtained SI engine knock characteristics vectors are input to the classifiers to accomplish knock intensity identification. Experimental results indicate that the proposed method can achieve high knock intensity diagnosis accuracy even under the condition of a very high engine speed of 5800 rpm.

1. Introduction

Engine knock causes many issues in spark ignition (SI) engines due to the abnormal combustion, such as excess pollution, passenger disturbance due to the metallic noise associated with knock and even the destruction of engine parts in severe knock conditions [1]. Therefore, it is critical to develop an effective approach for diagnosis of the intensity of knocking combustion.

In most cases, knock is detected from signals recorded in engines. These signals are especially acquired from a cylinder pressure or a block vibration sensor [2]. Cylinder pressure oscillations clearly indicate the condition inside the combustion chamber; however, they are not viable for production engines due to the high cost of the sensor. Measuring the vibration level of the engine block to determine the occurrence of knock is an indirect detection method. This type of nonintrusive vibration sensor has many advantages, such as easy installation, excellent reliability and low-cost [3-5]. But the engine vibrations induced by knocking combustion have to be detected against a complex background of heavy noise and other vibrations, especially at a high engine speed. Consequently, the intensity of knock is not readily obtained from the vibration data unless sophisticated signal processing techniques are employed.

To quantify the knock intensity, researches have defined many knock intensity factor (KIF) to describe knock state. The KIF has popularly been defined from the average-energy point of view in previous studies. The advantage of average-energy based method is that it is equivalent in both the frequency and time domains [6]. For instance, the data are band-pass filtered within the range of knock characteristics frequency, and then integrated during knocking, while a proper threshold is set to detect knock [7]. Unfortunately, such knock intensity diagnosis method cannot work reliable for vibration data when the engine running at a high speed, because a simply comparison with a reference threshold is sensitive to noise and lack of robustness.
Aiming at this problem, the paper presents a knock intensity diagnosis method based on signal processing pattern classification technique. In this method, the vibration signals are firstly decomposed by the ensemble empirical mode decomposition (EEMD). The EEMD is a data-driven and self-adaptive signal processing method and capable of decomposing a signal into a collection of intrinsic mode functions (IMFs), and each IMF represents a simple oscillatory mode [8]. Then, a series of temporal and frequency statistical characteristics are calculated from the IMF in which the knock characteristics appear. Finally, the obtained knock characteristics vectors are input to the pattern classifiers to accomplish knock intensity identification. Experimental results demonstrate the effectiveness of the proposed method.

2. Principle of EEMD

One of the major drawbacks of the classical EMD is the frequent appearance of mode mixing, which is defined as a single IMF including oscillations of dramatically disparate scales. Mode mixing is usually a result of signal intermittency, which could not only cause serious aliasing in time-frequency distribution but also make an individual IMF devoid of physical meaning.

To overcome the drawback of mode-mixing, Wu and Huang proposed a new noise-assisted method named the ensemble EMD, which significantly reduces the chance of undue mode mixing. Thus, the EEMD method represents a major improvement over the original EMD and a more mature tool for non-stationary time series analysis. In the EEMD, the true IMF is defined as the mean of an ensemble of trials. Each trial consists of the decomposition results of the signal combined with a finite amplitude white noise signal. The EEMD decomposition algorithm of a given signal can be shortly defined in the following steps [8].

(1) Given \( x(t) \) is an original signal, add a random white noise signal \( n_j(t) \) to \( x(t) \)

\[
x_j(t) = x(t) + n_j(t)
\]  

where \( x_j(t) \) is the noise-added signal, \( j=1, 2, \ldots, M \), and \( M \) is the number of trial.

(2) Decompose \( x_j(t) \) into a series of intrinsic mode function (IMF) \( c_{ij} \) utilizing EMD as follows:

\[
x_j(t) = \sum_{i=1}^{N_j} c_{ij} + r_{N_j}
\]  

where \( c_{ij} \) denotes the \( i \)th IMF of the \( j \)th trial, \( r_{N_j} \) indicates the residue of the \( j \)th trial and \( N_j \) is the IMFs number of the \( j \)th trial.

(3) If \( j < M \), then repeat steps 1 and 2, adding a different random white noise signal each time.

(4) Obtain \( I = \min(N_1, N_2, \ldots, N_M) \) and calculate the ensemble means of corresponding IMFs of the decompositions as the final result \( c_i \)

\[
c_i = \left( \frac{1}{M} \sum_{j=1}^{M} c_{ij} \right) / I, \quad i = 1, 2, \ldots, I
\]

From the above procedures, in each decomposition process, the added white noise helps to perturb the analysed signal and enables the EMD method to visit all possible solutions in the finite neighbourhood of the true final IMF. Based on the property of zero mean of white noise, the added white noise will be cancelled out in the final ensemble mean if there are sufficient trials and only the signal itself will survive in the final decomposition results [9].

3. Experimental setup and knock feature extraction

3.1 Experimental setup

The experimental setup consisted of a test gasoline engine, an AC dynamometer and variable control test equipment. The parameters of the test SI engine are presented in Table 1. The
dynamometer system was operated in speed control mode to maintain the desired engine speed. In this experiment, the knock was induced by increasing the spark advance with engine running at 5800 rpm and wide open throttle operation.

In order to determine the occurrence of knock, a piezoelectric in-cylinder pressure transducer accompanied with the spark was installed in the combustion chamber of the first cylinder to collect the in-cylinder pressure oscillations and an accelerometer was mounted on the cylinder head close to the first cylinder to measure the vibration level of the engine. The pressure and vibration signals were recorded simultaneously. The locations of pressure sensor and accelerometer are shown in Fig. 1. The pressure and vibration signals were recorded by a dynamic signal analyser, which converted the analogue signals to digital data at a sampling rate of 102.4 kHz.

Table 1: Parameters of the test SI engine.

<table>
<thead>
<tr>
<th>Items description</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylinder number</td>
<td>In-line 4 cylinders</td>
</tr>
<tr>
<td>Displacement</td>
<td>1.5 L</td>
</tr>
<tr>
<td>Stroke</td>
<td>4</td>
</tr>
<tr>
<td>Bore×stroke</td>
<td>75.5mm×75.5mm</td>
</tr>
<tr>
<td>Compression ratio</td>
<td>9.0</td>
</tr>
<tr>
<td>Advance ignition timing (nominal)</td>
<td>30° CA BTDC</td>
</tr>
</tbody>
</table>

Figure 1: Locations of the pressure and vibrational acceleration sensors.

3.2 Knock feature extraction

In current study, the collected vibration signals were classified into three states according to the levels of knock: non-knocking cycles, increasing knocking cycles, and heavy knocking cycles. The sample of each of the three states consists of the vibration signals in a whole engine cycle, which includes 720° of crank angle. Figures 2 and 3 illustrate the typical pressure and vibration samples of these three states.

To present various levels of knock clearly, the filtered pressure signals corresponding to each vibration sample were also shown in Fig. 3. Because the dominant resonant frequencies induced by knock of the test engine are within the range of 8 to 22 kHz given by Draper’s equation [10], the digital band-pass filter, with cut-off frequencies equal to 8 and 22 kHz, has been used in order to allow the detection of the main knock-related spectral components.

From Fig. 3, although the high-frequency pressure oscillations induced by engine knock can be observed in the pressure signal, we can hardly draw any meaningful conclusions by the vibration signal. To extract the characteristics of knock, the vibration signals are to be decomposed by EEMD in the following. Because the knock characteristics frequencies are relatively high, the Fig. 4 just illustrates the first three IMF components of the decomposition results.
Figure 2: The typical pressure samples of various levels of knock.

Figure 3: The typical vibration samples and their corresponding filtered pressure signals.

Figure 4: EEMD results of the typical vibration samples.

In IMFs $c_1$, as shown in Figs. 4(b)-(c), we could distinguish some impact components starting at about 11ms and decaying with time swiftly. According to the analysis results obtained by the filtered pressure signals illustrated in Fig. 3, we can draw a conclusion that these impact components are typical characteristics induced by knock. Besides that, on the other two IMFs $c_2$-$c_3$, at the time point mentioned above, we are unable to distinguish any significant impacts. Therefore, when using EEMD, the knocking signatures only appear in the first IMF component, and the remaining IMF components correspond to other characteristics and physical events of an engine. Furthermore, we could not find significant impact components in IMF $c_1$ around the peak pressure point in Fig. 4(a), because no knocking has occurred in this engine cycle.

From the above analysis, it is quite evident that the impact components induced by engine knock can be detected by EEMD and various levels of knock can be identified through IMF $c_1$. In order to achieve intelligent diagnosis of knock intensity, we need to define a series of statistical feature parameters to describe the characteristics of knock, and then feed them to pattern classifiers for
identification. To extract valid knock information in the time-domain, eight statistical feature parameters including peak value, mean, standard deviation, shape factor, skewness, kurtosis, crest factor and pulse index, are calculated to describe the distribution property of the signal at IMF $c_1$. The frequency-domain provides another description of a signal and it can reveal some information that cannot be found in time domain. In current work, one frequency-domain feature parameter $KIF$ for evaluating knock intensity is defined. It is calculated as follows.

$$KIF = \sum_{8\, \text{kHz}}^{22\, \text{kHz}} X^2(k)$$  \hspace{1cm} (4)

where $X(k)$ is the spectral data in 8-22 kHz of IMF $c_1$.

According to these nine statistical feature parameters in both temporal and frequency domains, the feature vector $T=\{f_1, f_2, \ldots, f_9\}$ is obtained and the mapping relationship of the feature vector with various levels of knock can also be constructed. The flow diagram of the proposed knock intensity diagnosis method is shown in Fig.5.

![Flow chart of knock intensity diagnosis procedure.](image)

Figure 5: Flow chart of knock intensity diagnosis procedure.

## 4. Knock intensity diagnosis

In order to evaluate the effectiveness of the proposed method, the first step is to make a database. The database is composed of nine statistical feature parameters and a label for each vibration sample. The label is determined by rapid and large oscillations of the filtered cylinder pressure signal (see Fig. 4). The database is generated over a range of operating conditions with spark advance variations: three different spark advances are tuned. They are assumed to lead to three different knock states: absence of knock, increasing knock, and heavy knock. In this study, we are provided a small data set composed of 70 samples as listed in Table 2.

<table>
<thead>
<tr>
<th>Knock state</th>
<th>Number of samples</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-knocking cycle</td>
<td>47</td>
<td>Class 1</td>
</tr>
<tr>
<td>Increasing knocking cycle</td>
<td>15</td>
<td>Class 2</td>
</tr>
<tr>
<td>Heavy knocking cycle</td>
<td>8</td>
<td>Class 3</td>
</tr>
</tbody>
</table>

For classification, three classical machine learning algorithms are employed, that is C4.5 decision tree (C4.5), radial basis function neural network (RBFNN) and support vector machine (SVM). All algorithms are implemented in WEKA which is data mining software in java and can be obtained at http://www.cs.waikato.ac.nz/ml/weka. Default setting of C4.5 whose eighth version is called J48 in WEKA is adopted. RBFNN was set to five intermediate nodes, that is, the samples are clustered into five classes. For SVM, the sequential minimal optimization (SMO) algorithm was
adopted for training a support vector classifier. The radial basis function kernel is selected and the complexity parameter $C$ was set to 1000. All algorithms are tested by ten-fold cross validation which divided samples into ten folds and then 9 folds are used for training and the remaining 1 fold for testing. The results of the 10 tests are given as a mean of all tests.

The classification accuracies obtained by using the above three pattern classifiers are reported in Table 3. The confusion matrixes of the classification results are given in Fig. 6. From Table 3 and Fig. 6, we can see that the classification accuracies of the three individual classifies range from 88.57% to 92.86% and the average accuracy is 91.43%.

Table 3: Classification accuracies.

<table>
<thead>
<tr>
<th>Method</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>C4.5</td>
<td>92.86%</td>
</tr>
<tr>
<td>RBFNN</td>
<td>88.57%</td>
</tr>
<tr>
<td>SVM</td>
<td>92.86%</td>
</tr>
</tbody>
</table>

![Confusion matrixes](image)

Figure 6: Confusion matrixes of the classification results for different methods.

5. Conclusion

In this paper, we have proposed a novel method for knock intensity diagnosis of SI engine based on the ensemble empirical mode decomposition and artificial intelligence identification technology. This method utilizes the EEMD to extract faulty characteristics from both temporal and frequency domains, and then makes decision through pattern classifiers to identify different knock states. The experimental results show that the proposed method is able to determine different levels of knock intensity for SI engine and at the same time obtain relatively high diagnosis accuracy even under the condition of a very high speed of 5800 rpm.

The proposed method applied here can also be used in other mechanical applications which contain a fault detection problem.

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REFERENCES


