Automobile Independent Fault Detection based on Acoustic Emission Using Wavelet

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Abstract
Wavelet transform is a well-known signal processing technique which has proven to be a successful technique in Non-Destructive Testing (NDT). Adopting this technique by Acoustic Emission (AE) method could result in better interpretation of data that are used for fault detection. In this study, AE signals emitted from automobile engines in both faulty and healthy conditions are analyzed using wavelet transform. Here, intention is to categorize the AE signals into healthy and faulty classes. The investigated fault is within the ignition system of the engines beside other possible problems that may affect the generated acoustic signals. A set of features are extracted from signals. Correlation-based Feature Selection (CFS) algorithm is used to reduce the dimensionality of the dataset. The case study is carried-out on 4 different types of automobiles using 480 automobiles to prove the independency of the proposed approach on the type of the automobile. Classification results are reported to be around 80%.

Keywords: Acoustic emission, wavelet, fault detection, condition monitoring, correlation based feature selection (CFS)

1. Introduction

Rapid growth in automobile industry made engine maintenance more important than ever. Therefore, development of an accurate condition monitoring and fault detection system that not only will reduce the maintenance cost but also will alert the operator about the engine’s operating condition at early stages will be valuable. Acoustic Emission (AE) wave is a stress wave that travels through the materials as a result of sudden release of strain energy [1]. AE has been widely used for non-destructive testing in many industries including pipe line condition monitoring, quality control of manufacturing process and structures (cranes, bridges, etc.). AE has also been utilized for fault detection and condition monitoring of mechanical components such as gearboxes [2], engines [3] and bearings [4]. Fortunately, AE waveforms usually include dynamic information about the condition of the monitored component. Internal combustion (IC) engines are considered as one of the classical types of rotating machineries to be analyzed using acoustic signals for fault detection and condition monitoring. Adopting the appropriate signal processing technique as well as extracting relevant features to detect faults in acoustic signals emitted from IC engines is a critical issue in fault detection and condition monitoring of such rotating machines. Wu and Chuang [5] have focused on the fault diagnosis application in cooling fan and drive axel shaft of vehicles with four cylinder IC engines. They have used visual dot pattern technique to produce a snowflake-shaped pattern of six fold symmetry for each acoustic and vibration signal. Adopting an automatic image template matching, they have completed fault diagnosis procedure. Jiang et al. [6] have focused on condition monitoring of four cylinder diesel engine with combustion faults using acoustic measurements. They have used one-port acoustic source theory and concluded that the strength of engine acoustic source can provide a better representation of engine combustion condition. While the acoustic signals emitted from engines are non-stationary, time-frequency signal analysis techniques seem to be helpful. Wavelet Transform (WT) is another state-of-the-art signal and data analysis technique that
has been widely used by researchers for the purpose of condition monitoring and fault diagnosis. WT is used to obtain both time domain and frequency domain information of the signals. Using resizable window sizes to be dilated for lower frequencies and sharpened for higher frequencies is the main advantage of WT technique. WT shows up in two forms namely, Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Wu and Chen [7] used CWT for both vibration and acoustic based fault diagnosis within two experimental works: IC engine and its cooling fan blade defects. Due to the fact that calculating CWT coefficients is a time-consuming process, DWT has been used instead. Wu and Liu [8] have investigated the fault diagnosis process of IC engine with different faults using DWT and neural networks. In another work, Kabiri and Makinejad [9] have investigated the combustion fault in Pride automobile with features extracted from acoustic signals using Fast Fourier Transform (FFT) and DWT.

In this paper, acoustic signals for four different engines in both healthy and faulty operating conditions are recorded and analyzed using DWT with different decomposition levels. A set of features are extracted from DWT coefficients. As the datasets may include irrelevant features that may affect the classification accuracy, feature reduction is needed. Feature selection algorithms not only select the more relevant features but also reduce volume of the dataset. For this purpose, the Correlation-based Feature Selection (CFS) algorithm is adopted. The reduced dataset is then classified using Support Vector Machine (SVM) classification method. It should be mentioned that the classification accuracy is validated and reported using 10-fold cross validation in which 10 percent of data is randomly selected for training and 90 percent for testing. The classification results show the efficiency of wavelet-based feature extraction for the proposed application.

2. Discrete Wavelet Transform

The mathematical formulation of DWT is based on a work reported by Gaing [10]. DWT has a Multi-Resolution Analysis (MRA) framework. DWT decomposes the signals through two digital filters: a high-pass filter and a low-pass filter. The high-pass and low-pass filters are called the wavelet function \( \psi(t) \) and scaling function \( \phi(t) \), respectively. The WT coefficients are calculated by passing the original signal from both digital filters. The high-pass filter generates the detailed version of the original signal and the low-pass filter generates the approximated version. The wavelet function and scaling function that must be defined before the WT is applied on the signal are defined by equations (1) and (2).

\[
\phi_{j,n}(t) = 2^j \sum_{c} c_{j,n} \phi(2^j t - n) \quad (1)
\]

\[
\psi_{j,n}(t) = 2^j \sum_{d} d_{j,n} \psi(2^j t - n) \quad (2)
\]

where \( \phi_{j,n}(t) \) and \( \psi_{j,n}(t) \) scale and translate the functions \( \psi(t) \) and \( \phi(t) \) and \( c_j \) and \( d_j \) are the scaling and wavelet coefficient at scale \( j \).

The original signal \( X_j(t) = (v_0,v_1,\cdots,v_{N-1}) \) is given with the length of \( N \) that \( N = 2^J \) is the sampling number and \( J \) is an integer. The DWT mathematical formulation is as follows:

\[
DWT(X_j(t)) = 2^{J+1/2} \left( \sum_{n=0}^{N-1} u_{j+1,n} \phi(2^{j+1} t - n) + \sum_{n=0}^{N-1} w_{j+1,n} \psi(2^{j+1} t - n) \right) \quad (3)
\]

\[
0 \leq n \leq \frac{N}{2^j} - 1
\]
where \( j \) is the translation coefficient and \( u_{j+1,n} \) and \( w_{j+1,n} \) are the approximated and detailed version at scale \( j+1 \) and are calculated as follows:

\[
\begin{align*}
  u_{j+1,n} &= \sum_k c_{j,k} v_{j,k+2n}, \quad 0 \leq k \leq \frac{N}{2^j} - 1 \\
  w_{j+1,n} &= \sum_k d_{j,k} v_{j,k+2n}, \quad 0 \leq k \leq \frac{N}{2^j} - 1
\end{align*}
\]  

\[ d_k = (-1)^k c_{2p-1-k}, \quad p = \frac{N}{2^j} \]  

The DWT decomposition and reconstruction process is depicted in Figure 1 [10]. In Figure 1 letter \( A \) stands for Approximation and the letter \( D \) stands for Detail versions. The high-pass filtered then low-pass filtered \( X(t) \) that are detail and approximation coefficients of \( X(t) \) in DWT, respectively, are down sampled to be half the length of \( X(t) \). The next decomposition level is performed by passing the approximation version of the previous decomposition level through the low-pass filter. This trend is repeated for a predefined decomposition level.

![DWT decomposition/reconstruction with three levels](image)

**Figure 1.** DWT decomposition/reconstruction with three levels

### 3. Feature extraction

In this paper, signals are decomposed into 3 different levels including 1-level, 2-level and 3-level decomposition. For each decomposition level, the following features are extracted from DWT approximation and detail coefficients.

\[
Mean = \frac{1}{N} \sum_{i=1}^{N} x_i
\]  

(7)
Correlation-based Feature Selection

CFS algorithm tries to find a subset of features not only to lower the dimensionality of the dataset but also to improve the classification accuracy. CFS defines a merit for each selected subset of features. The merit is based on this hypothesis that a promising subset of features involves those features that are uncorrelated or less correlated to each other while they are highly correlated to the class label. The merit is mathematically defined as Eq. 13 [11]:

$$Merit_s = \frac{k\overline{r_{c,f}}}{\sqrt{k + k(k-1)\overline{r_{f,f}}}}$$

where Merit_s indicates how worthy the feature subset S with k features is. Parameters $\overline{r_{c,f}}$ and $\overline{r_{f,f}}$ are mean feature-class and mean feature-feature correlations respectively, where f ∈ S. The predictive ability of feature subset S and the amount of redundancy among its features are calculated by the nominator and denominator of Eq. (7). The more the features are correlated to each other, the more redundancy there is among them. Thus Merit_s of a feature subset has a smaller value than the time when the features in the subset are uncorrelated with each other. Symmetric uncertainty shows the correlation between two features X and Y that is presented as Eq. (14) [11]:

$$Symmetric\ uncertainty = \frac{2 \times gain}{H(X) + H(Y)}$$

where $H(.)$ is the entropy of the feature and gain indicates the information gain. Entropy is considered to be a measure of uncertainty or unpredictability in a system. The entropy of feature X is calculated by Eq. (15).

$$H(X) = -\sum_{x \in X} p(x) \log_2(p(x))$$

Information gain is the amount of information gained about Y after observing X. Information gain is a symmetric measure. Eq. (16) [12] represents the information gain.

$$gain = H(X) + H(Y) - H(X,Y)$$
Before applying CFS to reduce the dataset dimensionality, features are normalized. If the feature space has \( n \) dimensions, number of the possible feature subsets will be \( 2^n \). Therefore, it seems necessary to use a certain search strategy to explore the feature space. Best First Search (BF) strategy has been used in this paper.

5. Experiments

The investigated engine defect is in the ignition system i.e. engines operate with one cylinder missing fire. In the reported work, the spark in the first cylinder is not happening. The engine acoustic signals are recorded in the workshop using a microphone 20 cm above the engine. The investigated engines are from 4 different automobiles including Pride (Kia motors), Peugeot 405, Peugeot Pars, and Iranian national automobile Samand. For each automobile, the acoustic signals of 60 different automobiles in both healthy and faulty conditions with engines operating with 1000 rpm and 44100 sampling frequency are recorded in WAV format. The recording process is carried-out in the central repair shop of the Iran Khodro car manufacturing company with the presence of its environmental noise.

5.1 Pre-processing

The recorded signals have been manually de-noised. Due to recording the signals in workshop, the sound of other working objects near the test subject and human voice is considered noise. As in the workshop the automobiles were to be checked by the repairman, the automobiles may or may not suffer from other possible faults. For example, the combustion timing defect causes the engine not to operate properly and this per se results in considerable acoustic abnormality. The analysed signals include both healthy and faulty operating conditions with the recording time of 5 seconds.

5.2 Classification train and test datasets

The total number of recorded signals is a dataset with 480 samples including 60 samples for each type of automobile with 2 classes: healthy and faulty. The dataset is divided into train and test datasets. For the training dataset, 10 percent of data is randomly selected by 10-fold cross validation strategy and 90 percent remained as the testing dataset. The aim of selecting only 10 percent of data for training is to prove the generalization capability of the proposed method.

6. Results

In the reported work the Daubechie discrete wavelet of order 3 is used. The recording sampling rate is 44100 samples per second and the covered frequency range is \([0-22050]\) Hz. For each decomposition level, the aforementioned features are extracted from wavelet approximation and detail coefficients. Without any dimension reduction, the normalized constructed datasets for each decomposition level are used for classification. Figures 2-4 depict the normalized feature set for each dataset matrix. Table 1 shows the number of extracted features for each dataset and the classification results obtained using those datasets. Classification results contain information about the Accuracy (A), True Positive Rate, True Negative Rate, False Positive Rate, False Negative Rate, Precision, Recall, and F-Score. To look closer at Table 1 it is obvious that the number of extracted features is unnecessarily high. After applying CFS on the primary datasets and then normalizing their features for classification (figures 5-7), Table 2 is resulted.
Table 1. The classification results using the constructed dataset for each decomposition level

<table>
<thead>
<tr>
<th>Decomposition level</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of features</td>
<td>12</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td>77.31</td>
<td>73.03</td>
<td>69.98</td>
</tr>
<tr>
<td>True Positive Rate (%)</td>
<td>77.19</td>
<td>74.49</td>
<td>76.52</td>
</tr>
<tr>
<td>True Negative Rate (%)</td>
<td>77.47</td>
<td>72.07</td>
<td>63.71</td>
</tr>
<tr>
<td>False Positive Rate (%)</td>
<td>22.53</td>
<td>27.93</td>
<td>36.29</td>
</tr>
<tr>
<td>False Negative Rate (%)</td>
<td>22.81</td>
<td>25.51</td>
<td>23.48</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>77.73</td>
<td>74.85</td>
<td>68.43</td>
</tr>
<tr>
<td>Recall (%)</td>
<td>77.19</td>
<td>74.49</td>
<td>76.52</td>
</tr>
<tr>
<td>F-Score (%)</td>
<td>77.24</td>
<td>71.11</td>
<td>69.43</td>
</tr>
</tbody>
</table>

Figure 2. Normalized dataset constructed from first level of decomposition

Figure 3. Normalized dataset constructed from second level of decomposition

Figure 4. Normalized dataset constructed from third level of decomposition

Table 2. The classification results using the constructed dataset after applying CFS

<table>
<thead>
<tr>
<th>Decomposition level</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of features</td>
<td>2</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td>80.67</td>
<td>78.40</td>
<td>79.51</td>
</tr>
<tr>
<td>True Positive Rate (%)</td>
<td>68.23</td>
<td>74.64</td>
<td>71.65</td>
</tr>
<tr>
<td>True Negative Rate (%)</td>
<td>93.28</td>
<td>82.31</td>
<td>87.44</td>
</tr>
<tr>
<td>False Positive Rate (%)</td>
<td>6.72</td>
<td>17.69</td>
<td>12.56</td>
</tr>
<tr>
<td>False Negative Rate (%)</td>
<td>31.77</td>
<td>25.36</td>
<td>28.35</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>91.66</td>
<td>81.93</td>
<td>85.82</td>
</tr>
<tr>
<td>Recall (%)</td>
<td>68.23</td>
<td>74.64</td>
<td>71.65</td>
</tr>
<tr>
<td>F-Score (%)</td>
<td>77.83</td>
<td>77.50</td>
<td>77.73</td>
</tr>
</tbody>
</table>

Figure 5. Normalized dataset constructed from first level of decomposition after applying CFS
Table 2 shows the classification results have improved and dimensionality of the dataset is considerably reduced. Comparing figures 2-7 before and after applying CFS proves that the proposed method can successfully distinguish between the faulty and healthy AE signals.

7. Conclusions

The reported work uses AE signal analysis to identify faulty combustion of an automobile engine regardless of the type of automobile. The analyzed AE signals are recorded in the workshop with a considerable amount of environmental noise, yet the proposed methodology can still operate. As the signals are recorded from four different types of automobile engines, one can claim that the methodology used in this paper has this potential to be used for different types of automobile engines. Therefore, it is possible to say that the proposed method is automobile independent. Considering the reported result, suitability of wavelet based features as well as CFS algorithm for feature selection is proved. The generalization capability of the proposed methodology is proven using only 10 percent of data for training and 90 percent for testing.

8. Future work

Future work is to be dedicated to improving the classification results not only in the domain of feature extraction but also in the domain of possible signal processing techniques. Also publicising the dataset used in this paper is expected via http://ial.iust.ac.ir/ in near future.

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References


