Automobile Independent Fault Detection based on Acoustic Emission Using FFT

Hamid GHADERI 1, Peyman KABIRI 2

1 Intelligent Automation Laboratory, School of Computer Engineering, Iran University of Science and Technology, 16846-13114, Tehran, Iran, h_ghaderi@comp.iust.ac.ir
2 Intelligent Automation Laboratory, School of Computer Engineering, Iran University of Science and Technology, 16846-13114, Tehran, Iran, Tel: +98 (21) 77240540 to 50, Ext. 3341; Fax1: +98 (21) 73223341, peyman.kabiri@iust.ac.ir

Abstract
Recently, research on effective Acoustic Emission (AE)-based methods for condition monitoring and fault detection has attracted many researchers. Due to the complex properties of acoustic signals, effective features for fault detection cannot be easily extracted from the raw acoustic signals. To solve this problem, Fast Fourier Transform (FFT) is utilized. This method depends on the variations in frequency to distinguish different operating conditions of a machine. In this study, the intention is to categorize the acoustic signals into healthy and faulty classes. Acoustic emission signals are generated from four different automobile engines in both healthy and faulty conditions. The investigated fault is within the ignition system of the engines while they might suffer from other possible problems as well that may affect the generated acoustic signals. The energy of FFT coefficients of acoustic signals for different frequency bands are calculated as representative features. Dimension reduction is performed on the dataset using Principal Component Analysis (PCA) method. 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 are reported to be more than 80%.

Keywords: Fast Fourier Transform (FFT), Condition monitoring, Principal Component Analysis (PCA), Fault detection.

1. Introduction

Rapid automobile industry growth has made engine’s maintenance to be of great importance. Therefore, it seems necessary to development accurate condition monitoring and fault detection systems for both reducing maintenance cost and alerting the operator about the engine’s operating condition before severe damages occur. Stress wave travels through the materials and is caused by sudden release of strain energy. This stress wave is called an Acoustic Emission (AE) wave [1]. AE as a non-destructive testing method has been widely used by a lot of researchers in many industries. For instance, fault detection and condition monitoring of mechanical components such as gearboxes [2], engines [3] and bearings [4] have been the target of AE based methodologies. Fortunately, the operating condition of such components can be monitored by their dynamic information that is present in AE wave forms emitted from them. Internal Combustion (IC) engines are typical types of rotating machineries. Fault diagnosis and condition monitoring of such engines using acoustic signals have been the target of a lot of research projects. Wu and Chuang [5] have investigated cooling fan and drive axel shaft faults of vehicles with four cylinder IC engines. Using visual dot pattern technique along with acoustic and vibration signals, they have produced a snowflake-shaped pattern of six fold symmetry. Their proposed fault diagnosis procedure is completed by adopting an automatic image template matching. In another work, Kabiri and Makinejad [6] have investigated the combustion fault in Pride automobile. They have used Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) for features extraction from acoustic signals. Jiang et al. [7] have focused on condition monitoring of four cylinder diesel engine with combustion faults using acoustic measurements. Using one-port acoustic source theory, they have concluded that a better representation of engine combustion condition is obtained by the strength of engine acoustic source. Wu and Chen [8] used
Continuous Wavelet Transform (CWT) for both vibration and acoustic based fault diagnosis of two experimental works: IC engine and its cooling fan blade defects. Wu and Liu [9] have investigated the fault diagnosis process of IC engine with different faults using DWT and neural networks.

One of the most significant issues is how to extract relevant features from acoustic signals to help fault detection and condition monitoring of those engines be carried out as accurately as possible. This issue is highly dependent on the appropriate signal processing technique used for feature extraction. Among many signal processing techniques used in the literature, FFT is one of the most popular ones and it is greatly utilized in condition monitoring and fault diagnosis [10]. FFT is a frequency domain analysis that is used to extract frequency domain features [11]. This method relies on the variations in frequency to isolate various faulty conditions. FFT transfers signals to the frequency domain, a process that results in using only frequency domain information regardless of time domain information.

In this paper, acoustic signals of four different engines in both healthy and faulty operating conditions are recorded and analyzed using FFT. Spectrum of the signals is divided into different frequency segments. The energy is calculated as a feature using FFT coefficients in each frequency segment. As the collected datasets may unnecessarily have high dimensionality, the Principal Component Analysis (PCA) is used for dimension reduction. 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 the test. The classification results show efficiency of the FFT-based feature extraction for the reported case study in this paper.

2. Fourier Transform

An energy-limited signal \( f(t) \) can be decomposed by its Fourier transform \( F(w) \), namely

\[
f(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(w) e^{jwt} \, dw
\]

where

\[
F(w) = \int_{-\infty}^{+\infty} f(t) e^{-jwt} \, dt
\]

\( f(t) \) and \( F(w) \) are a pair of Fourier transforms. Eq. (1) implies that \( f(t) \) signal can be decomposed into a group with harmonics \( e^{jwt} \). The weighting coefficients \( F(w) \) represent the amplitudes of the harmonics in \( f(t) \). \( F(w) \) is time independent and it represents the frequency composition of a random process, which is assumed that its statistics do not change with time.

3. Feature extraction

In this paper, the frequency spectrums of signals are segmented into 9 different bands including 50 Hz, 100 Hz, 250 Hz, 500 Hz, 1000 Hz, 1500 Hz, 2000 Hz, 3000 Hz, and 5000 Hz. Figure 1 shows the 2500 Hz segmentation of frequency spectrum of a signal. As the faults affect the signals of normal condition in the frequency domain, the aim is to find the best frequency segment where the fault has affected the signals significantly. On the other hand,
the frequency segmentation resolution influences the number of features extracted from the spectrum of the signals. Frequency segmentation resolution represents the precision of segmentation. For example, the 50Hz frequency segmentation has more segmentation resolution than the 1000Hz frequency segmentation, i.e., the 50Hz segmentation has focused on the spectrum of the signal in more detail. There is a kind of trade-off between the frequency segmentation resolution and the number of features.

For each band, the energy of the absolute value of FFT coefficients is calculated as a feature i.e., $x_i$ in the energy formulations that is shown in Eq. (3).

$$Energy = \sum_{i=1}^{N} |x_i|^2$$  \hspace{1cm} (3)

4. Principal Component Analysis

Principal Component Analysis (PCA) is a technique for multivariate data analysis that can be used to extract a set of uncorrelated principal components from a set of correlated variables. Principal components are mutually uncorrelated or less correlated. PCA is adopted to reduce dimensionality of the dataset and to extract the useful features. Hence, using PCA may improve the classification accuracy. 

Consider a dataset (matrix) $X$ consisting of $N$ observations each represented by $d$ variables (features):
$X = \begin{bmatrix} X_1^1 & X_1^2 & \cdots & X_1^d \\ X_2^1 & X_2^2 & \cdots & X_2^d \\ \vdots & \vdots & & \vdots \\ X_N^1 & X_N^2 & \cdots & X_N^d \end{bmatrix}$ (4)

$X_i$ is a column vector shown as follows:

$$X_i = \{X_i^1, X_i^2, \cdots, X_i^N\}^T$$ (5)

$\mu$ is the mean matrix and each $\mu_i$, $i = 1, \cdots, d$ represents the mean of a column in $X_i$:

$$\mu = [\mu_1, \mu_2, \cdots, \mu_d]^T$$ (6)

Covariance matrix is constructed as Eq. (12):

$$\Sigma \equiv \text{Cov}(X) = E[(X - \mu)(X - \mu)^T] = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} & \cdots & \sigma_{1d} \\ \sigma_{21} & \sigma_{22}^2 & \cdots & \sigma_{2d} \\ \vdots & \vdots & & \vdots \\ \sigma_{d1} & \sigma_{d2} & \cdots & \sigma_{dd}^2 \end{bmatrix}$$ (7)

Where $\sigma_{ij}$ is the covariance between $X_i$ and $X_j$:

$$\sigma_{ij} \equiv \text{Cov}(X_i, X_j) \equiv E[(X_i - \mu_i)(X_j - \mu_j)]$$ (8)

The eigenvalues $\lambda_i$, $i = 1, \cdots, d$ are calculated by Eq. (14):

$$\det(\Sigma - \lambda I)$$ (9)

Where $I$ denotes the $d \times d$ identity matrix. Eigenvectors are columns of matrix $W$ such that:

$$\Sigma = W D W^T$$ (10)

Where $D$ is the diagonal matrix of eigenvalues of covariance matrix $\Sigma$:

$$D = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \lambda_d \end{bmatrix}$$ (11)

Eigenvector $W$ satisfies the following condition:

$$\Sigma W = \lambda W$$ (12)

It should be mentioned that the more the eigenvalue of an eigenvector is, the more the data samples are scattered along it. The principal components matrix is the eigenvector matrix where the eigenvectors are sorted in a descending manner according to their eigenvalues.
5. Experiments

AE signals from 4 different automobile engines are analyzed in this study. The engines are suffering from a fault in their ignition system i.e. the first cylinder of the engines is missing fire. The engine acoustic signals are recorded in the repair workshop using a microphone 20 cm above the engine. The investigated engines are of Pride (Kia motors), Peugeot 405, Peugeot Pars, and Iranian national automobile Samand. For each automobile, the acoustic signals of 60 engines in both healthy and faulty conditions while operating with 1000 rpm and 44100 sampling frequency are recorded in WAV format.

5.1 Pre-processing

Besides other possible environmental noises, sound of other objects operating close to the test subject and human voice are considered major noises. The acoustic signals were listened to and a major noise free moment of them was selected. However, environmental noises are still present in the signals. 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, one of the most common faults besides the investigated fault is the combustion timing process fault. The analyzed signals include both healthy and faulty operating conditions with the recording time of 5 seconds.

5.2 Classification train and test datasets

The dataset consists of 480 samples. For each engine, the sounds of 60 different automobiles are recorded in both healthy and faulty engine condition. Train and test datasets are extracted from the original signal. 10-fold cross validation strategy is used to extract the aforementioned datasets. Using this strategy, 10 percent of samples are randomly selected for training and 90 percent for testing. The aim of selecting only 10 percent of data for training is to prove the generalization capability of the proposed method.

6. Results

As the recording sampling rate is 44100 samples per second, the covered frequency range is [0-22050] Hz. The frequency spectrum of each signal is segmented into some frequency bands. This frequency bands can be referred to as frequency segmentation resolutions. The segmentation resolutions are: 50 Hz, 100 Hz, 250 Hz, 500 Hz, 1000 Hz, 1500 Hz, 2000 Hz, 3000 Hz, and 5000 Hz. For each segment, the aforementioned statistical features are calculated using the absolute value of FFT coefficients of each segment as their parameters. The constructed datasets for each frequency segmentation resolution are normalized first and then without any dimensionality reduction they were used for classification. Table 1 shows number of the extracted features for each dataset and the classification results using those datasets. Classification results are presented in terms of the Accuracy, True Positive Rate, True Negative Rate, False Positive Rate, False Negative Rate, Precision, Recall, and F-Score. According to Table 1, number of the features for datasets, especially for datasets with low segmentation resolution, is high. Using PCA, datasets with reduced dimensionality are constructed by multiplying the primary datasets by the eigenvector matrix. Eigenvector matrix of a dataset is a $n \times n$ matrix where $n$ represents the number of features in the dataset. The threshold used for the selection of the number of Principal Components (PC) in this study is the cumulative variance of the selected number of PCs should be equal to or greater than 95.
percent of the cumulative variance of all the PCs. Figures 2-10 shows the Scree graph of the primary constructed datasets.

Table 1. The classification results using the constructed dataset for each segmentation resolution

<table>
<thead>
<tr>
<th>Segmentation Resolution (Hz)</th>
<th>50</th>
<th>100</th>
<th>250</th>
<th>500</th>
<th>1000</th>
<th>1500</th>
<th>2000</th>
<th>3000</th>
<th>5000</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of features</td>
<td>441</td>
<td>222</td>
<td>89</td>
<td>45</td>
<td>23</td>
<td>16</td>
<td>12</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td>57.94</td>
<td>61.37</td>
<td>67.45</td>
<td>73.45</td>
<td>70.09</td>
<td>71.06</td>
<td>77.64</td>
<td>77.38</td>
<td>71.25</td>
</tr>
<tr>
<td>True Positive Rate (%)</td>
<td>57.51</td>
<td>64.17</td>
<td>76.28</td>
<td>80.11</td>
<td>68.81</td>
<td>63.21</td>
<td>76</td>
<td>74.45</td>
<td>66.99</td>
</tr>
<tr>
<td>True Negative Rate (%)</td>
<td>59.37</td>
<td>59.48</td>
<td>59.03</td>
<td>66.83</td>
<td>71.71</td>
<td>79.20</td>
<td>78.69</td>
<td>80.35</td>
<td>75.67</td>
</tr>
<tr>
<td>False Positive Rate (%)</td>
<td>40.63</td>
<td>40.52</td>
<td>40.97</td>
<td>33.17</td>
<td>28.29</td>
<td>20.80</td>
<td>21.31</td>
<td>19.65</td>
<td>24.33</td>
</tr>
<tr>
<td>False Negative Rate (%)</td>
<td>42.49</td>
<td>35.83</td>
<td>23.72</td>
<td>19.89</td>
<td>31.19</td>
<td>36.79</td>
<td>24</td>
<td>25.55</td>
<td>33.01</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>69.89</td>
<td>66.74</td>
<td>65.52</td>
<td>70.92</td>
<td>72.15</td>
<td>76.41</td>
<td>79.43</td>
<td>79.79</td>
<td>74.50</td>
</tr>
<tr>
<td>Recall (%)</td>
<td>57.51</td>
<td>64.17</td>
<td>76.28</td>
<td>80.11</td>
<td>68.81</td>
<td>63.21</td>
<td>76</td>
<td>74.45</td>
<td>66.99</td>
</tr>
<tr>
<td>F-Score (%)</td>
<td>45.13</td>
<td>53.25</td>
<td>67.22</td>
<td>74.95</td>
<td>69.21</td>
<td>68.14</td>
<td>76.88</td>
<td>76.41</td>
<td>69.47</td>
</tr>
</tbody>
</table>

Figure 2. Scree graph of dataset of 50Hz frequency resolution

Figure 3. Scree graph of dataset of 100Hz frequency resolution

Figure 4. Scree graph of dataset of 250Hz frequency resolution

Figure 5. Scree graph of dataset of 500Hz frequency resolution

Figure 6. Scree graph of dataset of 1000Hz

Figure 7. Scree graph of dataset of 1500Hz
Table 2 reports the results after multiplying the eigenvector matrix by the primary datasets and then using the reduced datasets for classification.

<table>
<thead>
<tr>
<th>Segmentation Resolution (Hz)</th>
<th>50</th>
<th>100</th>
<th>250</th>
<th>500</th>
<th>1000</th>
<th>1500</th>
<th>2000</th>
<th>3000</th>
<th>5000</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of features</td>
<td>60</td>
<td>47</td>
<td>29</td>
<td>17</td>
<td>10</td>
<td>7</td>
<td>7</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td>50.74</td>
<td>50.58</td>
<td>64</td>
<td>75.58</td>
<td>79.54</td>
<td>83.45</td>
<td>82.59</td>
<td>83.29</td>
<td>83.19</td>
</tr>
<tr>
<td>True Positive Rate (%)</td>
<td>60.09</td>
<td>60.23</td>
<td>78.69</td>
<td>84.27</td>
<td>88.74</td>
<td>88.22</td>
<td>86.71</td>
<td>83.75</td>
<td>80.62</td>
</tr>
<tr>
<td>True Negative Rate (%)</td>
<td>42.31</td>
<td>42.21</td>
<td>50.15</td>
<td>67.18</td>
<td>70.42</td>
<td>78.73</td>
<td>78.51</td>
<td>83.11</td>
<td>85.88</td>
</tr>
<tr>
<td>False Positive Rate (%)</td>
<td>57.69</td>
<td>57.79</td>
<td>49.85</td>
<td>32.82</td>
<td>29.58</td>
<td>21.27</td>
<td>21.49</td>
<td>16.89</td>
<td>14.12</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>---</td>
<td>---</td>
<td>69.02</td>
<td>72.47</td>
<td>75.38</td>
<td>80.91</td>
<td>80.74</td>
<td>83.96</td>
<td>85.63</td>
</tr>
<tr>
<td>Recall (%)</td>
<td>50.18</td>
<td>60.23</td>
<td>78.69</td>
<td>84.27</td>
<td>88.74</td>
<td>88.22</td>
<td>86.71</td>
<td>83.75</td>
<td>80.62</td>
</tr>
<tr>
<td>F-Score (%)</td>
<td>---</td>
<td>---</td>
<td>60.88</td>
<td>74.67</td>
<td>81.15</td>
<td>84.18</td>
<td>83.28</td>
<td>83.04</td>
<td>82.56</td>
</tr>
</tbody>
</table>

Table 2 shows that the classification results are improved and at the same time the dataset dimensionality is considerably reduced.

7. Conclusions

This paper reports a work where AE signal analysis based on FFT is used to identify faulty combustion of an automobile engine regardless of the type of automobile. Major noises are removed from the acoustic signals by listening to them. Methodology proposed in this paper is capable of dealing with the signals that contain environmental noises and are static during
the recording time. For example, sound of a fan in operation. One can claim that the methodology used in this paper is suitable enough to be used for other types of automobile engines. Therefore, the proposed method proves to be automobile independent in its fault detection. 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

Intention is to improve the classification results using more appropriate feature extraction and signal processing techniques. For example, using the time-frequency transforms to use both time and frequency characteristics of signals are in mind. At the same time, detection of the automobile in the form of specific automobile detection or categorized detection of similar automobiles are considered. Adding more faults to the list of the faults and successful classification of them is also included in the future plan for the reported work. Publicising the signals used in this paper is expected via our laboratory website: http://ial.iust.ac.ir/.

Acknowledgement

Authors thank are to Irankhodro Powertrain COmpany (IPCO) a subsidiary of Iran Khodro Company a leading Iranian automaker (Mr. Izanloo) and Iran Khodro central repair shop number 5 (Mr. Saghi) that supported this work by giving us access to their facilities to collect samples.

References


