Enhancing acoustic emission signals from multi-cylinder diesel engine

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Abstract: This paper presents techniques which can be viewed as pre-processing step towards diagnosis of faults in a small size multi-cylinder diesel engine. Preliminary analysis of the acoustic emission (AE) signals is outlined, including time-frequency analysis, selection of optimum frequency band. Some results of applying mean field independent component analysis (MFICA) to separate the AE root mean square (RMS) signals are also outlined. The results on separation of RMS signals show this technique has the potential of increasing the probability to successfully identify the AE events associated with the various mechanical events.

Keywords: fault diagnosis, acoustic emission, mean field independent component analysis, RMS

1 Introduction

When a machine begins to fail, symptoms of failures may be noticed in advance using onboard systems. Therefore, condition monitoring and fault diagnosis are extremely important tools to ensure maximum productivity and safe machine operation. This potentially saves human catastrophes and industries millions of dollars in unexpected downtime.

Machine fault diagnosis is normally carried out widely by means of quantitative analysis on vibration, acoustic emission, pressure, temperature and the oil profile. Vibration signal analysis is the most commonly used technique and has been investigated for the last few decades. Unfortunately, vibration signals are only effective when the signal-to-noise ratio is high and above the background noise.

For this to occur, the defect size is often relatively large and may not provide sufficient lead time for remedial action. The main objective of all condition monitoring program is to be able to detect an impending failure, while the defect size is still very small. Acoustic emission (AE) technology has been used extensively in recent years to detect and locate crack initiation by some researchers [1-3].

The first step in this study outlines how AE techniques have been used to monitor a four-cylinder, four-stroke Ford diesel engine. Four AE sensors were located on the side of each cylinder to record the AE signals while the engine was running. The root mean square (RMS) energy signals calculated from the AE measurements have been used to monitor the combustion events for each cylinder. However, the AE noise from adjacent cylinders may corrupt the AE signals. This creates extreme difficulties to diagnose the health status of a particular cylinder. Therefore, mean field independent component analysis (MFICA) is used to enhance the performance of the algorithm in detecting individual events during the combustion process.

Independent Component Analysis (ICA) is commonly used to solve Blind Source Separation (BSS) problems. It assumes statistical independency among the source signals and separates them by using only the measured output data. It has been applied successfully in image processing [4], analysis of biomedical signals [5, 6] and separation of speech signals [7]. MFICA [8, 9] adds non-negative constraints on the sources and mixing process based on the instantaneous mixing ICA algorithms.

Section 2 describes the experimental setup and detection of AE sources. More importantly it analyses the time-frequency information and defines the range of useful frequency band. Section 3 briefly describes the MFICA algorithm and definition, and then concentrates on the AE RMS signal separation using MFICA. Finally, a comparison is made on the results before and after MFICA separation.
2 Experiment Setup

The experiment was carried out on a 47 kW Ford four-stroke, four-cylinder diesel engine located at the QUT Biofuels Engine Research Facility (BERF). The acoustic emission monitoring system consists of AE sensors, pre-amplifiers, bandpass filters and a data acquisition system.

The AE signals detected by sensors are elastic energy waveforms generated from intrinsic sources and propagated through the complex structure (boundaries and discontinuous) of the engine blocks and couplant (silicon grease) into AE sensors. The sensors then convert the surface motion into electrical signals. The use of couplant is to maximise signal transmission ability between the engine surface and the sensors.

The resonant type AE sensors (R-15) used in this experiment, are from Physical Acoustics Corporation (PAC). Figure 1 depicted four AE sensors were attached on the side of each cylinder block, and the locations of the exhaust/inlet valve and the injector where the AE sources might come from. The data were acquired at a running speed of 1700rpm. The measurements were interpreted regardless to the effect of resonant type frequency response from the sensors. Figure 2 shows the AE sensor locations and the experiment setup.

![Figure 1: Cylinder block and sensor locations top view](image)

![Figure 2: (a) AE sensors on the side of cylinder block and (b) Data acquisition setup](image)

The PAC pre-amplifiers were all switched to a gain value of 20dB. The AE signals were bandpassed between 0.02 MHz to 0.4 MHz before sampled at 1MHz to avoid aliasing. Before any pre-processing applied to the AE signals, the four channels AE signals were stored in order, and each of them
contained approximately two seconds of data. That is due to the maximum data acquisition system streaming capacity of each data transfer to the notebook. Therefore, there was no continuous observation for each channel for more than two seconds. The data recorded is equivalent to about 28 cycles at 1700rpm running speed.

2.1 Diesel engine acoustic emission

Before introducing the separation algorithm, it is important to have some understandings of how the diesel engine generates AE signals. Whilst running normally, the AE sources consist of combustion-related process, mechanical movements, and intake/exhaust activities [10]. Acoustic in [10] is referred to the audible noise which has low frequency with bandwidth from a few Hz to 20kHz. During a malfunction, possible AE sources related to the injection pump, clogging or wear of the injectors, excessive clearances in the cylinders and burn out of the valves [11].

All the AE generated for these possible sources mix and propagates through the complex engine structure are picked up by the AE sensors. The wave propagation suffers from reflection, refraction and mode interchanges [12]. Hence, the original AE sources may be seriously distorted. It is impossible to trace back the intrinsic sources; however this work attempts to recover the energy of the sources propagated to the surface. Making use of these energy responses of each cylinder, it is able to monitor the running condition of a diesel engine. Figure 3 shows the mechanical events plot generated using the given Ford diesel engine as can be seen a period consists of two crankshaft revolutions or 720 degrees.

![Figure 3 Simulated mechanical events in one period](image)

This paper groups all the mechanical events that belong to a particular cylinder as a single source. For example, INJ1 (fuel injection), COMB1 (fuel combustion), IVC1 (inlet valve closing) and EVC1 (exhaust valve closing) are all grouped as a single source (S1).

2.2 Time-Frequency interpretation

The short-time-frequency-transform (STFT) of the four sensors AE data are calculated using a window size of 200 data points with 80% overlapping. Figure 4 captures the EVC4, IVC2 and COMB1 events. Four AE sensors were used in the experiment and each of them was captured as an individual channel.

Each channel has the same concentrated energy at low frequencies below 0.1MHz. Comparing to the low frequency range, high frequency range from 0.1 to 0.4MHz shows stronger attenuation trend. In
Figure 5, EVC4 on channel No.4, there is a clear pulse from low to frequency, as high as 0.4MHz, and the high frequency content is getting smaller from left to right. On channel No.1, the high frequency content disappears. Similar to the IVC2, the high frequency also eventually disappear on channel No.4. In contrast to the COMB1 is not easy to see the decay trend intuitively. It is found that the valve activities actually create larger AE amplitudes from this research and also the report in [13]. These activities are also capable of generating higher frequencies.

![Graph showing frequency distribution](image)

**Figure 4: Trend of high frequency contents at EVC4 and IVC2**

### 2.3 AE energy calculation

This study is concerned with recovering the energies of a group of acoustic emission sources in a certain cylinder as they propagate towards a sensor. The energy of the signals was calculated by taking a square value over a time t, as follows:

\[ E = \int_0^t v(t)^2 \, dt \]  \hspace{1cm} (1)

where \( v(t) \) is the instantaneous signal voltage

The energy in distance \( x \) from \( E_0 \) is calculated using an exponential decay function and similar techniques can be found in [1, 13, 14].

\[ E(x) = E_0 e^{-kx} \]  \hspace{1cm} (2)

where \( k \) is the exponential decay coefficient

Root mean square (RMS) was used instead of square value, because some parts of this research utilise the RMS reading from a PAC instrument incorporated with crank angle information. The RMS is similar to the energy and still satisfies the exponential decay relationship. A short prove and definition can be found in Eqns. (3) and (4). The RMS used in this paper is as follows.

\[ V_{rms} = \sqrt{\frac{E}{n}} = \sqrt{\frac{v_1^2 + v_2^2 + \cdots + v_n^2}{n}} \]  \hspace{1cm} (3)

\[ \sqrt{\frac{E(x)}{n}} = \sqrt{\frac{E_0}{n}} e^{-kx} = \frac{E_0}{n} \sqrt{e^{-kx}} = \sqrt{\frac{E_0}{n}} \cdot e^{-\frac{kx}{2}} \]  \hspace{1cm} (4)
The calculated RMS was designed to take 200 AE data points with 25% overlapping and zero padding.

In this section, it assumes that the relationship between AE energy level and source propagation distances suits the exponential decay function, and also the AE high frequency components are much more localised than low frequency signal components. The property of localised means the high frequency AE signals contribute less and have less interference from the adjacent cylinders. However, the observations of bandpassed high frequency AE signals still show some interference from adjacent cylinders.

3 Source separation

ICA was first introduced by Herault and Jutten in 1986 [6], and has been found very powerful to handle blind source separation (BSS). For mechanical signals and dynamic systems, it is better to use convolutive BSS because of the delay and reflection [15] of the signals. However, from AE energy point of view, the output energy signals are linear instantaneous mixing of each cylinder. This potentially reduces the complexity of the separating algorithm from convolutive to instantaneous.

Consider a linear instantaneous mixing process,

\[ X = AS + V \]
\[ Y = WX \]

where
\( A(m \times n) \) is the mixing matrix, \( S(n \times N) \) is the source matrix, \( X(m \times N) \) is the observation matrix, \( V(m \times N) \) is the Gaussian noise matrix, \( W(n \times m) \) is the separating matrix, \( Y(n \times N) \) is the estimated source vector.

\( N \) is the length of the data set, \( m \) is the numbers of observation, and \( n \) is the number of sources. These three parameter should satisfy \( N > m \geq n \) (in this paper, \( m=n \)). The bold capital case letter stands for the matrix (e.g. \( W \)).

The task is to find \( W \), which is theoretically equal to the inverse of the unknown mixing matrix \( A \), i.e. \( W = A^{-1} \) and make \( Y = S \).

3.1 MFICA and assumptions

Algorithms for non-negative sources and mixing matrices are considered (mean field ICA [8, 9]) in this paper. The non-negative constraint has been found useful in image processing [16], since the image pixel value will not be negative. The positive constraints on the sources and mixing matrix match well on the AE energy signals. Hence the signals will be tested using an existing mean field ICA from ICA:DTU Toolbox (http://isp.imm.dtu.dk/toolbox/ica/) with some modifications.

The AE energy sources (\( S \)) are assumed exponentially distributed, because most of the time the cylinder ideally does not generating AE waves and the distribution is likely to be sparse. \( \eta \) is given a value of 20 to constrain those values which concentrate at low values.

\[ p(S) = \eta e^{-\eta S} \quad (S > 0, \eta > 0) \]  

The selection of the source distribution is important, since the sources are estimated from the mean of the posterior distribution such as \( (SS^T) \) [8]. The mixing matrix \( A \) and the noise covariance \( \Sigma \) are estimated by iteration based on the mean and the moment of the sources.

ICA can only handle maximum of one source which is Gaussian distributed [4]. Hence, it is necessary to verify the energy sources distributions before applying the ICA algorithms. Since the instantaneous mixing does not affect source distribution characteristics, it is necessary to check the measured acoustic emission signals [10]. Kurtosis is a traditional method to calculate the Gaussianity of a signal.
Kurtosis value equals to zero indicates the Gaussian distribution. For super-Gaussian distribution, kurtosis value is greater than 0, as sub-Gaussian the value is less than 0.

Thirteen periods of RMS values are randomly selected to calculate the kurtosis value. Figure 5 shows the kurtosis values of the RMS of each period of four channels AE data.

![Kurtosis values of 13 periods RMS, BP 0.1-0.4MHz](image)

Figure 5: Kurtosis values of 13 periods and 4 channels RMS, BP 0.1-0.4MHz

This figure shows that all kurtosis values are greater than 5, which indicates that the energy sources have a non-Gaussian distribution. Therefore, the MFICA is expected to separate the mixture of energy signals.

### 3.2 Test result

The RMS value is calculated using 200 data points at a 1MHz sampling rate. The overlap was 25% or 50 data points. In order to smooth the fluctuation of the RMS values, a five point moving average (MA) is added before the separation algorithm. Figure 6 shows two periods of RMS readings.

![Original RMS AE BP 0.1 - 0.4MHz (25% overlapping, MA=5)](image)

Figure 6: Original two periods of RMS plot
To see the attenuation effect on the energy levels of four sensors located at each side of the cylinder block, four channels energy will be plotted on the same figure. Note that, the cylinder firing order is 2-4-3-1 which matches the following section explicitly (e.g. section one represents to the combustion events of cylinder2 with some valve movements of the adjacent cylinders). The order in which engine events appear can be seen in Figure 3.

Figure 7 shows the plots of four RMS energy signals with very clear energy decay trend of mechanical events. By comparing the energy level of each sensor, it is possible to identify the sensor’s association with cylinder. Adding the prior knowledge of the diesel engine specifications, all the mechanical events can be identified. However, some energy level differences in the readings are not significant or overlapped between the channels for some mechanical events, e.g. INJ&COMB1, IVC1, IVC4 and EVC1.

The RMS signals were then passed to the MFICA algorithm. The mean field equation was solved using the expectation consistency solver [17], and the parameters were updated using the expectation maximisation optimiser. The sources were assumed with exponential distribution and positive mixing matrix. The noise was assumed to be isotropic.

The MFICA output is shown in Figure 8 and 9. As above, the firing order 2-4-3-1 matches to each section in Figure 9. At Table 1, a comparisons were made on how much the MFICA improves the signal to noise ratio (Vmax/Vmax_2nd and Vmax/Vmin) can be found on Table 1. Vmax/Vmax_2nd stands for the ratio of the average peak and the second peak of a certain mechanical event. It can be used as a quantity to measure how much the algorithm can attenuate the energies from adjacent cylinders. Vmax/Vmin stands for the ratio of the average peak and the minimum of a certain event.

Table 1 indicates that the MFICA enhances the separation ability. The improvements of Vmax/Vmax_2nd after MFICA algorithm are larger than 3dB (second last row). Vmax/Vmin are mostly larger than 10dB (last row). That means the algorithm separates the sources by suppressing the AE noise from adjacent cylinders. Hence, AE energy readings (INJ&COMB1, IVC1, IVC4 and EVC1) are significantly higher at their corresponding cylinder than adjacent cylinders.
For example, IVC1 at section 3 of Figure 7, channel 1 and 2 have the same energy level, overlap each other. However, after the separation algorithm, section 3 of Figure 9, channel 1 has the highest energy level. This is because IVC1 is the valve closing activity in cylinder 1. Thus it can be confidently said this mechanical event happened at cylinder No.1 not No.2. Overall, the improvement gives the ability to successfully allocate and identify the AE RMS to its location and related mechanical activity.

![Figure 8: Two periods RMS MFICA output](image1)

![Figure 9: Four sections MFICA output AE RMS signals](image2)
Table 1 Event energy level comparisons

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<th>I2C</th>
<th>EV3C</th>
<th>IV4C</th>
<th>IC4</th>
<th>EV4C</th>
<th>IV3C</th>
<th>IC3</th>
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<th>IC1</th>
<th>EVC4</th>
<th>IC2</th>
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</table>

4 Conclusions and future work

Although the output from MFICA did not totally remove the noise from the adjacent cylinders measured at the monitored position. It suppresses the AE energy from adjacent cylinders and finally leads to a significant peak at the corresponding channel.

This paper shows some good observations and event alignments. It encourages the use of AE technique as an analysis tool. Frequency range from 0.1 to 0.4 MHz of AE signal has also been found useful to monitor and interpret the engine activities.

Mean field ICA shows some promising results on the ability to enhance the separation. In the future, more effort may need to be spent studying AE signals from the single cylinder IC engines, in order to verify the frequency band (0.1 to 0.4 MHz) assumption and investigate the optimum location of the sensors.

The permutation ambiguity [4] can be overcome by the observation of the estimated mixing matrix, however, the scaling ambiguity of the separated sources remains the problem. Hence, looking for a method to quantify the RMS and indicate the faulty level will be the future work.

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References


