Cylinder Pressures and Vibration in Internal Combustion Engine Condition Monitoring

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Abstract: We focus on the detection of incipient faults in an internal combustion engine using a minimum number of sensory information. Inducing several faults in a 4 stroke diesel engine, cylinder pressure (P) and vibration (V) data are acquired. Two sets of artificial neural nets (ANN) are trained separately, using features from the pressure and vibration data. Both sets of nets show very good fault detection capabilities, thus demonstrating an alternative to the multi-sensory approach commonly adopted in fault diagnosis. In a separate study, P and V are fused together at the signal level and then used to train another set of ANNs which is shown to exhibit better reliability than either system. In the final study, the outputs of the 3 systems (P, V and fused P and V), are combined together in a majority voting system which outperforms all of its constituents in its diagnostic abilities, successfully identifying 2854 out of 3000 test cases with a confidence level of 90%.

Keywords: cylinder pressure, vibration, engine, sensor fusion, majority voter

1. Introduction

Faults in machinery usually have very simple origins. However, if undetected, they compound and manifest in different forms, making it progressively harder to pin-point the original cause. An effective diagnostic system should therefore, warn the operator as soon as the first signs of malfunctioning begin to appear, so that corrective action may be taken. A practical system should be easy to implement and, ideally, be based on a minimal number of sensory inputs, while being robust and reliable. Further, non-intrusive sensor fixing should be resorted to where practical. In this paper we explore the initial ground work carried out in the quest for such a system based on an Artificial neural network (ANN) model created out of cylinder pressure and vibration data acquired from a 4-stroke high speed diesel engine.

The explosion of the hydrocarbon-air mixture within the complex geometry of the combustion chamber causes both desired and undesired turbulence within a time span of milliseconds in a high speed engine making it almost impossible to accurately construct a mathematical model of the process. However, the varying pressures within the cylinder and the ensuing vibration levels could be used to build a reasonable semi-parametric model such as an ANN. Such a model would be very useful in developing early warning systems for engine component malfunctioning and would not rely on a large array of sensors for its functioning. An example of the multi-sensory approach can be seen in Autar (1996). Section 2 of this paper describes the experimental set-up, the nature of the induced faults and the type of data acquired. The cylinder pressure (P) developed within an internal combustion engine can be considered to be the pulse of the engine. In conjunction with the periodic events such as inlet and exhaust valve operations and fuel injection timings, it provides valuable information about the combustion characteristics of the engine. Section 3 illustrates the development of an ANN based diagnostic system based on a single sensory input, i.e. cylinder pressures.

Vibration levels (V) sensed from the engine cylinder head form a complex signal which has a strong correlation with the cylinder pressures. Unlike pressures the method of measurement is non-intrusive. Section 4 focuses on the vibration data. We perform frequency and short time frequency analysis on the data and show how such conventional methods are capable of performing diagnostic feats, albeit with certain limitations. We then illustrate how vibration amplitudes during the combustion process could be used to develop an efficient ANN based fault diagnostic system free from the constraints of the traditional approach.

Pressures and vibration waveforms synchronised with the crank angle information give a lucid understanding of the engine events. Mechanically they complement each other as a cause (P) and effect (V) phenomenon (Stone, 1992). In section 5 we explore how the two types of sensory information could be fused together to create systems which are more reliable and robust than either of them taken separately. The two data (P and V) are combined at the input level to create a third system PV, which demonstrates better generalisation properties than either the P or V system. Finally, the decisions of P, V and PV are used in a majority voter which outperforms all the systems discussed so far.

2. Experimental Set-up

2.1 Inducing Faults and Collecting Data

Four commonly occurring faults were induced (one at a time) in one unit of a twin cylinder, 4-stroke, air cooled, naturally aspirated diesel engine with a maximum power output of 10.4 kW at 3000 revolutions/minute (RPM). Engine speed was varied from 1800 to 2800 RPM during the data collection stage. The faults induced were

- Leaking exhaust valve (E) A fine cut of around 200 microns depth across the seat of the valve lid
- Leaking air inlet valve (I) Fault induced as above in the air inlet valve
- Blocked fuel injector (B) An injector nozzle with 1 out of 4 holes blocked in service
- Poor fuel atomisation (L) An injector nozzle with imperfect atomisation pattern (slight 'dribble')

Cylinder pressure was sensed with a Kistler 6125A quartz pressure sensor, while vibration was sensed with a Bruel&Kjaer Deltatron miniature accelerometer (4397) with an upper frequency limit of 25 kHz. However the vibration signal was band pass filtered from 20 Hz to 18 kHz using an analogue filter. Data was also acquired under normal (N) conditions when none of the components were faulty. The pressure and vibration signals were digitised by a 4-channel, non-multiplexing type analogue to digital (AtoD) card with 12 bit dynamic resolution and a maximum digitisation rate of 1.25 MHz per channel.

2.2 Data collection

Due to the non-linear dynamics of turbulence within the combustion chamber, no two engine cycles are identical (Heywood, 1988, Stone, 1992). The rotational speed is not steady within each cycle, rising and falling with the engine events such as fuel ignition and valve operations. Any assumption of steady speed within each cycle, is bound to cause erroneous and misleading results. However the engine events are mechanically predetermined (during design and operation) and can be treated as stationery mileposts within each operating cycle. Any continuously varying signal acquired from the engine, needs to be logged precisely in relation to these events. An incremental optical shaft encoder with an angular resolution of 0.1 degree, emitting 3600 TTL (Transistor to Transistor Logic) pulses per revolution was chosen to achieve this objective. This high frequency pulse was used as an external clocking mechanism for the AtoD card while the data collection process was triggered by a separate zero index BDC signal from the encoder. For more details about the data collection, see Chandroth & Sharkey (1999).

Fig 1 illustrates the final system. Pressure and vibration sample lengths were 7200 points each corresponding to 720 degrees of a 4-stroke cycle. Vibration data was also acquired using the internal clock of the AtoD card at 50 kHz sampling rate. Under each of the N, I, B, L, E conditions mentioned in section 2.1, 2400 samples of data representing cylinder pressure, vibration and acoustic emission were acquired. (Since this paper is limited to the work done on pressure and vibration, acoustic emission is not discussed any further). Thus in total there were 12000 samples of pressure and 24000 samples of vibration data (12000 each from the internal and external clock sampling methods). Only the externally clocked data was used in the work done with ANNs. These 12000 samples were divided into 3 sets: 7500 for training ANNs, 1500 for validating and 3000 for testing

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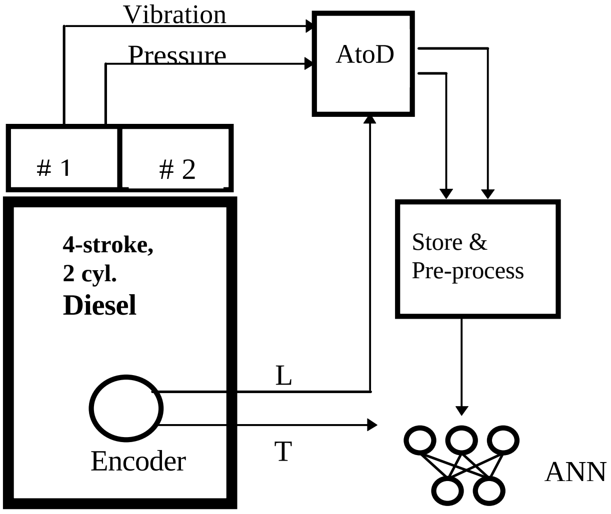

Figure 1: Schematic layout of the final data acquisition system. L is the external clocking signal and T is the BDC zero index trigger signal.

3. Cylinder Pressure in Fault Diagnosis

Cylinder pressures from a diesel engine have been used for tasks such as estimation of air-fuel ratio (Gassenfeit and Powell, 1989), estimation of ignition timing (Wilson *et al*, 1992) and direct engine control (Anastasia and Pestana, 1987; Kwamura *et al*, 1988). Of late, it has also been used in fault diagnosis (Gopinath, 1994; Sharkey *et al*, 1996 and Chandroth *et al*, 1998) and in supervision of injection (Leonhardt *et al*, 1995). Pressure traces over the entire engine cycle, captured at a fine resolution and synchronised with the crank angular position contains valuable information about the engine components participating in the combustion process.

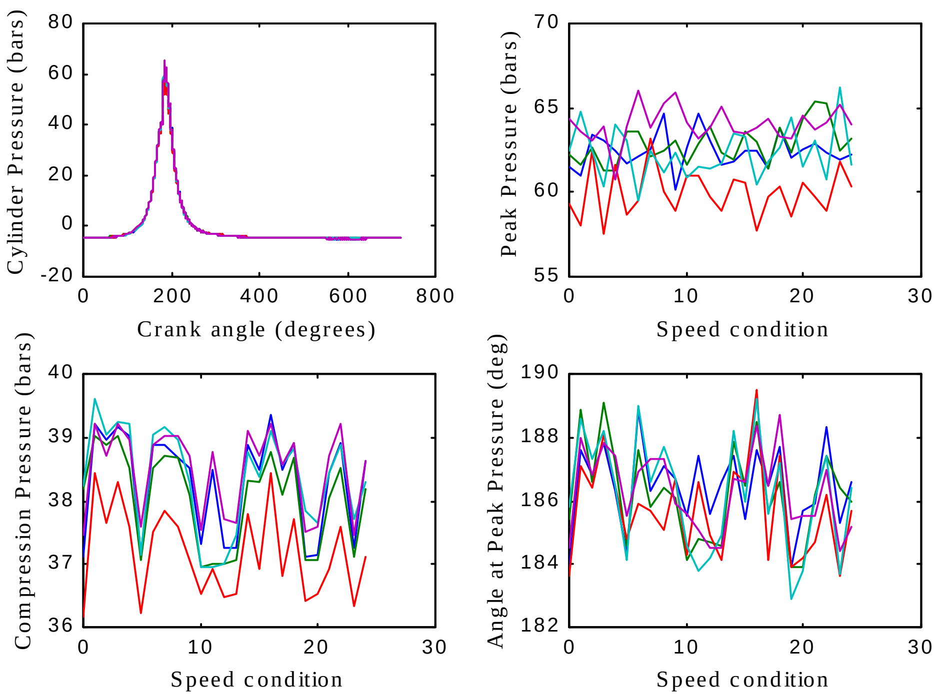

Figure 2 Clock-wise from top left. 1)Cylinder pressure traces of all 5 conditions. 2) Peak firing pressures 3) Compression pressures 4) Angle of peak pressure. (2,3 and 4 calculated under 25 different speed states)

In analysing the pressure data, it was decided to use a subset of the data representing each of the 5 classes (N,I,B,L and E) to test for various parameters such as peak firing pressure, the angle of attainment of the peak and compression pressure (see Figure 2). Maximum rate of change of pressure and the angle at which this change occurred were also checked by fitting a polynomial to the pressure curves and finding the location of maximum slope. Figure 2 (1) is an overlay of one sample each from the 5 classes (N,I,B,L and E). It is quite obvious that there are no visual clues to differentiate one type from another. Neither is it possible to distinguish them from each other using derived statistics (Figure 2 :2,3,4) except perhaps those belonging to the blocked injector fault which has consistently low peak and compression pressures. However when the pressure trace within the combustion zone was inspected more closely, it was seen that the pattern of gas pressure oscillations were quite different for each data sample and that inter data variances were the largest in the post TDC (Top Dead Centre) zone. For this reason, zooming in on the data set in the area of combustion and using a subset of these data points for training ANNs would be a sensible approach.

From the range 180 degrees to 200 degrees (TDC + 20^o), 50 points were used for training a fully connected feedforward multilayer perceptron using the backpropagation learning algorithm. The angular position of the crankshaft was not explicitly included in the input to the ANN. But the sequence in which the inputs were treated by the ANN always remained the same and thus a certain implicit idea of order was built into the system. Several nets were trained using a set of 7500 randomly mixed set of training samples and tested on a validation set of 1500 samples in order to determine which was the best net. The best net was then tested on the final test set with an error tolerance of 0.1. There were 3000 samples in the final test set which had not been used in training nor optimising the network parameters. The final result of the cylinder pressure based diagnostic system was 89.07% correct generalisation.

The results from this study clearly demonstrates that a single parameter, cylinder pressure in this case, could be effectively to develop a diagnostic system for a diesel engine provided that the data is always logged in relation to engine events. The method could also be adapted for a petrol engine or other high speed reciprocating machinery.

4. Vibration in Fault Diagnosis

Vibration in reciprocating machines is far more difficult to analyse than that in rotating machines. Several commercial diagnostic systems use base line signatures both in the time and frequency domain to serve as a 'normal' template for future comparisons. Trend analysis has also been established to be a reasonable technique in condition monitoring. Short time windowed Fourier analysis, Wigner-Ville distribution, time frequency analysis and wavelets analysis have also found varying degrees of success in this area. (Staszewski & Worden, 1997). All these methods require complex computations as well as averaging over several waveforms. Internal combustion engines, normally operate across a wide spectrum of speed and load. Time domain averaging of signals under varying speed conditions would lead to erroneous results. In an environment where fault detection has to be instant, it would be desirable to have a system with minimal computational requirements which could evaluate the machine condition on a per sample basis. The criterion for the selection of the best features for fault classification is a vital issue.

If simple statistics such as energy content, crest factor (peak value / root mean square value), kurtosis (the fourth statistical moment normalised to the square of the variance) etc. could be used to discriminate between the classes of data, they would be the most natural choice for the input parameters of any diagnostic system. It was found that there did not exist any clear demarcation within classes for any of these derived parameters. (Due to space limitations, these results are not reproduced here). As will be explained in section 4.2, using selected points in the post TDC zone of the crank-angle domain vibration data, to develop ANN based diagnostic systems proves to be an efficient approach to the problem.
In the next two sub sections, we take a brief look at the traditional approaches of frequency and short time window frequency analysis. It is argued that in a real time system, such techniques would not be the most suitable.

4.1 Frequency domain analysis

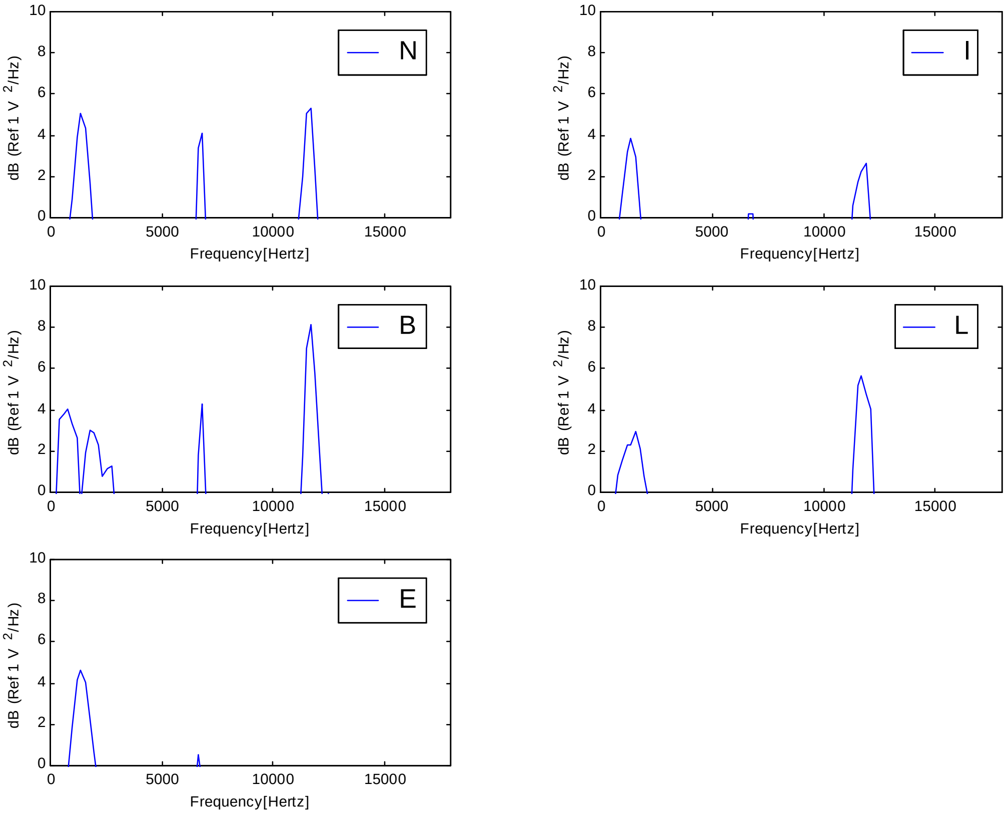

Figure 3 Power spectral density analysis of the 5 classes (N,I,B,L,E) of data within a band of 20 Hz to 18 kHz frequency range, averaged over 100 samples, at approximately 2750 RPM.

4.1.1 Power Spectral Density estimation

Spectral analysis of the internally clocked vibration signals were carried out to determine if the differences between engine states could be revealed in the frequency domain. Figure 3 is the average power spectral density (PSD) of 100 signals (at approximately 2750 RPM), using a 256 point FFT and a 256 point hanning window. A threshold of 0 dB was applied to visualise the spectra above this level. The differences between the 5 classes are apparent from the figure. However, it must be noted that such an approach would fail when the engine speed varies during operation as the spectral components would begin to shift laterally and any averaging would lead to erroneous results. (In the ongoing research, the application of cepstral techniques are being investigated with the aim of making the analysis invariant to speed changes).

4.1.2 Short time frequency analysis

To overcome the non-stationary nature of the vibrations signals from a variable speed engine (such as a marine propulsion engine), it is necessary to evaluate the waveforms within short time windows. If the signal in the time domain is represented by $x(t)$ then the windowed signal $x_w(t)$ is given by

$$x_w(t) = w(t)x(t) \qquad [w(t) \in L^2(\mathbb{R}) \text{ the space of square integrable functions}].$$

When the window is translated across the whole of the time domain and the Fourier transform is applied to the signal under each window, then we have a windowed Fourier transform. (Staszewski & Tomlinson, 1997). A spectrogram is the square of the modulus of the short-time Fourier transform. Figure 4 illustrates the contour plot of the absolute values of the spectrogram relating to 2 engine conditions (I and E). The contour plots show up the difference between the two classes quite dramatically. However, the two samples considered in Figure 4 were from single engine cycles and may not represent the true differences between the classes. Spectrograms of the two classes averaged over several engine cycles are likely to have less discriminant features in them.

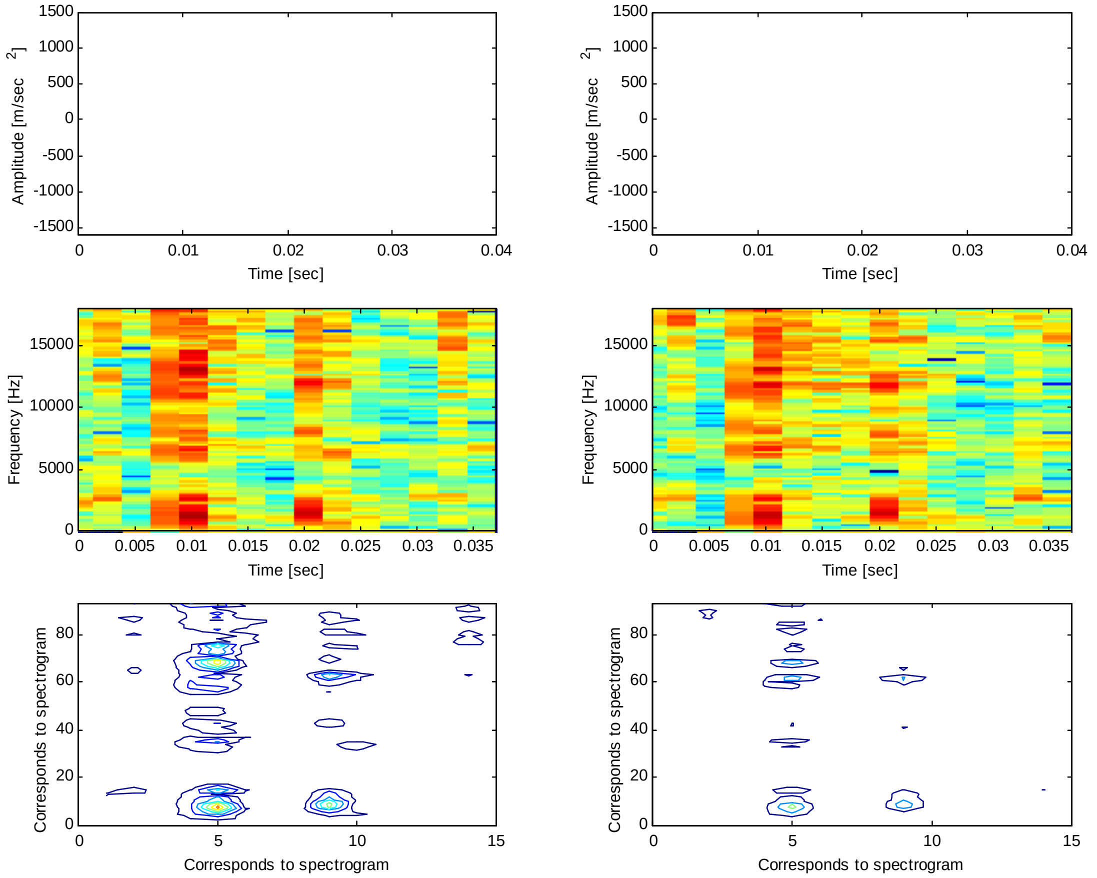

Figure 4 Row1: Representation of the time domain vibration signal belonging to 2 classes (E and I) with very similar faults. Row 2: Spectrogram of the time domain signals, with a 256 point window and 50% overlap. Row 3: The contour plot of the absolute values of the spectrogram.

The analysis in the two preceding sections, clearly illustrates the usefulness of traditional approaches in vibration signal processing and their potential, albeit limited, in the realm of fault classification. However, due to engine speed variation, a system which relies on averaging over several engine cycles would not be practical. The increasing computational complexity in conducting PSD estimation and short time window frequency analysis, is not justified when a simpler system (see next section) could carry out the classification task in real time, irrespective of the speed conditions.

4.2 Artificial Neural Nets Approach

An ANN using the backpropagation algorithm for learning from examples, often has a prolonged training period. But once the weights of the interconnections are computed, the actual task of real time classification boils down to elementary matrix operations. In order to create a simple but efficient classifier, vibration signals acquired using the external clocking mechanism were used to train fully connected feed forward ANNs using the backpropagation algorithm. The points selected were in the range of 180 to 200 degrees during the power stroke / exhaust stroke of the 4-stroke cycle. Due to the resolution of the shaft encoder being $1/10^{th}$ of a degree, there were 200 points within this set. After sub-sampling by a factor of 4, fifty points were extracted from each waveform. The absolute values of these 50 points were then normalised and this vector of 50 points made up one training sample. There were 5 binary outputs corresponding to each class. After training several nets with a set of 7500 samples and optimising the nets' performance on the validation set, the best system was tested to an error tolerance of 0.1 on a test set of 3000. The net produced a correct response to 90.23% of the test data.

The above approach makes use of the raw information in the vibration signals and does not rely on transforms to the frequency domain as in the more conventional approaches discussed earlier. It must be stressed that selecting points in the combustion zone was made possible due to the data being logged in relation to the crank angle. Otherwise, changes in engine speed will result in the data points being unrelated to the periodic events in the engine cycle.

5. Pressure and Vibration

It was seen in sections 3 and 4, that good classification results were obtained using either the pressure or vibration data. In this section, we explore the possibility of improving upon these results by combining the two. In a direct injection engine, there are 2 main excitatory forces: the unidirectional force due to combustion and the reversible forces which are mechanically induced. Due to the large rate of heat release during combustion, the pressure rise is extremely rapid in this zone and causes oscillations in the cylinder pressure. The pressure fluctuations, **P(t)**, cause the engine structure to vibrate and this response could be modelled as a linear spring-mass system of mass **M**, damping coefficient **C**, and dynamic stiffness **K**:

$$P(t) = Ma + Cv + Kx$$

where x is displacement, v velocity and a acceleration (Priede T, 1992).

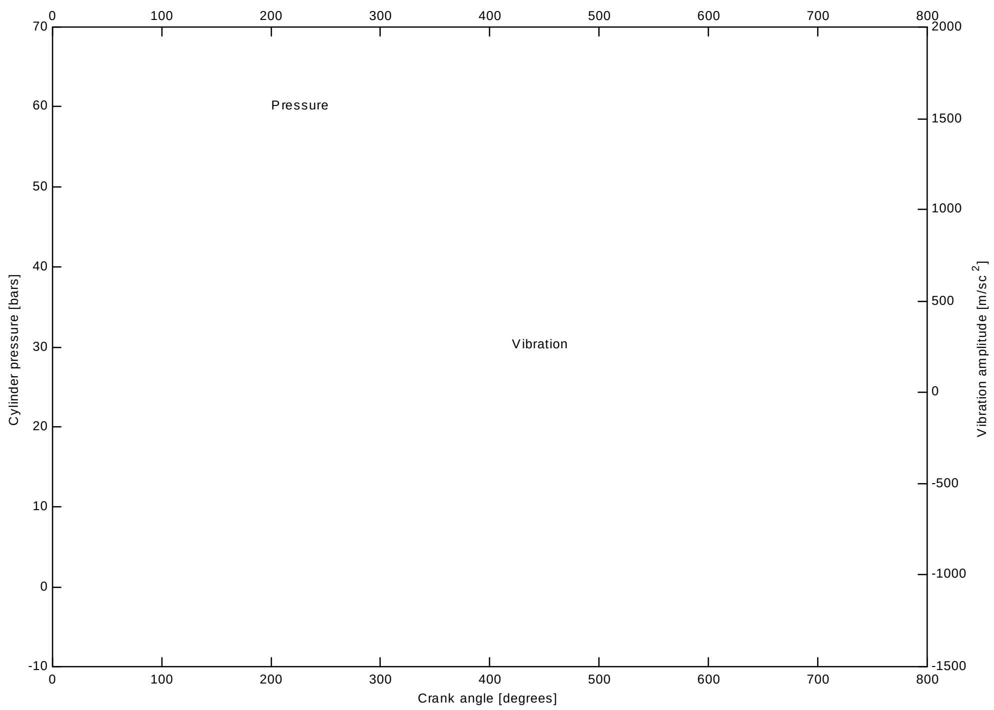

Figure 5: Cylinder pressure and vibration of one engine cycle at 2750 RPM, under normal operation. .

There is ample evidence that the pressure oscillations during combustion cause most of the vibration in a normally aspirated, high speed direct injection diesel engine. (Hince J O, 1949, Priede T, 1992). Figure 5 shows a plot of cylinder pressures and vibration which were sensed simultaneously during one complete cycle of the engine. It can be seen that the maximum amplitude of vibration corresponds to the peak firing pressure and also that the rate of pressure rise is very large during combustion. A close correspondence can be observed between the two signals each of which were represented by 7200 points. There was a one to one correspondence between each point on the pressure and vibration signals. Although both waveforms represent the same engine cycle, they convey the information about the engine events in very different ways. Hence fusing the two information together should prove beneficial as far as the fault classification task is concerned. In the following section the methods adopted for combining the pressure and vibration signals are discussed.

5.1 Sensor Fusion

Sensor fusion is an active area of research in defence related work, medical imaging and robotics (Brooks et al., 1997; Sharkey, 1997). It has also been used in condition monitoring (Chen, Du & Qu, 1995) though the techniques used are more direct and does not involve any feed back loops as in robotics. It has strong biological and cognitive foundations (Murphy, 1996). Human beings (and other animals) use multi-sensory information in everyday life. An experienced condition monitoring engineer, with the help of sight, smell, touch, hearing (and sometimes taste) can draw very accurate conclusions about the state of a piece of machinery. It is still not clear how exactly we integrate the sensory information to aid in the decision making process. However, studies have shown that the superior colliculus is the area of a mammal's brain where sensory information merges together and along with control signals from the cerebral cortex modulates or influences behaviour (Stein & Meredith, 1993).

Sensor fusion, in the context of machine learning, could be achieved at 3 levels (Brooks et al, 1997). Signal fusion is at the lowest level, either fusing the raw data together or extracting features from them before the fusion. In medium level fusion, statistical distributions of the data need to be known *a priori* and in decision fusion the final outputs are combined together in a voting system. In the next two sections, it is shown that fusing the pressure and vibration at the raw signal level and using the fused signals as training examples for ANNs, demonstrate improved generalisation performance. Further, it is also demonstrated, that by creating an ensemble of nets consisting of a net each of pressure, vibration and fused pressure-vibration could be used in a simple majority voting system, to obtain further improvements in the fault classification accuracy.

5.1.1 Signal Level Fusion

In total, 4 different systems were created from the 50 matching points in the combustion zone, taken from the crank angle domain waveforms of pressure and vibration. Let us represent the pressure data as P_i and vibration as V_i, ($i = 1 \ldots 50$). P_i and V_i were fused together using elementary algebraic operators as shown below:

- $P_i + V_i$ (point by point summation)
- $P_i - V_i$ (subtraction)
- $P_i * V_i$ (multiplication)

In another combination, 25 points from P_i and 25 from V_i made up the 50 point input vector to the 4th fusion system such that the inputs were interleaved as shown below:

- P_j alt V_k (Alternate points where $j = 1,3, \ldots ,49$ and $k = 2,4, \ldots ,50$; $j,k \in i$)

By training and validating several nets based on the fusion methods described in this section, the summation approach ($P_i + V_i$) was found to perform best. Table 1 shows the performance of the pressure system (section 3), the vibration system (section 4.3) and the $P_i + V_i$ sensor fusion system when tested on their respective test sets.

Data Source	Performance
Pressure (P)	89. 07 %
Vibration (V)	90 23%
P & V fused	92.27 %

Table 1 Performance of the 3 diverse systems (Pressure, Vibration and $\mathbf{P_i + V_i}$ **)** on the same set of test data

5.1.2 Decision Fusion

The decision level sensor fusion discussed by Brooks (1997) is equivalent to an ensemble combination of ANNs, in which the outputs, or decisions, of a committee of nets are combined to yield a single output. There have been a number of demonstrations of the improved performance that can result from combining a set of ANNs in an ensemble, as opposed to selecting the single best performing net (for reviews see Sharkey, 1996; 1999). Clearly there would be no advantage to combining a set of identical nets. What is required is that the component nets in an ensemble should be both as accurate as possible and diverse, in the sense that they show different patterns of generalisation. Where the errors made by the component nets in an ensemble are independent, the errors made by one net would be compensated for by the correct outputs from the other nets in the ensemble, and, when combined by means of a majority vote could result in improved performance.

The aim in ensemble creation is that of finding a set of nets that exhibit a minimum number of overlapping errors when tested on a validation set. Since the performance of an ANN depends on the data on which it is trained, it is likely that changes in the training data are likely to lead to the inference of a different function (Sharkey and Sharkey, 1997). The pressure, vibration and fused data are effectively data from different sources, trained to produce the same output. Hence it is likely that their pattern of generalisation will also be different. In the light of research on combining nets, an attempt was made to improve performance by combining a set of nets each trained respectively on pressure, vibration or fused pressure and vibration data. A variety of selection algorithms have been suggested, but the method used here was to exhaustively try all possible combinations of available nets until the best performing set of three nets was identified. The performance of the combined system was 95.67% when tested on the validation set and 95.13% on the final test set. It should be noted here that the constituents in the ensemble are not made up of the best performing nets from each category, but ones which were the most diverse in their generalisation capabilities.

Evaluated on	Net 1 (Pressure V)	Net 2 (Vibration V) %	Net 3 (PV fusion) %	Ensemble Performance
Validation set	88.5 %	90.23 %	92.27 %	95.67 %
Test set				**95.13 %**

Table 2 Performance of the final system comprising of nets trained on pressure, vibration and fused data

To quantify the results further, out of 3000 previously unseen test cases which contained an equal number of each of the 5 classes (N, I, B, L, E), the final system classified 2854 inputs correctly with a confidence level of 90% or more and mis-diagnosed 146.

6. Conclusion and Discussion

In much of the reported work in engine fault diagnosis, the faults considered are either too general or too severe. Just as it does not take an army of physicians to diagnose a common cold, it seems an overkill to propose sophisticated systems to diagnose blatant anomalies such as cylinder misfire, or several degrees of advanced fuel injection. Another lacuna in many diagnostic systems is that they depend on a large array of sensory information, which makes them infeasible outside the laboratory. What is needed is an approach where information from a minimum number of sensors could be used in the early detection of incipient faults. Our approach to the problem is based on this tenet.

In this paper, we have demonstrated that it is possible to use either cylinder pressure (P) or vibration amplitude (V) to detect and diagnose some commonly occurring combustion component faults in a 4-stroke twin cylinder diesel engine. Faults of a subtle nature were induced in the engine, and data was acquired. Data was also acquired during healthy operations. Two sets of artificial neural nets (ANNs) were trained with selected points from the P and then the V waveforms, respectively. The best performing nets showed a level of generalisation performance of 89.07% (P) and 90.23% (V) respectively.

In addition to these investigations of single sensor systems, the possibility of improving performance by means of either sensor fusion, or ensemble combination (decision fusion) was explored. Since the P and V signals were synchronised together by means of an external clocking mechanism, it was possible to fuse the P and V data at the signal level, and to train a number of ANNs on the fused data. The best performing net trained with the fused PV data displayed an improvement over both the P and V based nets. Ensemble combinations were created by exhaustively testing all combinations of P, V and PV based nets, and selecting the best combination. The ensemble performance was evaluated by using a majority voting system. The final system correctly classified 2854 out of 3000 test cases with a confidence level of 90% or more, a level of generalisation (95.13%) that outperforms both the single sensor and the fused sensor nets.

In summary, the results reported here indicate that although effective fault diagnosis can be performed on the basis of data from a single sensor, performance can be improved by means of sensor fusion, and through ensemble combination. It should be noted that these results are based on the system evaluating a single engine cycle at a time. In a practical context, it is easy to conceive of a method whereby several engine cycles are evaluated and the confidence in the diagnosis strengthened, depending on the number of times a particular fault is detected in a given period of time. The analysis of the vibration data using conventional methods clearly indicates that fault classes have discriminant characteristics in the frequency domain. Such traditional methods could be used off-line for retrospective analysis of major breakdowns or on-line as back-up systems to provide corroborative strength to the predictions of ANN based systems. Several issues remain to be addressed, if the system is to be implemented in practice. These issues are beyond the scope of the current research and we hope to address them in the future.

A large marine engine has a much slower rotational speed (around 90 to 120 RPM) compared to the high speed engine (1500 to 3000 RPM) used in our work. The changes in cylinder pressures and vibration patterns would be proportionately slower in the slow speed engines thus making it easier to record data with a much higher resolution. Hence the principles set out in this paper should be applicable to all engine types. Large engines are well monitored with various sensors such as exhaust temperatures, fuel and cooling water temperatures, scavenging air pressures and temperatures, fuel viscosity etc. Such sensory information could be used to develop rule sets to confirm the decision of the neural nets based diagnostic systems discussed in this paper.

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