ENGINE DIAGNOSIS SYSTEM FOR AUTOMATIVE INDUSTRY

ABSTRACT

The condition monitoring based on sound and vibration detection has benefited the machinery industry. Endless efforts have been put into the research of fault diagnosis based on sound. It offers concrete economic benefits, which can lead to high system reliability and save maintenance cost. Artificial Neural Network is a very demanding application and popularly implemented in many industries including condition monitoring via fault diagnosis. Artificial Neural Network has been implemented successfully in many aspects, but the implementation needs detailed knowledge and studies.

In this work, the noise from the vehicle engine is recorded using a suitable experiments setting up and the noise signature of the vehicle engine noise is obtained and identified. Tests have been carried out to record the noise signal from different vehicles of the same model to identify the noise signature. The acoustical signals are collected by a set of directional microphones, which transducer the sound pressure signals affected by mechanical vibrations emitted by the transmission. The set of signals collected will contain fault signatures as well as signals from other interfering sources.

The captured signal, which is in analog forms, is digitized. In digitizing process; the signals are digitized using different frequency octave. Here we are using full octave band. Digitized signals are used to generate frequency power spectrum. This permit the sound intensity level with its corresponding frequency obtained from the frequency power spectrum. These data will go through a pre-processing stage. The noise signature is obtained by applying two different methods of pre-processing, frequency spectrum analysis method and the Principal Component Analysis method. Both methods extract the noise signature of the recorded noise. The result of the pre-process will used as the input in the neural network model. Based on the noise signature, neural networks models diagnose the vehicle faults.

Two different neural network architectures are proposed in this research, back propagation network and Learning Vector Quantization network. The performances of the two different pre-processing techniques are evaluated and the neural network architectures are compared in terms of accuracy, efficiency and speed.

1. Introduction

Fault diagnosis is a process of predicting the current and future state or condition of a system. System may comprise of circuit board, components of any machinery, vehicle systems, industry machineries system, electric power equipments, robots and many more. A system under test is faulty or fails when it behaves and works differently from the expected behaviour. Faults diagnostics is difficult because it requires knowledge of a system, how it behaves before the faults present as well as after or when the faults present.

Faults diagnosis based on acoustic emission is popularly applied in various industries especially automotive industry. It has become a critical and popular because of the improving production quality, reducing maintenance cost and downtime and ensuring safety.

1.1. Fault Diagnosis Concept

A fault can be defined as an abnormal state of a system, dysfunction or malfunction (Shayler et al., 2000). A fault is always comes with its symptoms that an expert will associate them with external contribution factors. Diagnosis is a process of locating the physical faults of a system (Haves & Khalsa, 2000). It is a study of associating the symptoms, factors and faults. This is usually done by the system operators, experts, engineers and mechanics. The judgment of the system condition is often based on the visual inspection, audio inspection and through observation, which needs a high degree of skills. The system expert will have to analyze the differences of the system, compare the actual behaviour with the predicted faults with certain models and analyze the external parameters that may contribute to the faults condition.

1.2. Fault Diagnosis Based on Acoustic Emission

The noise emitted by a vehicle results from vibration or friction between the engine parts and also with the air. Noise of a vehicle engine produces noise signature which can indicate the condition of the vehicle engine. Similar vehicle model working under similar conditions produce similar type of acoustic signature (G. Pinero et al., 2002). A faulty engine often produces different kind of noise pattern and acoustic signal. There are a few factors that affect the acoustic signal from a vehicle engine, namely the engine type, changing in load, changing in speed, change of vehicle engine parts and etc. Traditional diagnosis method based on acoustic emission is often requires extensive experienced and certain degree of skills. This knowledge is difficult to conserve and transfer, and usually will lost during the knowledge passed along the way.

1.3. Need for the Project

The application of monitoring system via faults diagnosis on a system has become a critical consideration for manufacturers. It offers concrete potentialities and reliabilities for system monitoring applications through fault diagnosis.

Vehicle engine fault diagnosis has emerged tremendously in today's market. Its importance cannot be denied as it has shown high degree reliability and accuracy. Accurate diagnosis can save maintenance cost in terms of man power, time and money.

In this research, a simple method to diagnose the vehicle engine fault using Artificial Neural Network based on the noise signature is proposed. The noise emanated from a vehicle engine is recorded. These noise signals are then associated to the various faults in the vehicle engine. Two different methods of signal pre-processing are applied to obtain the noise signature. The first method of pre-processing proposed is obtaining the frequency spectrum of the noise signal. The second method is to obtain the eigen value of the noise signal using Principal Component. Different types of neural network architectures are applied to diagnose the faults.

1.4. Scope and Objectives

One of the main aims of this work is to identify the noise signature from the noise generated by the machine (vehicle engine). One model of vehicle is used as sample in the study. Method and setting up of experiments is explored and based on the Acoustical International Standard (ISO 9614 & ISO 3745) the recording of the vehicle noise is recorded. The recorded noise is analyzed and processed with certain method to obtain or extract the signature.

The second aim of this research work is to propose a neural network to diagnose the machine faults based on the noise signature. Different methods are applied to train the neural network.

Lastly, comparisons are made on the different methods of training.

The objectives of this work can be summarized as follows:

i. To study the settings up of the noise recording experiment.
ii. To study, analyze and obtain the noise signatures using Principal Component Analysis method.
iii. To study, analyze and obtain the noise signatures using frequency spectrum method.
iv. To propose different neural network architecture to diagnose the vehicle engine faults based on the noise signature.
v. To compare the performance of the different types of neural network architecture.

2. EXPERIMENTAL SETTING UP

There are controls and regulations on sound produced by vehicle since early 1970s. The regulation is made to control and limit the sound made by the vehicles. Today, there are different legislations that specify the standards used to do sound recording for different purposes. This legislation is to ensure that the measurement is made in a correct way to obtain accurate result.

The experiment procedure starts with the setting up of the measurement system; mounting the sound intensity probe, the microphones and connect it to a computer system with the SYMPHONIE card plugged and boot. All instruments are calibrated prior carrying out the measurements. The application software DBFA32 is activated, and through the software all specifications of the equipments are defined and the information of the experiment is recorded. The environment of the experiment is detailed using DBFA32. All measurements are given with a title and comments.

In this research, two different experiment set-ups are applied. Method I is to measure the acoustic signal from the vehicle engine and obtain the frequency spectrum. Method II is used to obtain the vehicle engine acoustic signal in analog form. The experiment details and sample details are recorded when the experiments are carried out. Table 2.2 shows the experiment details namely start and end time of the experiment, the location of the experiment, the nature of the ground and the equipment used for the experiment are recorded. Table 2.1 shows the details of the vehicle namely the date of purchase, the number of services done, the vehicle model, the engine capacity, the type of fuel, the total distance traveled and the faults of the vehicle.

Table 2.1: Vehicle details

Model	Kancil 850 EX
No. Services Done	1
Date Purchased	25/06/2003
Fuel	Petrol
Vehicle Faults	- Engine gasket - Oil filter Absorber problem
Engine Capacity (cc)	847 cc
Distance Traveled	8658

Table 2.2: Experiment details

Nature state of the ground	Hard
Start Time	11:05:11 am
Stop Time	11:05:21 am
Equipment	Sound Intensity Probe, Harmonie, Dell notebook, transducer cable
Location	Perodua service center

2.1. Experiment using Method I: Scanning Method

In this method, a sound intensity probe is used to measure the noise level. The noise level from the vehicle engine is recorded from various sides of the engine. The surface of the measurements are selected, a parallelepiped surface. With this the dimension of the surface are defined in DBFA32 software. The measurements are carried out after the target is defined. A sound intensity probe is used to measure the noise level because it measures only the noise emanated from the source directly pointed by it; thus it avoids the background noise being measured. Using the sound intensity probe, the sound of the vehicle engine is recorded from different angles, namely the front part, the right part, the rear part, the left part and the top part of the engine compartment as shown in Figure 2.1. The sound intensity probe is kept approximately 0.05 meter above the left corner of the engine (point A in the Figure 2.2).

The noise level emanated from the top surface of the engine is measured by moving the sound intensity probe from the left top corner of the engine to the bottom right corner of the engine (Point B in Figure 2.2). The direction and the path of scanning are shown in Figure 2.2. The noise level at the other sides of the vehicle is measure in a similar manner. The time taken for scanning the side of the engine is maintained constant at 10 seconds. The measurement is carried out in automatically manner, which the probe will stop measuring after 10 seconds. The measurements are made in full octave band and saved in cmg (Campaign Mode file) format.

These procedures are repeated for different speeds of 1000rpm and 4000rpm. 1000rpm is chosen as the minimum speed as most of the car's idle engine speed is around 1000rpm. Further, the comfortable maximum speed of the car engine is around 4000rpm and hence this speed is selected for measuring the sound intensity. The vehicle is kept stationery and made run at 1000rpm and 4000rpm. Using DBFA32 (Real Time Frequency Analysis Software), the frequency spectrum of the recorded signals are obtained. Fifty vehicle engines of the same model and make are used in this experimental study.

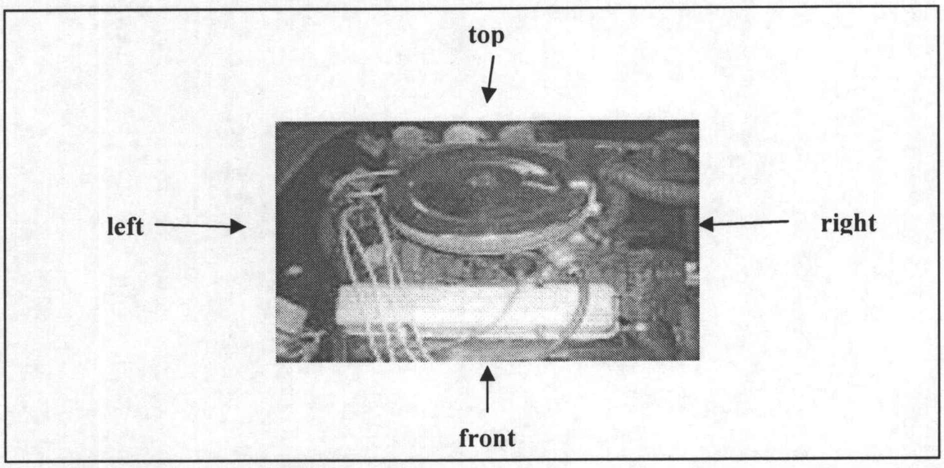

Figure 2.1: Vehicle engine recording angles

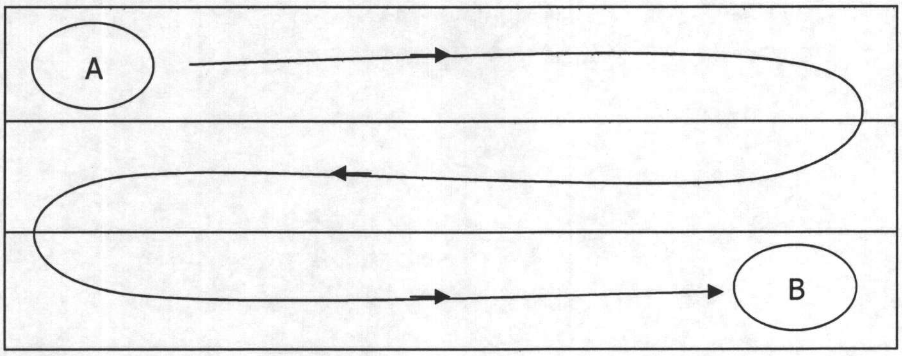

Figure 2.2: Scanning path and direction

2.2. Experiment using Method II

The settings up of the equipments are as shown in Figure 2.3. To measure the noise level the sound intensity probe is kept 1.2 meter above the ground level and 1 meter distance from the center of the vehicle engine. The measurements are made in full octave band and saved in cmg (Campaign Mode file) format. The recorded noise is saved in analog form. The vehicle is kept stationery and made run at 1000rpm, 2000rpm, 3000rpm and 4000rpm. Fifty vehicle engines of the same model and make are used in this experimental study.

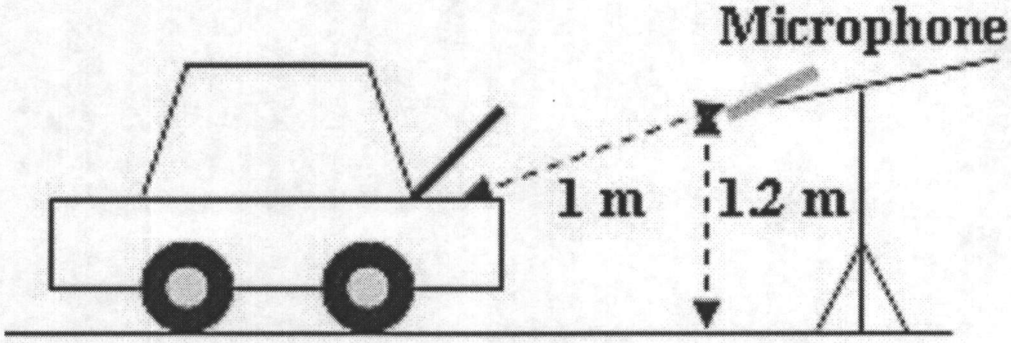

Figure 2.3: Experiment Set-Up, Method I

2.4. Experiment Results and Conclusion

50 samples of noise from the same manufactured vehicles are recorded for this research. The recorded sound signal is saved, stored in cmg file format, later converted to Windows Audio Video (.wav) format for future used. The vehicle engine faults are summarized in Table 2.3. The table shows the type of numbers of vehicles and the faults encountered by the vehicles.

Table 2.3: Vehicles sample with faults distribution

Vehicle Engine Faults	Number of Vehicle
Gasket Problem	21
Oil Filter Problem	22
Engine Oil Problem	21
Valve Problem	4
Absorber Problem	4
Belting Problem	5
Timing Problem	2
Gear Problem	2
Carburetor Problem	3
rpm Problem	2
Cooling Fan Problem	2

Two different experiment setting-ups are used in this research. Experiment Method I result is the frequency spectrum and the result from experiment Method II is in analog form. The results from the experiment are pre-processed using two different methods which will be discussed in the next section, Section 3.

3. DATA PRE-PROCESSING

3.1. Data Pre-processing: Method I

Data pre-processing Method I is applied after the vehicle engine noise is recorded using experiment setting–up: Method I, which is using the scanning method. This pre-processing is carried out automatically after the scanning/measurement of the vehicle engine noise. It is carried out according to standard ISO9614 Part 2. The analog signal recorded from the vehicle engine is digitized using DBFA32 (Data Frequency Analysis) software.

The surface of the recorded target is scanned and with this the average of the sound intensity of the specific surface is obtained and multiplies with the target surface area to obtain the sound power in decibel unit. Then the sound powers of the target surface are summed up. Please refer to Appendix E for the detail procedures of this pre-processing method. Figure 3.1 shows the procedures involved in data pre-processing II.

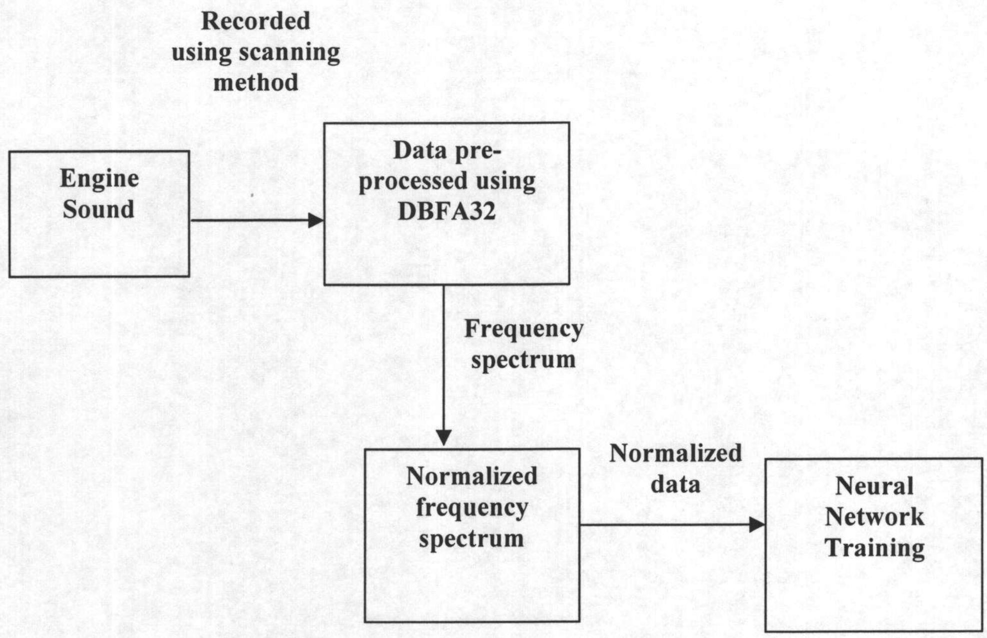

Figure 3.1: Data Pre-processing Method I Overview

On analyzing the frequency spectrum obtained from DBFA32, of all the vehicles; it is observed that the variation of sound intensity at the higher frequency is insignificant. Please refer Figure 3.2 to view the example of frequency spectrum data. Figure 3.2 shows the frequency spectrum; the y-axis indicates the decibel values of the frequency spectrum and the x-axis shows the frequency range from 63 hertz to 8 k hertz.

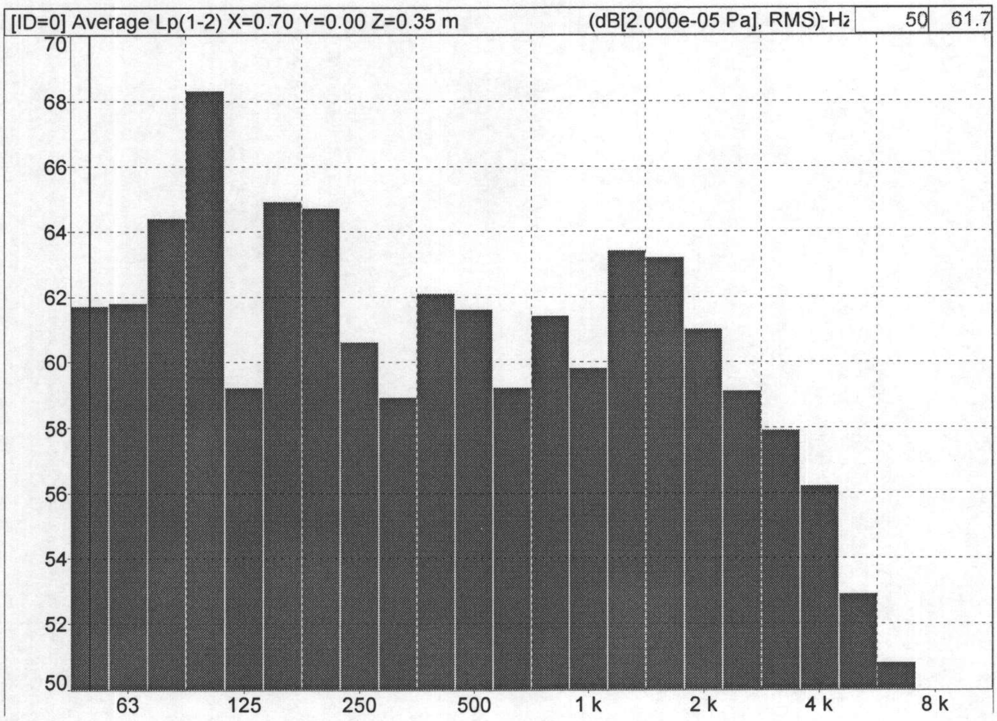

Figure 3.2: Frequency spectrum of vehicle engine noise at idle speed

The variation can be seen up to 6.3 kHz; therefore 50 Hz to 6.3 KHz is selected as the frequency range for the study. The frequency range is automatically digitized by dBFA32 into 22 octave band levels. The 22 digitized octave band sound spectrum levels are then normalized using Equation 3.1. The data is normalized using binary normalization. Please refer to Table 3.1. for the example of normalized data. The normalized data is then used as training pattern to the neural network.

$$\chi_n = \frac{0.8(\chi_i - \chi_{min})}{\chi_{max} - \chi_{min}} + 0.1 \tag{3.1}$$

Where χ is the normalized value,

χ_i is the actual value,

$\chi_{\min}$ is the minimum value and

$\chi_{\max}$ is the maximum value of the sound spectrum levels.

Table 3.1: Data distribution of normalized frequency spectrum of a vehicle engine at idle speed.

Hz	Normalized Data
50	0.60
63	0.60
80	0.72
100	0.90
125	0.49
160	0.74
200	0.74
250	0.55
315	0.47
400	0.62
500	0.59
630	0.48
800	0.58
1 k	0.51
1.25 k	0.68
1.6 k	0.67
2 k	0.57
2.5 k	0.48
3.15 k	0.42
4 k	0.35
5 k	0.20
6.3 k	0.10

After normalization the data is ready to be used in the neural network training.

3.2.Data Pre-processing: Method II – Principal Component Analysis

The data which is in analog form is obtained from the experiment setting-up Method II, is used in this pre-processing method. This method uses the Principal Component Analysis method to extract the noise signature.

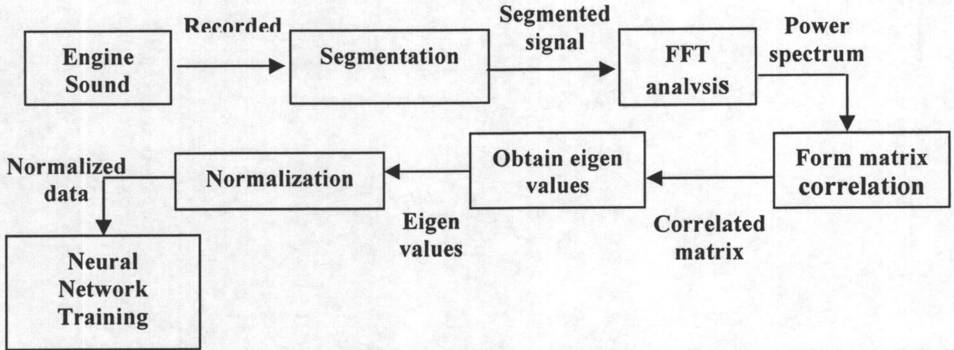

Figure 3.3: Data Pre-processing Method II: Principal Component Analysis Method overview

The recorded signal has a frequency-sampling rate of 51.2 kHz. The signal is sliced into N with M number of components in each frame. Each frame consecutively overlaps on number of components between the adjacent frames, as shown in Figure 3.4.

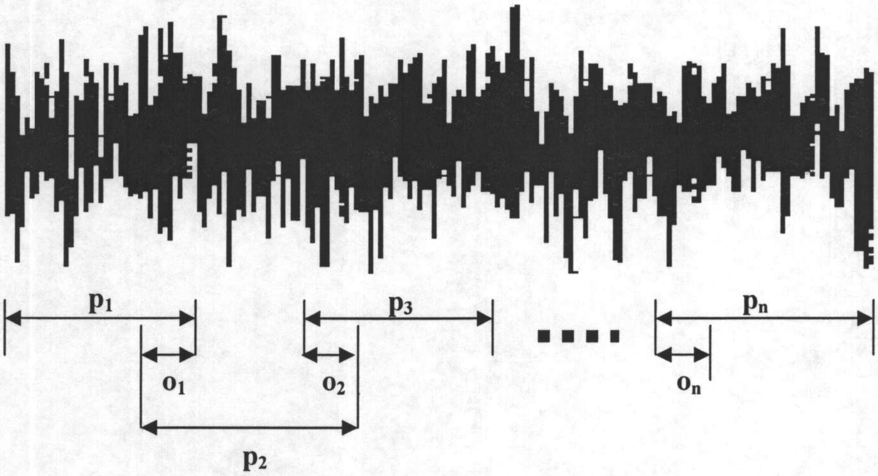

Figure 3.4: Segmenting sound signals into different frames

After segmenting, FFT standard algorithm is applied to each frame, converting the time series data into frequency domain to obtain the power spectrum. The data obtained from the recording is a time-series data, which will have certain amount of noise polluting the signal or the data required is only in certain part in the time-series data. Therefore filtering is needed to remove the noise data or to extract the targeted signal. In FFT analysis, the frequency components are obtained from the signal, example by taking the 5120-point Fast Fourier Transform (FFT).

$$y = \mathrm{fft}(y_1,5120); \qquad (3.2)$$

The power spectrum, a measurement of the power at various frequencies, is coded as:

$$PS = Y.* \mathrm{conj}(Y) / 512; \qquad (3.3)$$

The n^{th}-segmented frame can be written in terms of the power spectrum components as:

$$p_n = [p_{n1}, p_{n2}, p_{n3}, p_{n4}, \dots, p_{ni}] \qquad (3.4)$$

Where X_n = the nth segmented frame;
$\underline{p_{ni}} = i^{th}$ power spectrum component in the nth frame.

The average power spectrum for the nth frame can be defined as:

$$V_n = \frac{1}{m}\sum_{i=1}^{m} p_{ni} \qquad (3.5)$$

Where V_n is the average power spectrum of the n^{th} frame.

The deviation of the power spectrum component with the respect to its frame average value can be written as:

$$\Phi_{ni} = p_{ni} - V_n \qquad (3.6)$$

The deviated power spectrum vector can be written as:

$$n_i = [n_1 \quad n_2 \quad n_3 \quad n_4] \qquad (3.7)$$

Normalized measures of linear relationship strength between the components are obtained by seeking the correlation coefficient of the matrixes which can be defined as in equation (3.8). The obtained correlation coefficients are formed into matrixes, M_n.

$$M_n = n^T . n \qquad (3.8)$$

For the correlation coefficient matrix M_n, the eigen values are obtained and used as a feature vector to represent the n^{th} frame of the signal. The obtained eigen values are normalized using binary normalization shown in equation 3.1 and are used in the neural network training.

Pre-processing Method I, using the DBFA32 to obtain the frequency spectrum is a lot easier and faster to do as it is carried out automatically by the software. The processing is carried out in automatically manner right after the measurement. The noise signature from the frequency spectrum is vast as it considers the decibel value of 22 frequencies. The 22 octave band decibel value is normalized and used in the neural network training.

Pre-processing Method II, using the Principal Component Analysis extracts the significant features from the data obtained. The significant characteristic signature is extracted by obtaining the eigen value of each component in each frame. This has narrow down the noise signature to 17 components compared to the first method, 22 components. These 17 components of noise signature are used as input neuron in the neural network training.

4. BACKPROPAGATION NEURAL NETWORK TRAINING

Among the numerous Artificial Neural Network which have been proposed, back propagation networks network which is also known as the Generalized Delta Ruled has been extremely popular in use. It is first developed by Rumelhart at al. in 1986. The popularity of the usage is mainly due to its effective general method of training which can be applied in many applications, example in the forecasting and diagnosing.

A back propagation neural network is a multilayer network which consists of an input layer, an output layer and a hidden layer. Generally the network involved three stages of processes, namely the feedforward of input training pattern, the back propagation of the calculated error and lastly the weight adjustment based on the error calculation. Activations flow from the input layer through the hidden layer, then to the output layer.

4.1 Backpropagation Neural Network Training

The neural network training is categorized into two parts. The first part discusses the training using data from pre-processing Method I – the frequency spectrum. The second part discusses the training using the data resulted from Principal Component Analysis, Method II.

In Part I, the training is trained using two different sets of data. The first set of data consists of noise recorded from 50 vehicles, at the speed of 1000rpm and the noise from the top of the engine only is considered. The second set of data consists of noise recorded from 50 vehicles, at the speed of 1000rpm and 4000rpm and the noise from five different angles are considered. At the end of the training, comparisons is made on the performance of the neural network using different sets of data.

In Part II, the neural network is trained using 50 samples data which is pre-processed using Principal Component Analysis.

4.2. Neural Network Training with Data Set I

The neural network architecture consists of 3 layers, the first layer is for the input neuron, the middle layer is for hidden neurons and the last layer is for the output neurons. For training the neural network, twenty two input neurons are used, eighteen input neurons to indicate the sound signal magnitude at various frequency octave, one input neurons to indicate the vehicle engine model, one to represent the age of the vehicle, one input neuron to represent the distance traveled and one input neuron to represent number of services undergone. Please refer to Table 4.1 to view the input neuron representation. Of the recorded 50 data samples, 18 data samples are used for training and all the 50 data samples are used for the testing.

Twenty two input neurons, nine hidden neurons and nine output neurons is considered. The output neuron represents the nine faults encountered by the vehicles. The following vehicle faults considered in this training are the engine oil, engine gasket, oil filter, valve, belting, carburetor, rpm, absorber and gear problem. Table 4.2 shows the representation of output neuron parameter. The hidden and input neurons have a bias value of 1.0 and are activated by binary sigmoidal activation function, shown in equation 4.1.

$$f(x) = \frac{1}{(1+e^{-x})} \tag{4.1}$$

Table 4.1: Representation of input neuron parameters

Number of input neuron	Representation of input neuron	Input neuron details	Input neuron representation examples
1 input neuron	Vehicle Model	Engine 660	1
		Engine 850	0
1 input neuron	Distance traveled	-	2000 km (Normalized)
1 input neuron	Number of services done	-	3 (Normalized)
1 input neuron	The age of the vehicle	-	9 months (Normalized)
18 input neurons	The octave band of the spectrum	-	61.0 Hz (Normalized)

Table 4.2: Representation of output neuron parameters

Oil Filter	1	0	0	0	0	0	0	0	0
Engine Oil	0	1	0	0	0	0	0	0	0
Engine gasket	0	0	1	0	0	0	0	0	0
Absorber shock fault	0	0	0	1	0	0	0	0	0
Carburetor problem	0	0	0	0	1	0	0	0	0
Valve misfiring	0	0	0	0	0	1	0	0	0
RPM High	0	0	0	0	0	0	1	0	0
Gear replacement	0	0	0	0	0	0	0	1	0
Belt in too loose condition	0	0	0	0	0	0	0	0	1

The initial weights for the above network are randomized between -0.5 and 0.5 and normalized. Each trial consists of 50 sets of randomized weight samples. The sum squared tolerance is fixed as 0.01 with the learning rate of 0.45. The minimum epoch used for training the network is 783 while the maximum epoch used is 1167. The cumulative error versus epoch graph plot for the vehicle diagnosis is shown in Figure 4.1.

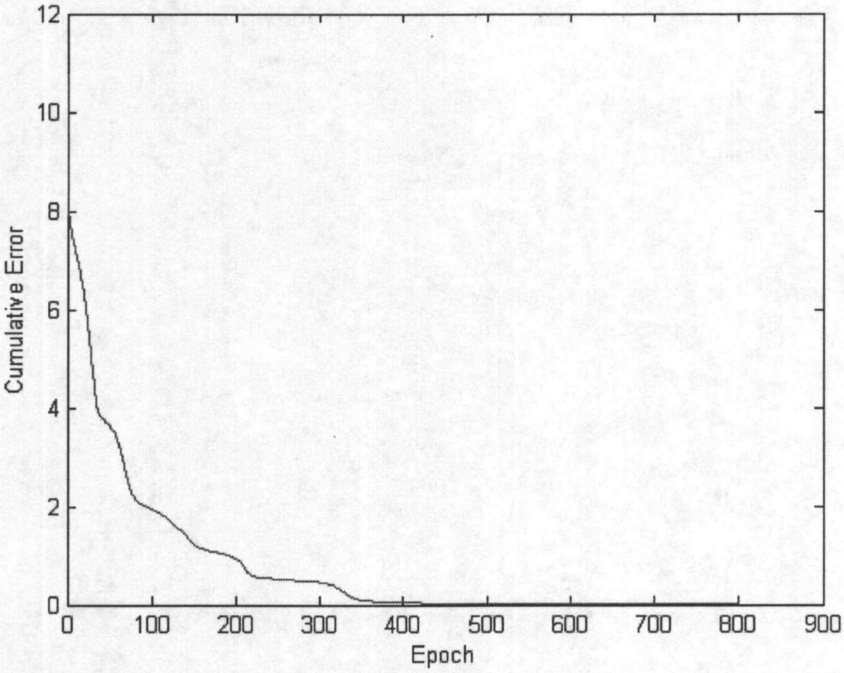

Figure 4.1: Cumulative error versus epoch plot

4.3. Neural Network Training with Data Set II

The proposed network has thirty input neurons, ten hidden neurons and eleven output neurons. Of the thirty input neurons, three input neurons are used to represent the measurement side of the vehicle engine, one input neuron represents the vehicle engine model, one input neuron represents the distance travel by the vehicle, one input neuron represents the number of services undergone by the vehicle, one input neuron represents the age of the vehicle, one input neuron indicates the speed and 22 input neurons are used to represent the octave band sound spectrum level of the engine. Please refer to Table 4.3 for the representation of the input neuron for each parameter.

Table 4.3: Representation of input neuron parameters

Number of input neuron	Representation of input neuron	Input neuron details	Input neuron representation examples
3 input neurons	Measurement Sides	Front	001
		Right	010
		Back	100
		Left	011
		Top	101
1 input neuron	Vehicle Model	Engine 660	1
		Engine 850	0
1 input neuron	Distance traveled	-	2000 km (Normalized)
1 input neuron	Number of	-	3

	services done		(Normalized)
1 input neuron	The age of the vehicle	-	9 months (Normalized)
1 input neuron	The speed of the vehicle	1000 rpm	0
		4000 rpm	1
22 input neurons	The octave band of the spectrum	-	61.0 Hz (Normalized)

The faults considered in this study are the engine oil, the engine gasket, the oil filter, the valve, the carburetor, the RPM, the gear, the timing problem, the belt problem, the absorber and the cooling fan problems.

In this network training, the sound intensity level of 50 different vehicles of the same model, on five different sides at two different speeds namely 1000rpm and 4000rpm are vehicles are obtained. This gives a total sample of twenty eight into five into two. Of the 500 samples, 100 samples are used for training the network and 500 samples are used to test the network. The hidden and input neurons have a bias value of 1.0 and are activated by binary sigmoidal activation function. The initial weights for the above network are randomized between -0.5 and 0.5 and normalized. A trial weight set consists of 100 sets of randomized weight samples. Five such trial sets are used in this experiment. The sum squared tolerance is fixed as 0.0001. The learning rate is chosen as 0.09. The network is trained by conventional back propagation procedure. The cumulative error versus epoch graph is shown in Figure 4.2. The network is trained with five trial sets of weights.

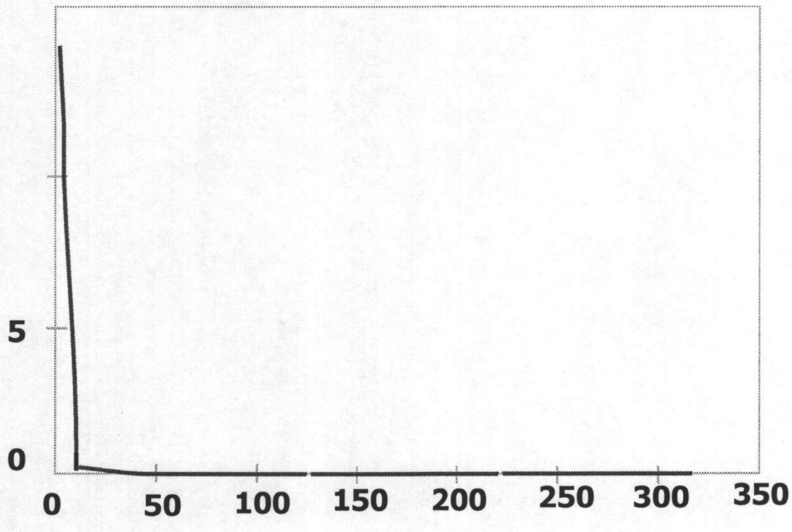

Figure 4.2: Cumulative error versus epoch plot

Comparisons of Neural Network Training, between Data Set I and Data Set II Based on the neural network training results, it is obviously showing that the neural network model trained by the back propagation procedures with Data Set II produces a better result, with maximum mean classification of only 3.2%. The neural network model trained with Data Set I has 5% of maximum mean classification. This happen because neural network model with Data Set II has more input neurons that is 100 samples for training. Therefore, the network model has more resources to enable it to learn better compare with the network model trained with Data Set I, only 18 samples as input neurons for training. Table 4.4 shows the comparisons of the mean success percentage for the neural network model trained with Data Set I and Data Set II.

Table 4.4: Comparisons between testing result of Backpropagation Network trained with Data Set I and Data Set II

Number of Trial	Back Propagation Network trained with Data Set I	Back Propagation Network trained with Data Set II
	Mean Success Percentage	
1	95.5%	97.25%
2	95.5%	97.0%
3	95.5%	96.86%
4	95.5%	97.0%
5	95.5%	96.8%

4.4. Backpropagation Network Trained with Principal Component Analysis Data

The proposed network has eighteen input neurons, twenty hidden neurons and five output neurons. Of the eighteen input neurons, one input neuron represents the vehicle engine model, one input neuron represents the distance travel by the vehicle, one input neuron represents the number of services undergone by the vehicle, one input neuron represents the age of the vehicle, and fourteen input neurons are used to represent eigen values of the sound spectrum level of the engine. Each one of the output neurons represents a fault in the vehicle. The faults considered in this study are the engine oil, the engine gasket, the oil filter, the valve and the absorber problems. Table 4.5 shows the representation of the input neurons of the network.

25 samples are used for training the network and 50 samples are used to test the network. The hidden and input neurons have a bias value of 1.0 and are activated by binary sigmoidal activation function. The initial weights for the above network are randomized between -0.5 and 0.5 and normalized. A trial weight set consists of 50 sets of randomized weight samples. Five such trial sets are used in this experiment. The sum squared tolerance is fixed as 0.1.

Table 4.5: Representation of input neuron parameters

Number of input neuron	Representation of input neuron	Input neuron details	Input neuron representation examples
1 input neuron	Vehicle Model	Engine 660	1
		Engine 850	0
1 input neuron	Distance traveled	-	2000 km (Normalized)
1 input neuron	Number of services done	-	3 (Normalized)
1 input neuron	The age of the vehicle	-	9 months (Normalized)
14 input neurons	Eigen values	-	67.5 (Normalized)

The learning rate is chosen as 0.1. The network is trained by conventional back propagation procedure. The cumulative error versus epoch graph is shown in Figure 4.3.

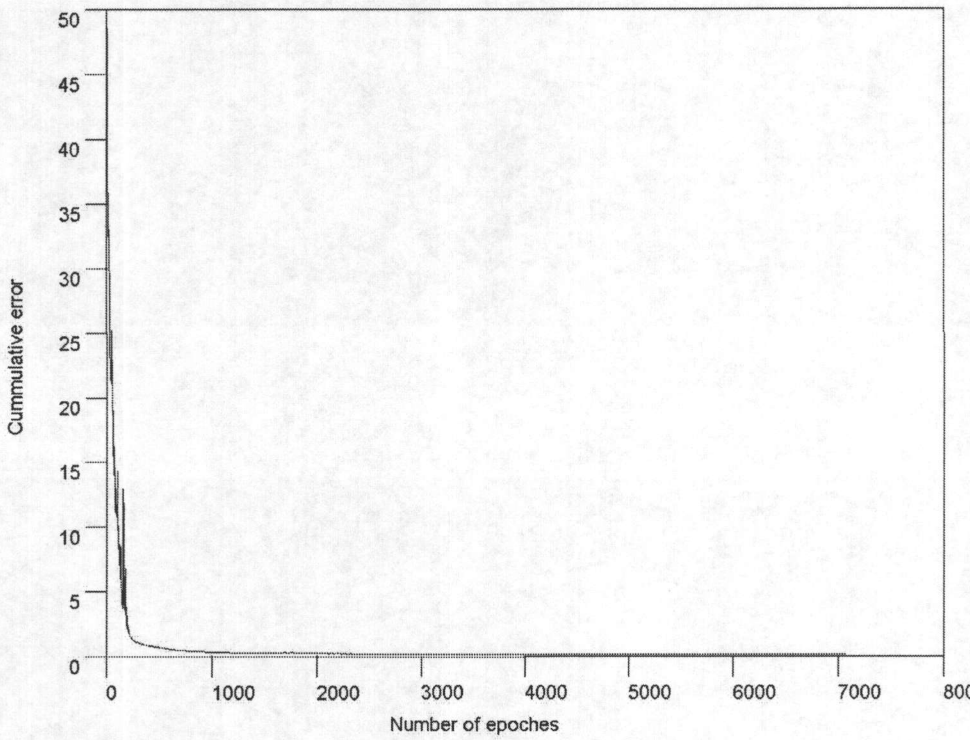

Figure 4.3: Cumulative error versus epoch plot (vehicle engine faults diagnosis)

Three different sets of data have been applied to the back propagation network model. The first set of data consists of 50 samples with noise recorded at 1000rpm and the noise emanated from the front part of the engine is considered. The second set of data consists of 50 samples with noise recorded at 1000rpm and 4000rpm, and the noise emanated from five different angles are considered; with this 50 samples into two different speeds and into five different angles, it comes to 500 samples as input neuron for the network training. The network with the second set of data shows a better result as it has more input neuron to let the network to be trained better. The last set of data consists of data resulted from Principal Component Analysis method. The data set consists of 25 samples to train the network and 50 samples to test the network. Table 4.6 shows the comparisons of the performance of the same network but trained using different sets of data.

Table 4.6: Comparisons between testing result of Backpropgation Network trained with Data Set I, Data Set II and Data Set III

Number of Trial	Back Propagation Network trained with Data Set I	Back Propagation Network trained with Data Set II	Back Propagation Network trained with Data Set III
	Mean Success Percentage		
1	95.5%	97.25%	91.30%
2	95.5%	97.0%	92.86%
3	95.5%	96.86%	92.85%
4	95.5%	97.0%	93.21%
5	95.5%	96.8%	93.47%

5. LEARNING VECTOR QUANTIZATION NEURAL NETWORK TRAINING

5.1. Learning Vector Quantization Network

Learning vector quantization is originated from self-organizing maps and also known as the Kohonen feature maps. It is an algorithm proposed by Kohonen in 1986 (Kohonen, 1990). The algorithm objectives are to estimate the size of a class by applying the vector quantization and minimize the classification error. Vector quantization is a compressed data or a reduced data dimension and also known as the vector codebook. Vector codebook is used to represent the boundaries of class boundaries.

The Learning Vector Quantization network applies supervised learning. In a supervised manner, the network learns by detecting regular patterns and correlations of the input neurons and lastly matches with the output accordingly. Example a given set of data, *M* is grouped into *Y* groups by recognizing the similar input vector within the region. This group is called as a class. The definition of vector quantization is a technique where the input space is divided into a number of distinct regions and for each region a code book vector is defined (Sivanandam & Paulraj, 2003).

5.2. Learning Vector Quantization Network Architecture

The architecture of a Learning Vector Quantization network is similar to the Kohonen's self organizing map. The network consists of two layers, an input layer and an output layer. The two layers are connected with each other and it represents a set of reference vectors. This reference vector also known as the weights of the two layers connections. Figure 5.1 shows an example of Learning Vector Quantization network architecture.

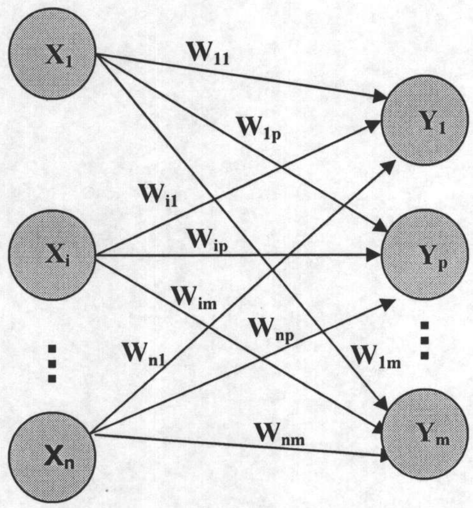

Figure 5.1 Learning Vector Quantization network architecture

The training starts with determining the closest reference vector for each training pattern. The correspond output neuron is called as the winner neuron. The weights of the connecting neurons are adjusted. The adjustment depend on the degree of matches between the class of training pattern with the correspond class of the reference vector. The reference vector moves nearer to the training pattern if the training pair matches with the correspond class or else it moves farther away. The movement of the reference vector can be controlled by a parameter known as the learning rate, which controls the movement step of the reference vector to the training pattern.

5.3. Learning Vector Quantization Algorithm

Learning Vector Quantization Training Pseudocode
Start

1.0 Assign first q input vectors as reference input vectors
2.0 Generate weight file
3.0 While stopping condition is false, repeat steps 3 to 7
4.0 For every each training input vector X, do steps 4 to 5
5.0 Obtain the winner so that the error $(X - W_p)$is minimum
6.0 Update W_p when the winner correspond to the current class;
    i. If $R = K_j$ then
        1. $W_p(\text{new}) = W_p(\text{old}) + \alpha\ [X - W_p(\text{old})]$
    ii. If $R \neq K_j$ then
        1. $W_p(\text{new}) = W_p(\text{old}) - \alpha\ [X - W_p(\text{old})]$
7.0 Update learning rate, α as

$$\alpha\,(\text{new}) = \frac{\alpha(old)}{1+\alpha(old)}$$

8.0 Test for stopping condition.

5.4. Learning Vector Quantization Network Training

Similar with section 4, the neural network is trained with two sets of data. The first set of data is obtained from pre-processing Method I – the frequency spectrum. The data is the data noise recorded from 50 vehicles, at the speed of 1000rpm and the noise from the top of the engine only is considered. The second set of data is resulted from Principal Component Analysis, Method II.

5.4.1.Learning Vector Quantization Network Training with Data Set I

Twenty-two input neurons are considered in this network training. Of the twenty two input neurons, one input neuron to represent the vehicle model, one input neuron represents the distance travel by the vehicle, one input neuron represents the number of services undergone by the vehicle, one input neuron represents the age of the vehicle, and eighteen input neurons are used to represent the frequency spectrum value of the engine. Five output neurons are considered in the network. Each output neuron represents a fault in the vehicle. The faults considered in this study are the engine oil, the engine gasket, the oil filter, the valve and the absorber problems. 25 samples are used for training the network and 50 samples randomly picked are used to test the network. The initial weights for the above network are randomized between -0.5 and 0.5 and normalized. The sum-squared tolerance is fixed as 0.01. Table 5.1 shows the training result.

Table 5.1: Average Learning Vector Quantization network results for five vehicle engine faults- trained with Data Set I.

Trial	1	2	3	4	5
Sample correctly clustered out of 50 samples	49	49	48	50	49
Percentage Samples Successfully Clustered	95%	95%	90%	100%	95%

5.4.2.Learning Vector Quantization Network Training with Data Set II

In this neural network training, data from Principal Component Analysis is used to train the network. Eighteen input neurons are considered in the training. Of the eighteen input neurons, one input neuron represents the vehicle model, one input neuron represents the distance travel by the vehicle, one input neuron represents the number of services undergone by the vehicle, one input neuron represents the age of the vehicle, and fourteen input neurons are used to represent eigen values of the sound spectrum level of the engine.

Five output neurons are considered in the network. Each output neuron represents a fault in the vehicle. The faults considered in this study are the engine oil, the engine gasket, the oil filter, the valve and the absorber problems. 25 samples are used for training the network and 50 samples randomly picked are used to test the network.

The initial weights for the above network are randomized between -0.5 and 0.5 and normalized. The sum-squared tolerance is fixed as 0.01. The training testing result shows that the Learning Vector Quantization has succeeded to learn to classify the pattern of the noise signature that is extracted using Principal Component Analysis method. The maximum correctly clustered percentage is 100% and the minimum clustering is 95%. Table 5.2 shows the average sample correctly clustered.

Table 5.2: Average Learning Vector Quantization network results for 5 vehicle engine faults – Data Set II.

Trial	1	2	3	4	5
Sample correctly clustered out of 50 samples	49	49	48	50	49
Percentage Samples Successfully Clustered	95%	95%	90%	100%	95%

Comparisons Between Learning Vector Quantization and Back propagation Networks Table 5.3 shows the comparisons of the network training result. The performance of Learning Vector Quantization network trained with Data Set II, the data resulted from Principal Component Analysis shows a better performance compared to the Data Set I – frequency spectrum.

Table 5.3: Comparisons between testing result of Data Set I and Data Set II trained by Learning Vector Quantization network.

Trial No.	Data Set I	Data Set II
	Mean Success Percentage	
1	95%	93.5%
2	95%	94.8%
3	90%	92.8%
4	100%	94.3%
5	95%	93.5%

6. Conclusion

Using the noise signature extracted from the noise recorded from the vehicle engine, the diagnosis of the vehicle faults is obtained. This is carried out by incorporating the diagnosis and opinions of the experts with the noise signature and the external vehicle factor, use them as input in the neural network training. Different pre-processing techniques are applied to obtain the noise signature and two different networks are proposed in this research. The results of the network are very convincing. Further research can be carried out to improve the noise signature extraction method and the network training time. Vehicle engine faults diagnosis based on noise signature is a promising approach in the automotive industry as it contributes accurate diagnosis, save energy, time and cost.

6.1. Suggestion for Future Work

Suggestions and ideas are identified which could be of help to improve this research and also the progress of the research work. The suggestions are summarized as below:

- To have a better condition monitoring, it is suggested to obtain at least two vehicles which can be monitored constantly in the lab. One vehicle without any faults and another vehicle is applied with loads or modified; this is to monitor the differences of noise produced by the vehicles.
- To narrow down the investigation to a smaller part of vehicle engine, example gearbox to obtain a better fault diagnosis and condition monitoring.
- Perform the fault diagnosis based on the vehicle engine noise signature real time.
- Includes in more acoustic criteria example sharpness, roughness and skewness (psychoacoustic) in the acoustic signature analysis.

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