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Engine fault diagnosis and condition monitoring using acoustic emission techniques: A Review

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Abstract –*Condition monitoring program applied to IC engines,improves safety,productivity, increase serviceability and reduces maintenance cost. Investigation of a naval condition monitoring system for IC engines is attracting considerable attention due to both increasing demands placed upon engine components and the limitations of conventional techniques.*
This study conducted to access the monitoring capabilities and acoustic emission analysis. A review of the AE sources in diesel engine and how to represent the AE signals generated is presented. Three AE analysis methods are time domain analysis, frequency domain analysis and time –frequency domain analysis. New acoustic emission signal analysis techniques are also discussed.

Key Words:acoustic emission, condition monitoring.

1.INTRODUCTION

Even minor faults can contribute to a reduction in the useful life of high-cost engines, and it is in the self-interest of companies to avoid such potentially unnecessary losses. Faults not only directly reduce the performance of an engine, they can also cause secondary damage to other parts of the engine; this can lead to significant economic loss for the user and in some cases to personal injury. Different predictive maintenance methods and techniques such as vibration, acoustic and acoustic emission monitoring, using time and frequency domains have been developed to detect and diagnose faults, improving maintenance and, hence, the performance of both engines and systems. When the faults are less serious, early detection and diagnosis not only provides information about the nature of the problem but also allows maintenance personnel to plan the necessary corrective action. Thus, the production losses can be minimized. Such an approach will result in lower labor and parts costs, less downtime and more efficient use of maintenance resources. In the past twenty year's development of CM techniques, particularly acoustic emission monitoring, has greatly improved the maintenance of rotating machinery. However, over that period, reciprocating machinery such as reciprocating engines has been largely ignored. This is predominantly because the acoustic emission generated during normal operation of reciprocating engine is impulsive, because of impact forces resulting from the different sources, which makes the diagnosis of problems relatively difficult. Presently diagnostic systems capable of detecting incipient faults in engines are limited due mainly to the extremely difficult task of detecting and interpreting the low level of signal from a fault in its early stages. [1]

2. LITERATURE REVIEW

Imitation of the act of diagnosing engine faults by an expert auto-mechanic just by hearing the noise from defective vehicle has been attempted with a robust instrumentation technique is observed by D. P. Jena and S.N. Panigrahi. They present experimental work having the prime objective is to establish a process to identify the piston-bore defect by analyzing the engine noise. The aim is to develop a robust filtering algorithm in order to be able to use the technique in the natural environment of an auto workshop. The algorithm uses engine noise data from healthy and defective vehicles acquired in the natural workshop environment.[2]

Dislocation superimposed method for extracting fault components from abnormal acoustic signals and automatically diagnosing diesel engine faults is presented by N. Dayongetal. The method named dislocation superimposed method (DSM) is based on the improved random decrement technique (IRDT), differential function (DF) and correlation analysis (CA). The aim of DSM is to linearly superpose multiple segments of abnormal acoustic signals because of the wave form similarity of faulty components. Theme tonuses sample points at the beginning of time when abnormal sound appears as the starting position for each segment. In this study, the abnormal sound belonged to shocking faulty type thus; the starting position searching method based on gradient variance was adopted. The coefficient of similar degree between two same sized signals is presented. By comparing with a similar degree, the extracted fault component could be judged automatically. The results show that this method is capable of accurately extracting the fault component from abnormal acoustic signals induced by faulty shocking type and the extracted component can be used to identify the fault type.[3]

Yuefei Wang et al proposes a method of diagnosing faults in reciprocating compressor valves using the acoustic emission signal coupled with the simulated valve motion. The actual working condition of a valve can be obtained by analyzing the acoustic emission signal in the crank angle domain and the valve movement can be predicted by simulating the valve motion. The exact opening and closing locations of a normal valve, provided by the simulated valve motion, can be used as references for the valve fault diagnosis. The typical valve faults are diagnosed to validate thefeasibility and accuracy of the proposed method.

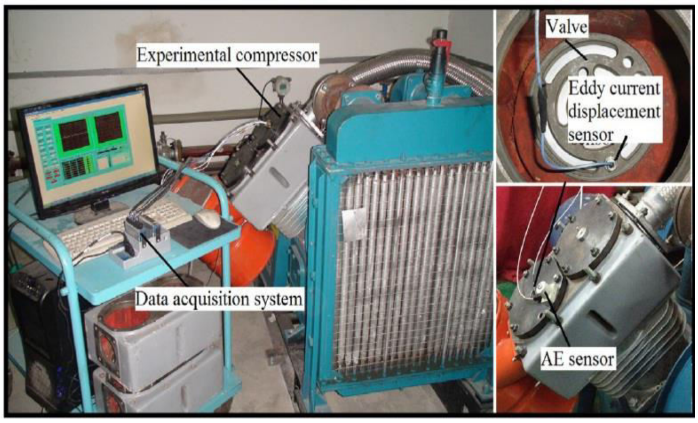

Fig – 1: valve fault diagnosis test-bed

feasibility and accuracy of the proposed method. The experimental results indicate that this method can easily distinguish the normal valve, valve flutter and valve delayed closing conditions. The characteristic locations of the opening and closing of the suction and discharge valves can be clearly identified in the waveform of the acoustic emission signal and the simulated valve motion.[4]

In 2007 Jian-Da Wu et al presents a prototype of an expert system for fault diagnosis in scooters platform using fuzzy-logic interference with adaptive order tracking technique is developed. The adaptive order tracking based on Kalman filter extracts the order features of the scooter test platform. They then are used for creating the data bank in the proposed intelligent fault diagnosis system. Fuzzy logic inference is used for fault classification in the proposed system. The experimental results indicated that the proposed system is Most of the conventional methods for fault diagnosis using acoustic and vibration signals are primarily based on observing the amplitudedifference of the time or frequency domain.[5]

Unfortunately, the signals caused by damaged elements in practical application, such as those buried in broadband background noise or those caused by smearing problems, are not always available. In 2005 Jian-Da Wua and Chao-Qin Chuang presented a paper in which, a visual dot pattern technique using acoustic and vibration signals is used to identify faults in an internal combustion engine, cooling fan and drive axle shaft in a vehicle. An automatic image template matching system was developed for the purpose of fault diagnosis. The experimental results indicated that the proposed algorithm was effective in fault diagnosis for experimental cases. [6]

3. ACOUSTIC EMISSION AS A CONDITION MONITORING TECHNIQUE

Nowadays engine performance together with high economy is a very important operating characteristic, and CM is being used to ensure that this characteristic is not only maintained but optimized. The conventional attitude to engine upkeep has been to follow a fixed routine maintenance program based on the engine manufacturer's instructions. This approach has two disadvantages. 1. The maintenance schedule is based only on past experience of similar engines. There is no guarantee that an individual component would be in perfect condition throughout this interval. 2. The component is sometimes still in good condition even after the elapsed interval and it would be a waste of time and money to repair or replace a perfectly healthy component. Many techniques are being used for machines condition monitoring; this subsection explains the use of some of these techniques for fault detection and diagnosis in diesel engines.[1]

Acoustic emission has been widely applied to, amongst other things, pipeline testing, evaluation of ageing aircraft, transformer testing, rocket motor testing, production quality control, inspections of valves in steam lines, wind turbine monitoring, ship hull monitoring and earthquake prediction. AE is defined as mechanical waves, naturally generated by an abrupt release of stored energy within a material, which can be observed in rupture processes such as the snapping of dry twigs and the cracking of rocks. AE measurement techniques involve the detection of the stress waves, usually within a range of 100 kHz to 1 MHzThis frequency range is relatively high and has the useful consequence that a better signal to noise ratio can be achieved than with vibration signals or acoustic signals. AE is the predominant technique for detection of microscopic changes in material where the atomic rearrangement in a material during cracking and deformation generates elastic waves. By using piezoelectric transducers, the waves travelling through the material can be detected. AE is also sensitive to phenomenon such as cavitations, impact and turbulence. An AE is an acoustic wave generated by a material and an AE signal is the electrical signal produced by a sensor in response to this wave. Burst type AE signals are often represented by a decaying or damped sine wave. The mathematical model of such a signal is described in Equation.

$V(t) = V_o \exp(-B\,t)\sin(\omega\,t)$

Where,

$V(t)$ = Output voltage of the AE sensor,

V_o= Initial maximum signal amplitude,

B = Damping factor / decay constant (greater than 0),

t = time (variable),

$\omega = 2\pi f$, is the angular frequency

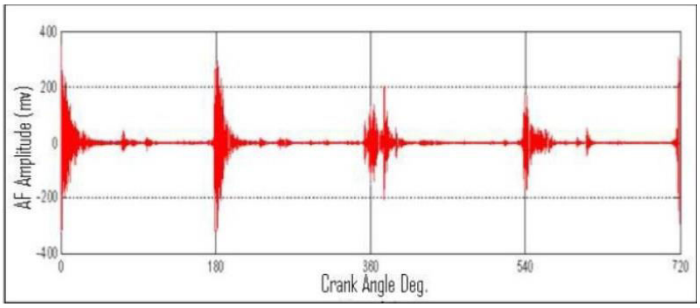

Chart-1: angular domain of acoustic emission Waveform signal of two crankshaft revolution.

1. Discrete or burst emission: this is high amplitude, energy emission where the individual stress waves representing definite activity in a process can be observed.

Phenomena such as crack growth can be observed with burst emission.
2. Continuous emission: this is low amplitude, low energy emission useful for continuous observation such as monitoring leaks in processes and dislocation in metals. Charat-1 shows a AE sensor output representing the AE waveform signals for two crankshaft revolutions. AE can be generated by a wide range of possible impulsive sources which, in reciprocating machinery, can include combustion, piston slap, valve clatter, gas flow and many other mechanical and fluid events. Such sources also produce acoustic noise and vibration, although acoustic waves and lower frequency vibrations can both suffer from the difficulties of interfering sources (e.g. wind noise, structural vibration), which make the diagnostic information from the sensor signal more difficult to extract. For this reason, AE has great potential for revealing the internal operating characteristics of the machine, whilst using non-intrusive sensors. [1]

4. DIESEL ENGINE ACOUSTIC EMISSION SOURCESAND DATA PROCESSING

Development of modern heavy duty diesel engines is driven by three major factors: fuel economy, pollutant engine-out emission, and customer satisfaction. To satisfy these requirements, advanced technologies are needed for all aspects of engines, including lubrication oil, fuel and engine components. The performance of the engine is directly affected by the friction, wear, blow-by gas flow (one of the important sources of AE) and oil consumption, which are in turn closely related to the listed three factors. Therefore, a detailed understanding of acoustic emission sources is crucial for developing advanced condition monitoring of diesel engine.

4.1 Diesel Engine Acoustic Emission Generation

The AE signals encountered on diesel engines are mostly stress waves travelling on the surface of the engine. Mechanical events that generate AE include impacts and crack formation; in addition, fluid and gas flows also generate AE. The propagation of the acoustic emission waves through the engine is very complex; with non-uniform wave dispersion/attenuation, reflection/transmission needing to be considered. Neill, et al., and Fog have shown that for AE measurement, the distance between sensor and source should be reduced as much as possible so that AE signals are far more localized, i.e., virtually coming only from the source where they are generated. This means, however, that differential damping of different sources will be crucial in sensor location considerations due to material interfaces along the signal path. Of course, it is necessary to ensure good signal conductivity from the surface to the sensor. Virtually all the theory and knowledge from vibration monitoring can be applied to AE since the two types of signal are generated by the same events, e.g., impacts and frictional movement, both lead to small movements of the structure (vibration), and micro cracking inside the material. The magnitude of AE signals are functions of the amplitude of the forces and wear involved, and thus many of the phenomena that have been used for monitoring vibration also appear in AE but because of the frequency ranges involved with less contaminating noise – and noise has always been the most significant problem with vibration measurement.

A review of an engine's AE sources shows that the generation of engine AE involves many different sources and mechanisms and that makes the AE signals very complex, in addition AE wave propagation in a real structure is additionally complicated by factors including internal damping, reflection, refraction, conversion mode and diffraction. These AE signals contain not only stationary waveforms but also non-stationary transients, pulses and embedded noise. [1]

The various sources through which acoustic emission are generated are mechanical impact , friction , fluid and gas flow , background noise.

4.2 Measurement of Acoustic Emission

There are several methods of measuring absolute surface displacement which involve capacitive, electromagnetic and laser-optical measurement techniques. However, practical difficulties in applying these methods in an industrial environment have meant that the vast majority of A monitoring has used resonant transducers based on piezoelectric elements. These sensors have proven to be suitably sensitive and robust to the extent that they have become accepted as the norm. The materialused for the active element is most usually lead zirconatetitanate (PZT), apiezoceramic; although it has been shown that it is equally feasible to use other piezo-activematerials such as polyvinylidenediflouride (PVDF).

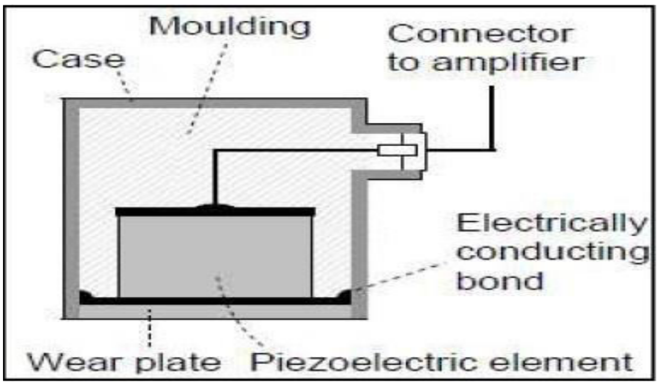

Fig-2: Schematic of an AE sensor

The construction of a piezoelectric AE sensor is shown schematically in Figure 4.2. These sensors rely on the fact that a voltage is generated in proportion to the compression of the piezoelectric element; hence nanometer surface displacements are converted into an electrical signal. However, the output of most piezoelectric sensors is not an accurate description of the surface movement under inspection. Rather, the AE signal, i.e. the sensor output, is the sensor's response to the forcing transient waves.[1]

4.3 AE Analysis And Signal Processing Techniques

There are two basic types of AE signal. The first is burst-type emission, where the signal consists of clearly defined 'events'.These events are characterized by amplitude significantly larger than the background level, distinct sharp signal rises and close to exponential decays, and individual pulses can be wellseparated in the time-domain. The second type is continuous emission; this occurs when burst generation is so rapid that the signal appears continuous and resolution of individual events is not possible.

Typically, signals acquired from machinery will be a combination of both to varying degrees, for example, chart-2(b) shows a raw AE signal measured from the surfaceof a running engine in which a number of overlapping burst- and continuous- type events of varying amplitude are evident.

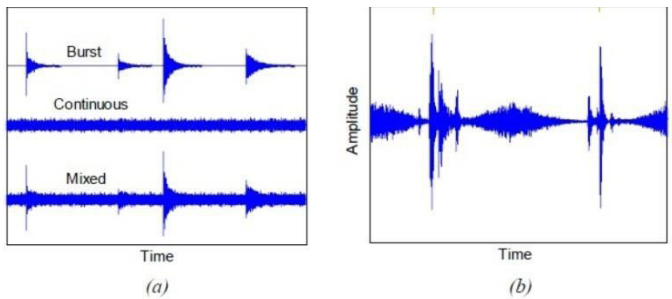

Chart- 2: (a) Examples of AE emission types, (b) typical AE signal acquired from a running engine.

4.3.1 Time-Domain Analysis

There are various means by which AE signals can be processed and evaluated in order to extract information useful for condition monitoring, the most fundamental being the characterization of signals with regards to the behavior of the object under observation. The most common method for achieving this is time-domain characterization of burst-type events through extraction of waveform parameters. This typically involves monitoring the sensor output continuously for activity that exceeds a predefined threshold level. When this occurs an event is registered and the signal is then processed to extract parameters such as those identified in Figure 4.6, these include; peak amplitude, event rise time, event decay time, signal duration, AE event count and AE count rate. Of all the waveform descriptors, the measure of threshold crossing counts has probably been the most widely used, likely due to the simplicity of measurement system required and the applicability for both burst and continuous type emissions. However, there are disadvantages associated with the sole use of count parameters to describe AE signals.

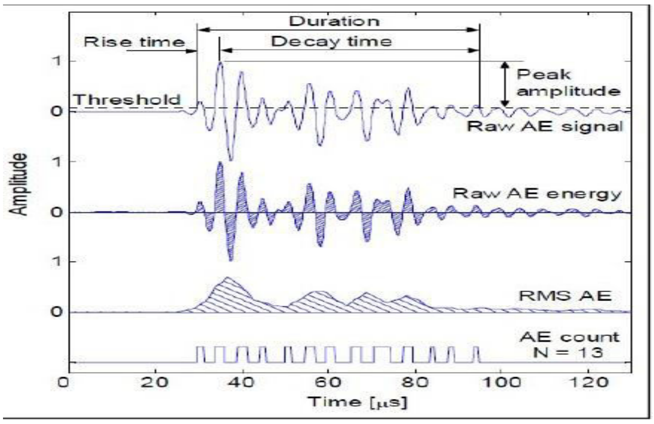

Chart-3: Typical time-domain parameters extracted from AE Signals.

AE energy is a measurement parameter used extensively in AE monitoring. However, the calculation of energy is open to interpretation. The energy is taken as the area under the absolute of the signal.

4.3.2 Frequency-Domain Analysis

Frequency-domain analysis offers further options for investigation of AE signals, and is a proven technique for machinery diagnostics. This has been established through a long association with vibration monitoring where spectral analysis is considered one of the principal analytical tools and is used in many commercial monitoring packages. Since AE is regarded by some as an extension of vibration monitoring, in that both are measurements of surface motion as a function of time, the transfer of many diagnostic principles from the latter to the former has been accomplished. In general, frequency analysis involves the decomposition of timeseries data into the frequency domain; this is typically achieved as an estimatethrough an algorithm known as the Fast Fourier Transform (FFT). For many applications this method alone is sufficient to describe the signal. However, other algorithms have been developed which implement the FFT in order to estimate the distribution of the signal energy in the frequency domain, the principal methods for this are known as the Power Spectral Density (PSD) and Welch's PSD estimate.[1]

4.3.3 Time- Frequency Domain Analysis

Time- frequency domain analysis is an attractive approach which analyses AE signals in the time frequency domain. The most widely used time-frequency methods include the Short-Time Fourier Transform (STFT), Wavelet Transforms (WT) and Wigner-Ville Transform (WVT). The Wigner-Ville Distribution (WVD) was first successfully used to analyze transient AE signals for condition monitoring by Newland at the University of Manchester. [1]

5. METHODS OF SIGNAL ANALYSIS

Acoustic and vibrations signals of engine soften provide significant dynamic information on mechanical system conditions; these mixtures of signals contain fault acoustic signal, other normal acoustic signal, and background noise [2]. The fault feature, which is useful for ensuring safe running of engines, can be extracted either from the mixture signal to diagnose the engine condition or detect the fault source. Many useful signal analysis methods for fault diagnosis have been set up such as four retransform, wavelet analysis, empirical mode decomposition, blind source separation and acoustic emission.

5.1 Fuzzy Logic Inference For Fault Diagnosis

Fuzzy logic is a useful approach to simplify a complex system in engineering application. In the present study, a fuzzy-logic inference is used to calculate complex numerical analysis with a membership value easily interpreted by humans (Awad&Wafik, 1999). After extracting the features of the proposed adaptive order tracking amplitude figures, fuzzy logic is used to automatically diagnose the faults in the designed scooter experimental platform. The fuzzy-logic inference is proposed to establish the diagnostic rules of the data bank in this fault diagnosis system. The amplitudes of different order can be calculated for extracting the features of the order figures. The energy of order figure amplitude is calculated by using root-mean-square (rms) as the input values:

$$W = \sqrt{\frac{1}{H}\left(\sum_{h=1}^{H} Y(h)\right)}$$

where W is the rms value of order amplitude, Y is an order amplitude, and H is the number of the order amplitude. After obtaining the order feature of the order figures, the data analysis includes finding the mean value and standard deviation of each order after the extracting feature procedure has finished. The decision of the membership functions also a key point and especially punctilious for fuzzy-logic inference. The fuzzy membership function has represented variable sets that include S, p, triangular and gauss. In the present study, the triangular and p membership function will be used to develop the fuzzy logic inference (Mechefske, 1998). [7]

5.2 Multi-Layer Feed Forward Back Propagation Neural Network

Artificial Neural Network (ANN) is the most widely chosen data-based model which has drawn substantial attention in the engineering field for defect detection and classification. ANN is a computational model that mimics the human brain structure. It is powerful enough to construct near perfect approximations of systems with insufficient knowledge. A neural network can be thought of as a massively parallel distributed processor that has a built in structure for storing observed knowledge over a long period of time and uses this experiential knowledge in intelligent decision making. ANN gains knowledge through a learning process. ANN learns about the initially unknown system by adaptively adjusting its weights by observing a series of inputs and the corresponding outputs. This process is usually called the training of an ANN. There are various types of neural network models based on different kernel functions. Feed-forward Back-propagation Neural Network (FBNN) structure is the most widely used neural network structure in machine fault diagnosis and condition monitoring purpose. In this study, a multi-layer (with 10 hidden layers) Feed-Forward Back-propagation Neural Network (FBNN)is designed and used. An analogous network, with six inputs, one hidden layer and two outputs, is shown in Fig. 2.The thumb rule of selecting number of hidden layers can be estimated with number of inputs and outputs, i.e., two third of total number of inputs and outputs. However, the quality of approximation hinges highly on the number of training samples. In the present case, the analysis starts with six inputs and one output, which in a subsequent analysis gets increased to a total of 13.As per the mentioned thumb rule, the number of hidden layers, should be 9. From experimental validation, it is also observed that change of 9 to 10-hidden layers reduces the training error by 2%.Further increasing the number of hidden layers did not increase the efficiency significantly.

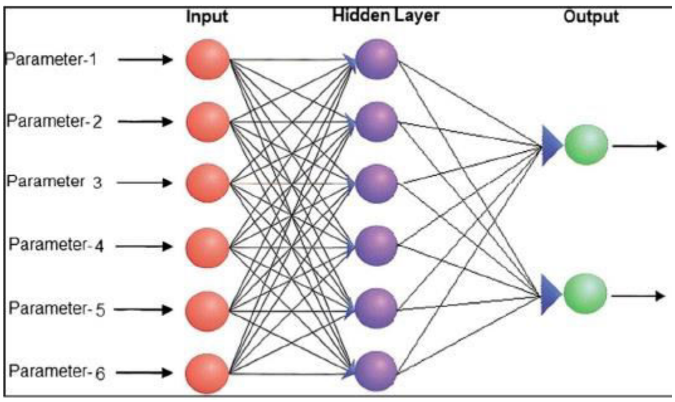

Fig.-3: Schematic of neural network with six inputs, single hidden layer and two outputs.

In FBNN, each propagation is involved with two steps, i.e., forward propagation and backward propagation. In forward propagation, a training pattern's input through the neural network in order to generate the propagation's output activations while in the backward propagation, the output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons. [2]

5.3Visual Dot Pattern of Acoustic and Vibration Signals

The acoustic emissions or vibration signals generated by rotating machinery can be represented as the superposition of sinusoidal signal. The proposed visual dot pattern is a method for visually expressing the problem in an easy-to understand figure. The display characterizes signal waveforms using patterns of dots and requires very limited computational times. Changes in the amplitude and frequency of sound and vibration signals can be easily identified. It involves the transformation of the sound pattern into a set of dots having mirror symmetry, in which the time waveform of the sound signal is visualized as a snowflake-shaped pattern of six-fold symmetry. This pattern provides a stimulus by which local visual correlations are integrated to form a global percept. It can potentially be applied to the detection and characterization of significant features of any sound the principle for plotting visual dot patterns of acoustic and vibration signals. The visual dot pattern is obtained bytransforming the correlation of value F(t) of the time-axis signal at time t and its value F(tCn) at time t Cn into polar coordinates P(r(n), f(n), Q(n)). One set of data(F(n), F(tCn)) is plotted so as to be linearly symmetrical with the initial line of the polar coordinate graph. Then, a figure symmetrical with a point is created by repeatedly rotating the axis of linear symmetry and plotting. The transformation from the discrete signal F(n) at a fixed sampling time n to polar coordinates is given by the equation

$$r(n) = \left(\frac{F(n) - L}{H - L}\right)g,$$

where r(n) is the radius of the visual dot pattern, F(n) is asound or vibration signal, H is the maximum value of F(n),
L is the minimum value of F(n), g is a gain value of signal, n is the number of dots.

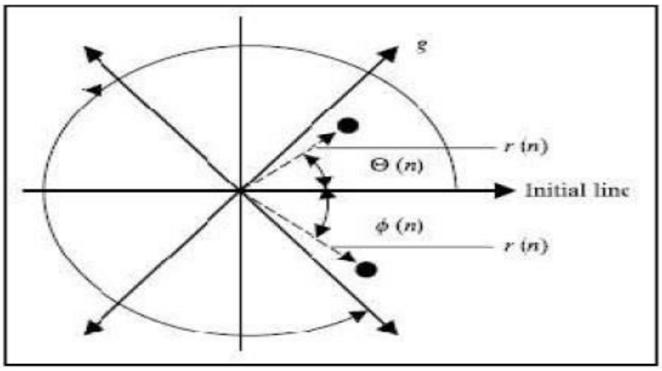

Fig- 4 Principle of visual dot pattern.

For the engine fault diagnosis, the signals are recorded from the engine operation conditions of a normal operating state and four different faults at engine speeds from 750 to 3000 rpm. The faults include one cylinder miss; two cylinders miss firing, lag of spark ignition, and a leaking of the intake manifold. The acoustic emission and vibration signals will obviously increase in an engine with faults because of change in the balance of theengine and fluctuations in pressure.

5.3.1. Principle Of The Image Template Matching System

Interest in digital image processing methods stems from two areas of application: improvement in pictorial information for human interpretation, and the processing of scene data for autonomous machine perception. In this study, we conclude our coverage of digital image processing by developing a technique for image template matching for fault diagnosis.

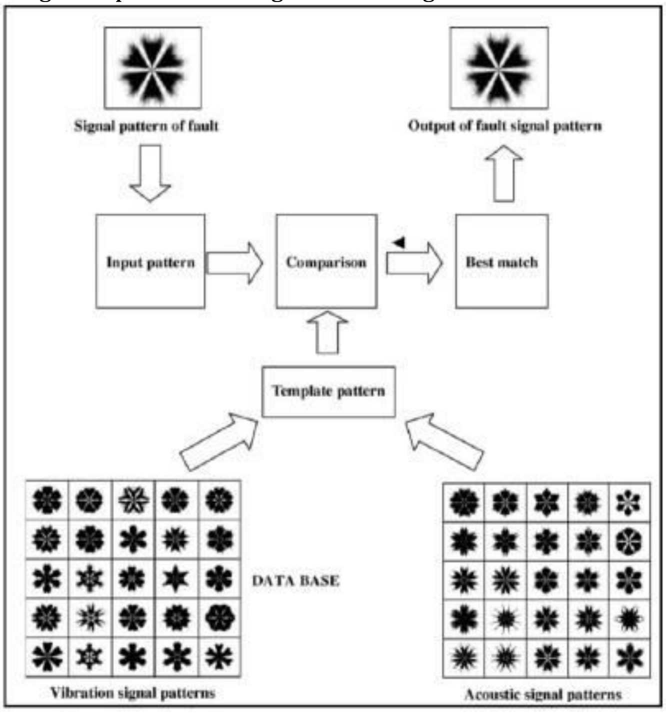

Fig.-5 Template matching of visual dot patterns in fault diagnosis.

Template matching is one digital method that can be used to compare the pattern of images. In the system, unknown signal pattern was input into the template matching system from the data record system. According to the unknown pattern property, the matching system will find the match pattern is the fault condition pattern for the experiment. processing method that can he best matching pattern from the databank. The best match pattern is the fault condition pattern for the experiment. [6]

6. CONCLUSION

In this way we have studied the methods of engine fault diagnosis and condition monitoring using acoustic emission.

Here we have discussed the various condition monitoring techniques, various acoustic emission fault components in diesel engine as well as acoustic emission analysis methods such that Fuzzy logic inference, ANN, visual dot pattern method. At the end we came to know that acoustic emission is one of the best condition monitoring technique for IC engine.

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