Engine Fault Diagnosis Using Sound Analysis

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***Abstract*—Vehicle engine faults are major faults which take place inside the engine of vehicle. Diagnosis of these faults is highly related to the technical expertise of the person and results in low success rates, so there is duly need of improving the diagnosing methods by improvising the innovative algorithms for faults diagnosis. A fault detection and diagnosis method for an engine's comprises of collecting a sensor signal from an acoustic of bike engine, extracting a feature set from the sensor signal using Mel-Frequency Cepstral Coefficients (MFCC) algorithms. Fault and non-fault states are reported based on comparison between the feature set and a library of fault and non-fault feature profiles corresponding to fault and non-fault states of the bike engine with inspected bike engine. In this paper we have presented the fault diagnosis method using the sound analysis by implementation of MFCC algorithm.**

Keywords*—fault diagonsis; acoustic; condition monitoring; segmentation; MFCC; discrete fourrier transform (DFT)

I. Introduction

Diagnosis of different types of faults that arise in vehicle engines is very critical in subject of repair and maintenance of a vehicle. Distinguished sound pattern generated by different faulty engines contains features of the particulars related to the corresponding faults, detection and correction of these faults results in improvement of the efficiency and life of the engine. Motorcycles are the favourite mode of transport in India. Sound patterns produce by vehicle under different working conditions are different when in motion. Service mechanics can diagnose faults based on the sounds produced by using the expertise acquired over many years. Vehicle as well as fault identification based on acoustic signals adds further difficulty to analysing sound patterns. The most influential factors include the non-stationary nature of the sound, and changes in speed, engine condition, road condition, and the surrounding atmosphere [6]. Some speech processing techniques such as the hidden Markov models are not suitable for these applications because of the lack of alphabet sounds. The proposed work is divided into two stages: fault detection, and type of fault. In the fault detection stage, the chain codes of the pseudo spectrum of the sound signal are used as feature vectors. A sound sample of a motorcycle is identified as faulty in the first stage, it is subjected to the type of fault stage. The work employs Mel-frequency cepstral coefficient (MFCC) features for type of fault, which are used for speech and speaker recognition. The work intends to alert riders to the possibility of accidents by indicating faults well in advance. It is also useful for service station experts in their preliminary analysis of faulty vehicles.

II. Engine Fault Diagnosis Using Sound Analysis

First, confirm that you have the correct template for your paper size. Fault detection determines whether the motorcycle engine is healthy or faulty, whereas the fault location stage recognizes the accurate source of the defect. Fig. 1 describes a block diagram of the proposed methodology. The extracted feature vector is used as input to the DTW classifier [10]. The second stage employs MFCC characteristics of the acoustic signals as input to the DTW classifier. The test feature vectors are compares with the reference feature vectors by the DTW classifier. The smallest of the DTW distances specifies whether the sample is healthy or faulty in the first stage, and it indicates the type of fault in the second stage. Database of engine sound recordings is prepared, database contains the ideal engine sound from healthy engine and a faulty sounds from different faults used for diagnosis. Input sound signal are initially trained for feature extraction, this includes the segmentation [5], frame blocking and windowing followed by the Fourier frequency transformation (FFT). These extracted features from trained input signals are used for comparison after implementation of the MFCC algorithm which uses Mel-frequency wrapping and cepstrum for the final results.

III. Methodology

Enrichment of recorded audio database is one of the important factor which directly related to the success rate of the accurate fault diagnosis results. Acquisition of sound samples includes collection of audio recording of healthy engine and audio recordings of faulty engine. Noise plays important part in database collection, data must be collected with minimum noise level as possible.

Collecting audio samples for healthy and faulty engine in different environmental condition increases the success rate of the results, and also helps in real time application of the diagnosis process. Sound samples of motorcycles under idling conditions are recorded using voice recorder. The recording is performed with 44.1-kHz sampling frequency and 16-bit quantization. The recordings are obtained from service stations. So it may have additional disturbances from human speech, sounds of other vehicles

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being serviced, air-compressors, and other automobile repair tools. Hence recorder is held very close to one end of engine in a real-world environment.

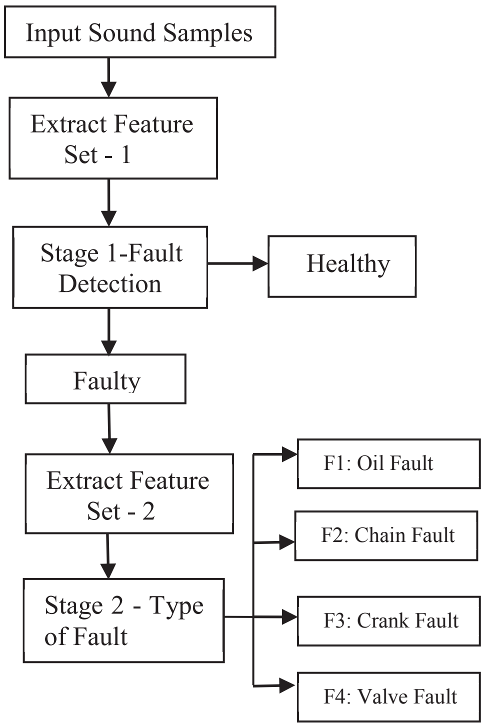

Fig. 1. Block diagram of the proposed methodology

A brief description of the engine faults considered is given below:

1. **Oil fault:** This may occur when quality of engine oil degrades and not able to provide smoothing motion to piston of engine that leads harsh sound of piston.

2. **Chain fault:** The main function of the timing chain is to operate the valves. Not firmly fixed chain vibrates and results in a change of sound.

3. **Crank fault:** Destruction of either oil ring, first ring or second ring may result because of crank fault.

4. **Valve fault:** A substantial increase in peak combustion chamber pressure which leads to a change in engine sound is because of any deviation of between 5–10° in valve opening and closing.

Sound samples from healthy motorcycles are collected from those machines that are one-year old and Sound samples of faulty motorcycles are collected from machines of varying age. The sound samples of motorcycles should be from same model and manufacturer as acoustic of engine varies from model to model by different manufacturer [10]. Recording of the engine sound samples must be collected at the same RPM of engine and for the identical time period this helps to get the similar amplitude intensity audio recording and algorithm implementation becomes less complex.

IV. ALGORITHM

Fast and accurate automatic audio identification technology requires digital processing of audio signal and feature identification algorithm. The audio signal contains very large information. A direct inspection and synthesizing the complex audio signal is required because signal contained too much information [11]. Therefore the digital signal processes such as Feature Extraction and Feature Matching are introduced to represent the audio signal. Several methods such as Liner Predictive Coding (LPC), Hidden Markov Model (HMM), Artificial Neural Network (ANN) are evaluated with a view to identify a straight forward and effective method for audio and voice signal [6]. First the Pre-processing or filtering signal is performed and then identification, matching process is implemented.

Fig. 2 represents block diagram of algorithm flow. In block diagram training process and pre – processing regions are labelled accordingly.

A. Segmentation / Packet formation and Pre-processing –

In segmentation and windowing the audio input sound is divided into the segments of 12 / 14ms packets. For pre – emphasis High pass FIR filters are used these high pass filters work in time domain. Filtering in the time domain gives the pre - emphasis signal $S_1(n)$:

$$S_1(n)=\sum_{k=0}^{M-1} h(k)s(n-k) \tag{1}$$

B. Windowing –

Audio spectrum distortion is reduced by applying the windowing concept. Audio Signal distortion and discontinuity in each frame is minimized with application window from both ends.

After Fourier transformation the signal get introduced with the glitches at regular interval of time this restrict smooth connection of two adjacent frames, these ends are processed by windowing for the Smooth connection commonly used windowing functions are Kaiser Window and Humming Window.

C. FFT analysis and coefficient extraction –

Fourier analysis converts time domain signals into frequency domain signals. An FFT rapidly computes such transformations by factorizing the Discrete Fourier transform (DFT) matrix into a product of sparse factors [8].

The DFT is defined by the formula,

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j2\pi k\frac{n}{N}} \tag{2}$$

Where $k = 0, 1, 2 \ldots\ldots\ldots N-1$

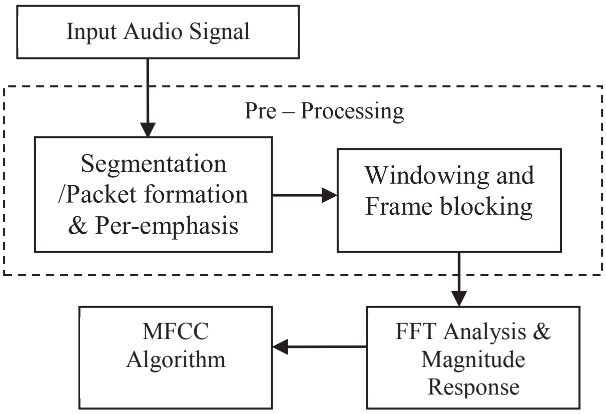

Fig. 2. Block diagram of algorithm flow

D. Mel Frequency Cepstral Coefficients (MFCC) –

MFCC's are used as identification techniques. Mel frequency cepstral coefficients (MFCCs) feature widely used in automatic speech and Speaker recognition. For simplification short time audio signal are considered because an audio signal is constantly changing and contains large information. Therefore we frame the signals into 20-40ms frames. Then power spectrum of each frame is calculated. The next step is Mel filter bank processing where our filters get wider when frequencies increases. We are less concerned about variations, where as we are only interested in roughly how much energy occurs at each spot. The Mel scale tells us exactly how to expanse our filter-banks and how broad to make them.

The frequency to Mel scale is converted as,

$$M(f) = 1125 \ln(1 + \frac{f}{700}) \quad (3)$$

Then the Discrete Fourier Transform of the frame is taken,

$$S_i(K) = \sum_{n=1}^{N} s_i(n) e^{-j2\pi kn/N} \quad (4)$$

$$1 \leq k \leq K$$

where h(n) is an N sample long analysis window and K is the length of the DFT.

Now the filter banks will start at the first point, the formula for calculating peak and zero is given by,

$$H_m(k) = \frac{k - f(m-1)}{f(m) - f(m-1)} \qquad f(m-1) \leq k \leq f(m)$$

$$H_m(k) = \frac{f(m+1) - k}{f(m+1) - f(m)} \qquad f(m) \leq k \leq f(m+1)$$

$$H_m(k) = 0 \qquad f(m-1) < k > f(m+1)$$

Where the m is no if filters we want, and f ( ) is the list of M+2 Mel-spaced Frequencies.

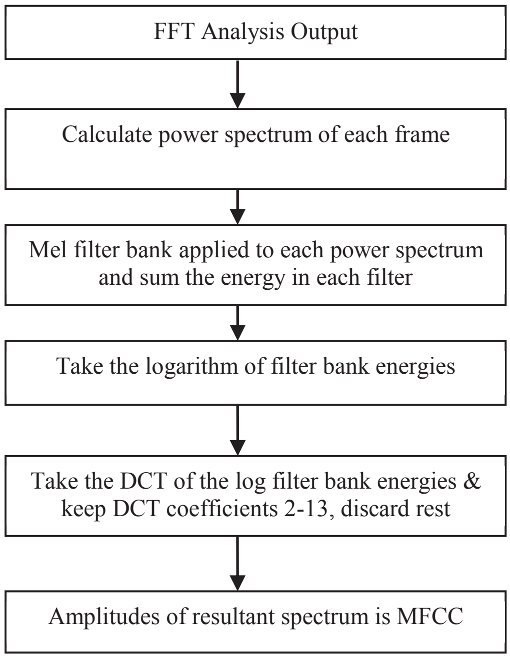

Fig. 3. MFCC algorithm Procedural flow

V. PERFORMANCE RESULTS

The two bikes are used engine fault diagnosis are Pulsar from Bajaj auto and Unicorn from Honda India Automobiles. Oil fault and chain fault diagnosis results are showed in the graphical representation of MFCC algorithm plots.

MATLAB is used for the effective implementation of MFCC algorithm. Sony voice recorder is used for the recording of engine sounds.

Time domain plot and MFCC frequency domain plot are shown below.

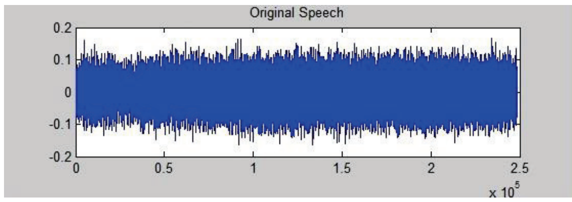

Fig. 4. Pulsar bike healthy engine sound waveform

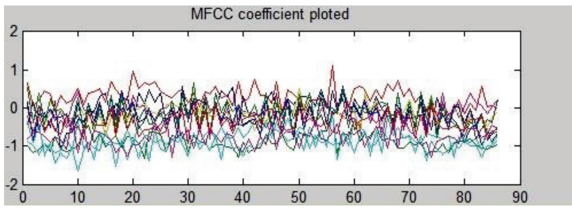

Fig. 5. Pulsar bike healthy engine MFCC Plot

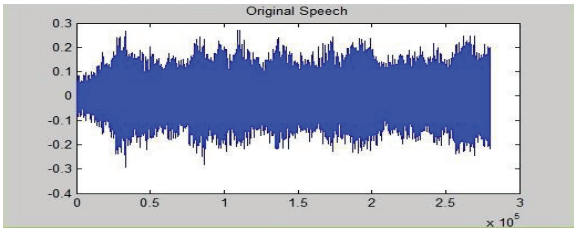

Fig. 6. Pulsar bike with oil fault engine sound waveform

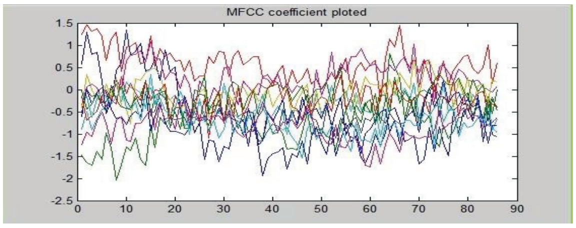

Fig. 7. Pulsar bike with oil fault MFCC Plot

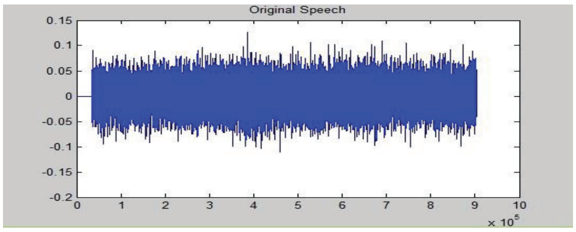

Fig. 8. Pulsar bike with chain fault engine sound waveform

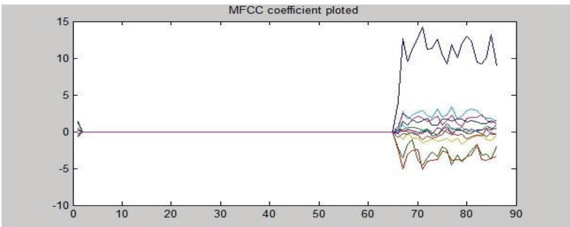

Fig. 9. Pulsar bike with chain fault MFCC Plot.

TABLE I. PERCENTAGE SIMILARITES BETWEEN RECORDED SOUND OF FAULTY BIKES WITH THOSE OF HEALTHY BIKES

Sr. no	*Model*	*Condition*	*Recording Duration*	*Percentage %*
1	Honda Unicorn	Oil fault	20 sec	73.48
2	Honda Unicorn	Chain fault	20 sec	55.94
3	Honda Unicorn	Value fault	20 sec	74.62
4	Bajaj Pulsar	Oil fault	15 sec	78.64
5	Bajaj Pulsar	Chain fault	15 sec	52.38
6	Bajaj Pulsar	Value fault	15 sec	71.54

VI. CONCLUSION

In this paper engine fault diagnosis using MFCC algorithm is described with relevant algorithm flow and block diagrams. All the stages in the algorithm are explained with formulae. Different engine faults such as oil fault, valve fault, crank fault, chain fault are recorded, analysed and corresponding MFCC are plotted. Motorcycle healthy engine sound is also recorded, analysed and MFCC plotted. Inspected motorcycle's sound is recorded, analysed and MFCC are plotted. After comparing MFCC of inspected motorcycle with MFCC of healthy engine and faulty engine, engine fault can diagnosis. Results for healthy engine and different fault types are added along with corresponding MFCC Plots.

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