Multi-stage Acoustic Fault Diagnosis of Motorcycles using Wavelet Packet Energy Distribution and ANN

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Abstract

Motorcycles generate different sound patterns under dissimilar working conditions. The generated sound pattern gives a clue of the fault. Mainly the parts of the engine that lead to change in sound are cylinder kit, crank, timing chain, and valve. The parts of the exhaust system that change sound under fault are muffler and silencer. In this study, we analyze the sound signals produced by motorcycles to locate the faults in subsystems. The work proceeds in three stages, the first stage detects the fault, the second stage identifies the faulty subsystem and finally the third stage locates the fault. The overall classification accuracy of the first stage is 0.8019. The work finds interesting applications in troubleshooting of machinery, electronic gadgets, musical instruments and the like.

Keywords: *Fault localization, acoustic fault diagnosis, wavelet packet energy, neural networks*

1. Introduction

Motorcycles are the most preferred means of travel by economically middle-class citizens of India, due to their affordability, fuel economy and road conditions. Indian automobile market is dominated by motorcycles with nearly 77% of the total vehicle sales [1]. The sales are projected to exceed 10 million units by 2012-13. Normally after two years of usage, the vehicles turn faulty due to wear and tear of parts, road conditions and lack of proper maintenance. Repair and maintenance of faulty motorcycles is a tough task, especially due to scarcity of expertise.

Non-speech sound signal processing is a challenging task due to lack of sound alphabet. Especially, the vehicle classification and fault diagnosis based on sound is more difficult since the sound patterns change with variations in speed, health condition, road condition, surrounding environment and the like. However, the sound patterns give a clue of the fault. Sound of a moving vehicle helps the rider to know the condition of vehicle and that of a stationary vehicle helps the garage mechanics to assess the faults. Garage mechanics take test rides to assess the condition of the vehicle. Automatic fault diagnostic systems are necessary for a vehicle in remote places and in places of scarce expertise. The sound sources in a vehicle include rotary parts, crank, piston, timing chain, push rod, tyre friction, exhaust and clutch plate.

The main problem this paper addresses is the fault diagnosis of motorcycles based on the sound signals. The process should resemble the way people with different levels of expertise attempt to diagnose the faults. The proposed work proceeds in three stages: fault detection, subsystem identification and source localization. Energy distribution in the wavelet packet subbands are used as features. ANN classifier is used at all the three stages for classification.

The literature survey is carried out to know the state-of-the-art in applications of signal processing to automobile industry and other allied areas. Studied literature is organized into four parts: engine fault diagnosis, gearbox fault diagnosis, medical diagnosis, and applications of wavelet packets.

Signal processing techniques are successful to some extent classifying the vehicles into healthy and faulty [2], bike and scooter [18]. Fault diagnosis of engine [3-5], and gearbox [6-8] are found in the literature. [2] present a fault detection system for motorcycles based on acoustic signals. The approach employs 1D central contour moment, their invariants, of wavelet subbands and DTW classifier. The same authors present a methodology for classification of motorcycles into bikes and scooters. It uses time-domain and frequency-domain features input to the neural classifier. [3] discuss the mechanisms of engine front noise generation and the corresponding countermeasures of a diesel engine using sound intensity method. [4] develop a mechanical fault diagnosis system for a scooter engine platform, using continuous wavelet transform and artificial neural network. [5] use an empirical mode decomposition (EMD) and wavelet packet backpropagation neural network for engine fault diagnosis.

[6] designs a methodology for fault diagnosis of Massey Ferguson gearbox using root mean square (RMS) and power spectral density (PSD). [7] constructs a system for detection of the vibration signals of a gearbox employing adaptive wavelet filter. [8] provides an approach for the classification of the working condition of gear. The approach decomposes the vibration signals into a finite number of intrinsic mode functions and then establishes the autoregressive (AR) model of each intrinsic mode function (IMF) component and finally generates the corresponding autoregressive parameters. The autoregressive parameters and the variance of remnant are regarded as the fault characteristic vectors and are used as input to the support vector machine (SVM) classifier.

Auscultation is a valuable medical diagnostic tool. Auscultation methods provide the information about a variety of internal body sounds originated from the heart, lungs, bowel and vascular disorders. [9] investigates a framework for the analysis of cardiac signals. The approach approximates the processing stages of heart sounds and estimates the effectiveness of each step in extracting relevant information from patient data. [10] illustrates a technique for heart sound analysis, which employs time-frequency distribution (TFD) analysis and Mel frequency cepstrum coefficient (MFCC). [11] employs a multi-resolution wavelet transform for electrocardiogram (ECG) feature extraction system. Condition monitoring application provided by [12] uses features such as magnitude of the signal, natural logarithm of the magnitude and MFCC. The features are used as input to various pattern classifiers. [13] compare the fault detection alternatives for induction machines according to the information required for the diagnosis, the number and relevance of the faults that can be detected, the speed to anticipate a fault and the accuracy in the diagnosis. [14] relate a multi-resolution wavelet analysis with a neural network for the fault analysis of industrial robots. [15] applies wavelet analysis of accelerometric signals for detection of wheelflat faults in railway. [16] demonstrates a structure for monitoring the state of a turbocharger and supervising the air pressure in vehicle wheels. The structure involves fuzzy inference mechanism based on neural units. [17] illustrate a de-noising method based on the wavelet technique for feature sound extraction for diagnosis of machines. [18] employ simple time domain and frequency domain features as inputs for neural network for classifying motorcycles into bikes and scooters, based on acoustic signatures.

The rest of the paper is organized into four sections. Section 2 gives a review of literature. Section 3 discusses the proposed methodology with a brief on tools and techniques. The experimental results are elaborated in Section 4. Finally, Section 5 concludes the work.

2. Review of Literature

The reported works on vehicle detection, classification and fault diagnosis are mainly based on processing of acoustic signals, images, and infrared signals. Vehicle recognition by these means are sensitive to Doppler effects, noise produced from moving parts and atmospheric variations. Further, these methods are expensive and require extra hardware. Some of the limitations of the reported works are:

- Dependency on the knowledgebase in case of neural network based approaches, hence posing a serious limitation when tested with new data [14].
- Lack of transparency due to large number of features [16].
- Lack of real-time applicability due to simulations [17].
- Computationally expensive and lack of robustness [26].
- Limitation of the technology to processing of near-periodic signals [28].

Recently many researchers are working on wavelet packets for diverse application areas. [20] develop a data fusion algorithm for distributed sensor arrays by integrating the classification results from different sensors. [29] analyzed the EEG signals by the wavelet packet transform (WPT) and the wavelet packet energy entropy (WPEE). Rhythms of the EEG signals are extracted by using WPT and the relative WPEE reflects the energy distribution among rhythms during acupuncture. Effects of acupuncture on rhythms and order of brain activities are investigated by these methods. [30] propose a method based on wavelet packet transform to extract the features from surface electromyography (EMG) signal. In this method, the features are relative wavelet packet energy (RWPE), which is evaluated from several selected frequency bands of surface EMG signal. A generic approach identifies and differentiates among signals of wide range of problems [31]. The signatures are constructed by the distribution of the energies among blocks of wavelet packet coefficients. An efficient procedure is developed for adaptive selection of the characteristic blocks. The modified classification and regression trees (CART) algorithm is used as a decision unit. A fault diagnosis method for rolling bearing [32], based on the integration of improved wavelet packet, frequency energy analysis and Hilbert marginal spectrum is presented. An automotive mechanic usually performs a diagnosis in the ignition system of the engine to check any exceptional symptoms. [33] present a case-based reasoning (CBR) approach for diagnosis based on the signals. [34] present a methodology to deal with simultaneous noise suppression and signal compression of quasi-harmonic signals. [35] propose a method for traffic information extraction based on wavelet packet analysis.

Existing works focus on the fault diagnosis of engines, gearbox, machinery, robots and the like. Features are extracted based on the wavelets. Fuzzy classifier and variants of ANNs are used for classification. To the best of our knowledge the amount of reported work for fault diagnosis of motorcycles, based on their sound patterns is almost negligible. Hence, the proposed work. Since the existing works employ different databases, recording environments and denoising schemes, it is difficult to compare the findings of our work with the reported works. Our work is more suitable for real-time implementation since it successfully classifies the sound signals recorded in real-world environment.

3. Proposed Methodology

The aim of this study is to locate the faults in motorcycles based on the sounds produced. Wavelet packets are sensitive to small changes. The distribution of energies among the approximation and detailed coefficients of wavelet packet subbands are explored as features. Acquired sound signals are segmented prior to feature extraction. The extracted feature vectors comprising of the percentage distributions of the wavelet packet energy are used for classification. Classification performance is analyzed using the energy distributions among approximation coefficients of the first five subbands.

Figure 1 depicts the overview of the methodology. It comprises of three major stages: fault detection, subsystem identification and fault source localization. Each of these stages uses the same features and classifiers. The decision vector of the first stage is input .to the second stage along with the feature vectors. The decision vector of the second stage is input to the third stage along with the input features. The decision vector helps in considering only the relevant samples for the following stages. For e.g., assume that sample s50 is classified as faulty in the first stage. The decision vector generated resembles (0, 1). The generated decision vector along with the feature values of s50 are input to the second stage. If the second stage classifies this input as engine subsystem fault, then the decision vector resembling (1, 0) is generated. This decision vector and the feature vectors of s50 are input to the third stage. In case s50 is identified to be crank fault then the last stage ANN output resembles (0, 0, 1, 0, 0, 0, 0).

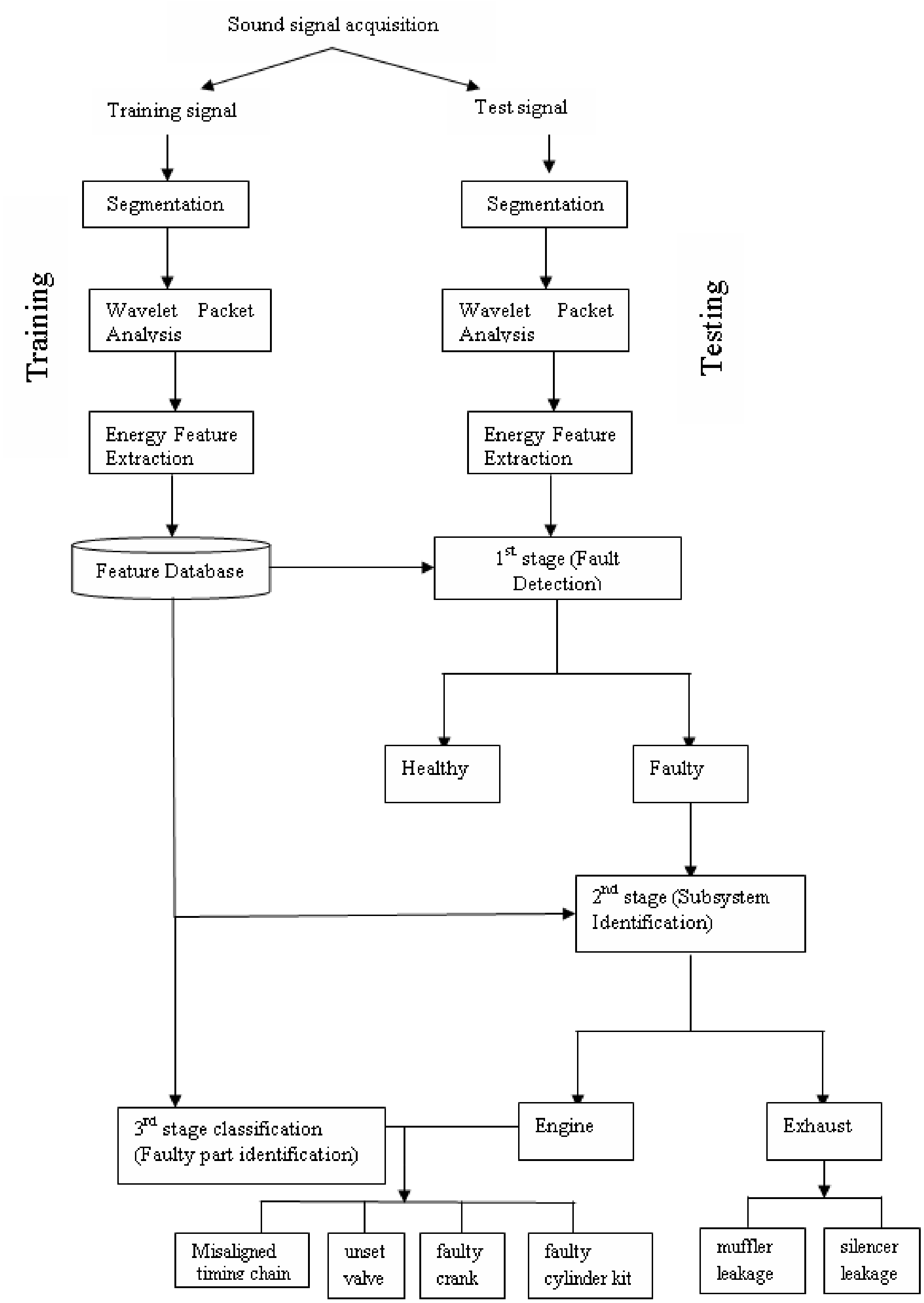

Figure 1. Block Diagram of the Approach

The approach uses energy distribution in the wavelet packet coefficients as features. Energy distribution in the first five subbands is considered for feature extraction. Following subsections discuss fault diagnosis in substages.

3.1. Acquisition of Sound Samples

The sound signals of the motorcycles are recorded using Sony ICD-PX720 digital voice recorder. The sampling frequency of 44.1 kHz with 16-bit quantization is used. Recording is carried out under the supervision of expert mechanics. The recording environment has disturbances from human speech, other vehicles being serviced, air-compressor and auto-repair tools. Recorder is held closer to the engine to minimize the influence of disturbances. Figure 2 depicts the environment for recording of the motorcycle sounds. The recorder is held 500 mm from the centerline of the exhaust end, and at an angle of 45°. The 500 mm distance is critical since an 80 mm error either way results in up to one decibel change in sound level. The engine starts the throttle is controlled by expert mechanic simultaneously.

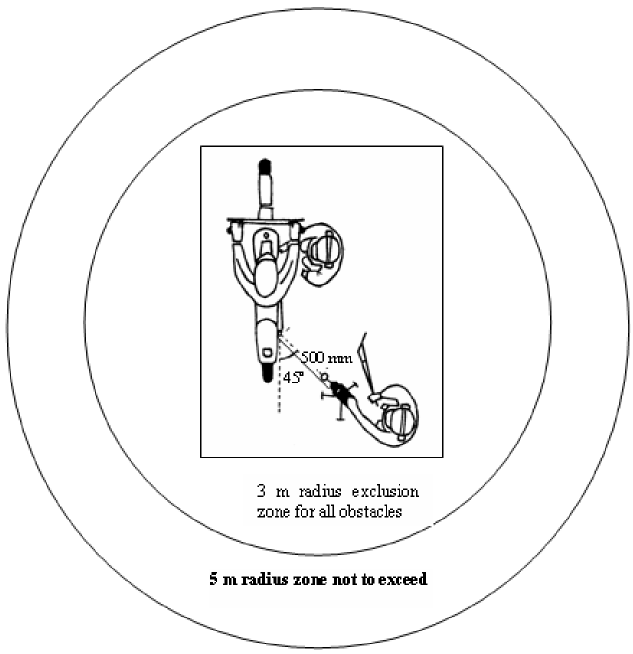

Figure 2. Recording Environment

3.2. Segmentation

Acquired sound samples are segmented into samples of one-second each for uniformity in processing. The portion of the signal of duration one-second, beginning from local maxima in the first 50 ms span is considered as a segment. Next segment begins at local maxima in the next 50 ms duration from the end of the current segment.

3.3. Wavelet Packet Feature Extraction

Combined fault signature in the time-domain is transformed to time-frequency domain using Daubechies' DB4 wavelets. In the discrete wavelet transform (DWT), each level is calculated by passing the previous approximation coefficients though a high and low pass filters. However, in the wavelet packet decomposition (WPD), both the detail and approximation coefficients are decomposed. Wavelet packets form bases which retain many of the orthogonality, smoothness, and localization properties of their parent wavelets. The coefficients are computed by a recursive algorithm. For n levels of decomposition, the WPD produces 2n different sets of coefficients (or nodes) as opposed to (n +1) sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy. Figure 3 depicts a wavelet packet decomposition tree. More details of WPD can be found in [37].

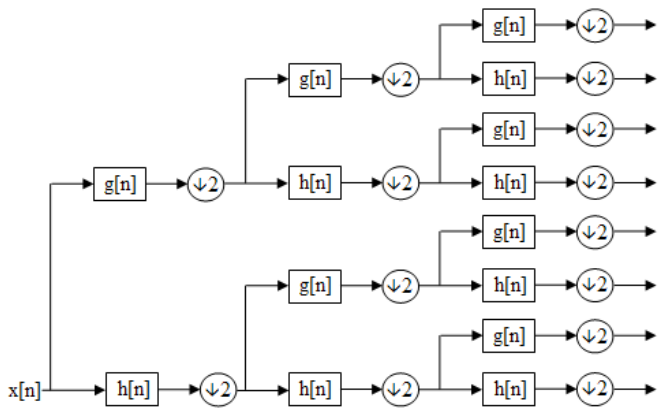

Figure 3. Wavelet Packet Decomposition

The energy in the approximation coefficients of the wavelet packet decomposition exhibits good separability for different faults. The energy in the approximation coefficients of wavelet packets is computed. The percentage energy values of the first five subbands form the feature vector, later used for classification. The faults are chosen in combinations of engine and exhaust subsystems. The separability analysis of the features is carried out and the results of comparison of energies in the first five subbands of decomposition are presented. Figure 4 shows the separability of the energy distribution for the fault signatures of cylinder kit problem and muffler leakage.

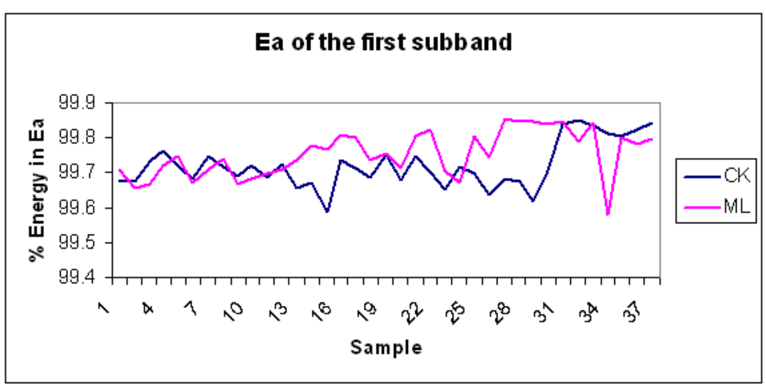

Figure 4. (a) Percentage Energy in Approximation Coefficient of the First Subband

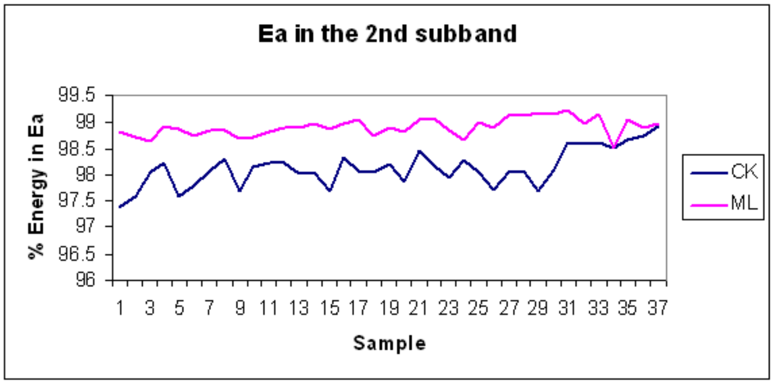

Figure 4. (b) Percentage Energy in Approximation Coefficient of the Second Subband

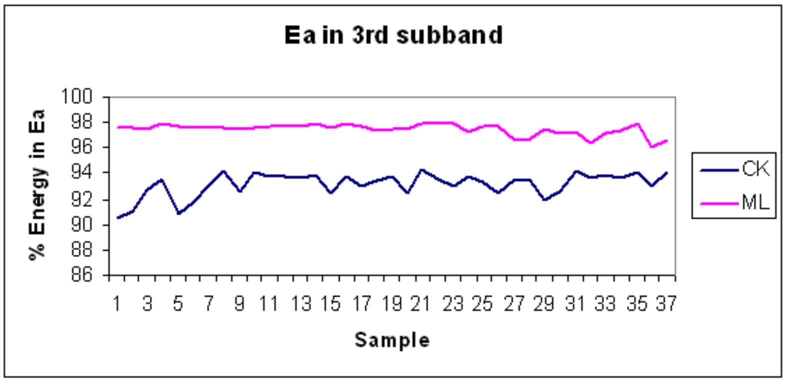

Figure 4. (c) Percentage Energy in Approximation Coefficient of the Third Subband

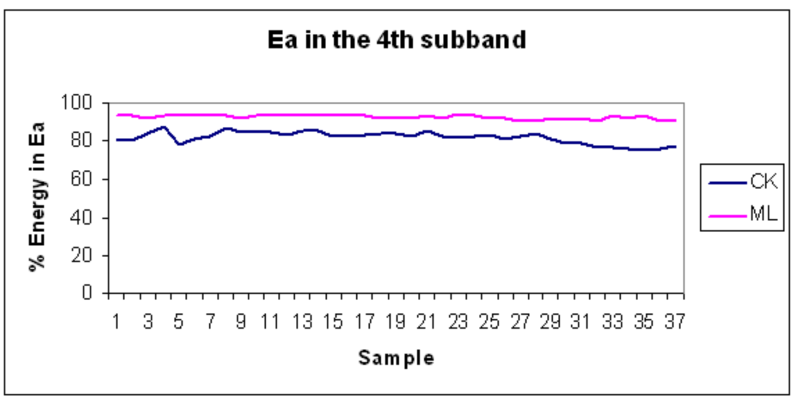

Figure 4. (d) Percentage Energy in Approximation Coefficient of the Fourth Subband

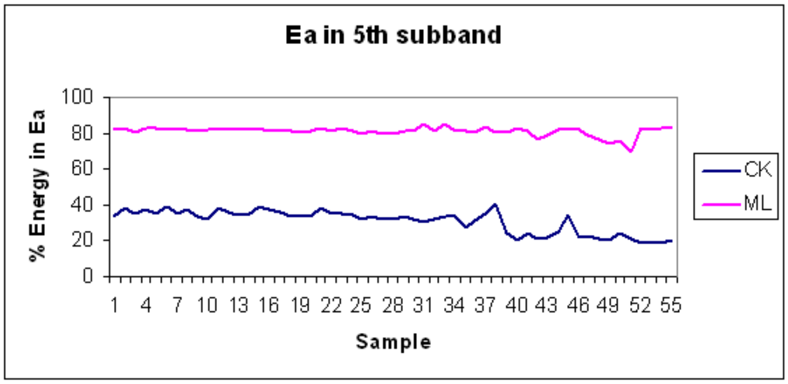

Figure 4. (e) Percentage Energy in Approximation Coefficient of the Fifth Subband

From Figure 4, it is evident that the separability among the faults CK (Cylinder kit) and ML (muffler leakage) increases with levels of decomposition. This is attributed to the variations in temporal and spectral behavior of the faults belonging to different subsystems. The features are extracted from the samples recorded from the cluttered environment because of which the developed methodology has potential of adaptation for real-world applications. The chosen features exhibit better separabilities even without samples being denoised.

3.4. Artificial Neural Network

Despite the advancements in biologically inspired computing techniques, ANNs are still accepted for classification problems with scope for approximation. Figure 5 outlines the architecture of the neural network. Features extracted from wavelet packet decomposition are input to the neural network. Seven output nodes correspond to the seven-bit output vector (values nearer to 0 are interpreted as 0s and the predominant values interpreted as 1s) indicating the type of the fault in the motorcycle. Number of nodes in the hidden layer is varied for each stage based on the evaluation criterion. ANN is trained using backpropagation algorithm.

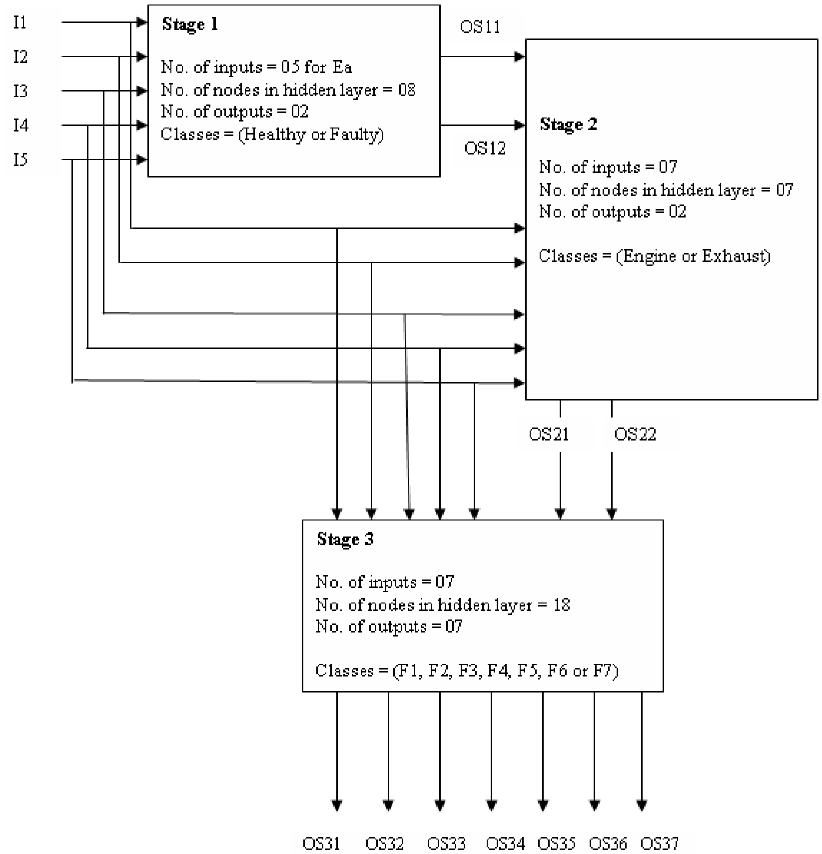

Figure 5. Multi-stage ANN Architecture

Generally the classification performance will be appreciable for smaller sample sets. When the goal meets, the observed MSE is almost zero. Validation is performed for Ea features (energy in approximation coefficients), to decide the number of nodes in the hidden layer. The optimal number of hidden layer neurons is chosen using the criterion [36] given in Equation (4):

$$n = C\sqrt{\frac{N}{d \log N}} \qquad \cdots(4)$$

where, n=Number of hidden layer neurons, C=Constant to yield optimal performance, d=Number of features, and N=Number of rows in the training sample matrix.

The approach tries an increasing sequence of C to obtain different number of hidden nodes. The n that generates the smallest mean squared error (MSE) is noted. MSE is computed for the sample sets with 70% of the samples used for training, 15% for validation and 15% for testing. Figure 6 shows the validation MSE plotted for the first stage of classification.

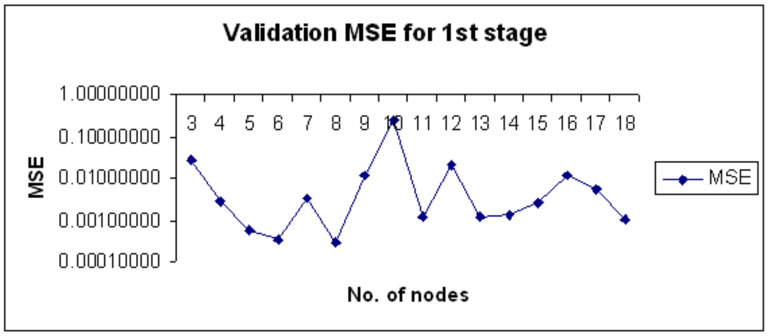

Figure 6. MSE Plot for the First Stage

The minimum MSE is observed for eight neurons in the hidden layer of the ANN. Hence, the neural network has five nodes in the input layer, eight in the hidden layer and two in the output layer, for the first stage. Similarly the number of nodes in the hidden layer, for second and third stages is empirically found to be 7 and 18 respectively. Inputs to the second stage are augmented with the decision of the first stage. Hence, the outputs generated by the first stage are input to the second stage along with the input feature vectors. Inputs to the third stage of the ANN are augmented with the generated output decision vector of the second stage. So the third stage of the classifier has seven inputs. The last stage yields seven outputs indicating one of the seven faults, belonging to either the engine or exhaust subsystem.

4. Results

Motorcycles manufactured by Hero Honda (Now Hero Motocorp), Honda motors, TVS Motors, Bajaj are considered. The sound database consists of 443 samples of faulty motorcycles. Healthy motorcycles are about one year old, run approximately 6000 km and regularly serviced. Faulty sample database includes the sounds generated by the motorcycles with one of the faults, namely, valve setting problem (VS), faulty crank (FC), timing chain problem (TC), cylinder kit problem (CK) which, are all from engine subsystem. The faults drawn from the exhaust subsystem are muffler leakage (ML), silencer leakage (SL) and excess smoke (ES). Sony ICD-PX720 digital voice recorder is used for recording.

MATLAB version 7.11.0.584 (R2010b) is used for effective implementation. The subband energies of the healthy and faulty motorcycles are analyzed. In case of first subband, the percentage energy in the approximation coefficients of the wavelet packets differs slightly. But for the subbands from two to six, the percentage of energy in of wavelet packet subbands varies for healthy and faulty motorcycles. This can be attributed to the uneven cycles of operation of the engine in presence of a fault. Further, the faults related to exhaust system, like silencer leakage, result in drastic change in sound.

ANN classifier is used for classification for all the three stages. The output of ANN indicates whether the test input is of healthy or faulty motorcycle in the first stage. The outputs of the samples classified as faulty are combined with the feature inputs to form the input vector for the next stage. The output of the second stage indicates whether the fault is with engine or exhaust. This output and the input vectors are input to the third stage for identifying the faulty part. The third stage generates a seven-bit output indicating the exact type of the fault. Testing is carried out with seven faults for combinations of 10, 20, 30 and unequal number of samples.

4.1. Stage 1. Fault Detection

The features are generated from the energy distribution in approximation coefficients of the first five subbands of the wavelet packet decomposition are input to the classifier. An ANN with five inputs, eight hidden layer neurons and two outputs is used. The outputs of the ANN indicate whether the input feature vector is healthy or faulty. Table 1 shows the fault detection results for the first stage.

Table 1. Results of First Stage of Classification

Legend: 433 samples are drawn as: VS-85; FC-83; CK-37; TC-83; ML-56; SL-57; ES-32
VS-Valve setting; FC-Faulty crank; CK-Cylinder kit; TC-Timing chain; ML-Muffler leakage; SL-Silencer leakage; ES-Excess smoke

Total number of test samples			Target	
			Healthy	Faulty
Healthy	Faulty	Output		
70	70	Healthy	70	0
		Faulty	0	70
140	140	Healthy	140	0
		Faulty	1	139
210	210	Healthy	210	0
		Faulty	1	239
433	433	Healthy	433	0
		Faulty	1	432

4.2. Stage 2. Subsystem Identification

Feature vectors labeled as faulty are input to the second stage to know whether the fault is with the engine or exhaust. It takes the same five input features which were input to the first stage, augmented with the decision vector generated from the first stage. Since 50% of the samples are healthy and 50% are faulty, the output vectors (0, 1) among the second half of the list are considered for the second stage. Predominant output values are interpreted as 1. For e.g., (0.0053, 0.9234) is interpreted as (0, 1) by the next stage classifier. Some of the samples of healthy might have been misclassified as faulty. Such samples are not considered for the next stage of classification. Table 2 summarizes the results of second stage of classification.

Table 2. Results of Second Stage of Classification

Total number of test samples			Target	
			Engine	Exhaust
Engine	Exhaust	Output		
40	30	Engine	40	0
		Exhaust	0	30
80	60	Engine	79	0
		Exhaust	1	60
120	89	Engine	119	0
		Exhaust	1	89
289	143	Engine	288	4
		Exhaust	1	139

4.3. Stage 3. Fault Source Localization

Input to the third stage classifier is formed by augmenting the five input feature vectors with the decision vector of the second stage. The samples identified as engine subsystem faults are further classified into F1 (VS), F2 (CK), F3 (FC) and F4 (TC). The samples identified as exhaust subsystem faults are classified into F5 (ML), F6 (SL) and F7 (ES). The sizes of the samples sets are 10, 20, 30 and unequal number of samples of each type of fault. Table 3 shows the classification performance for the third stage of classification process.

Table 3. Results of Third Stage of Classification

No. of samples	Output	Target F1	F2	F3	F4	F5	F6	F7
10	F1	**10**	0	0	0	0	0	0
10	F2	0	**10**	0	0	0	0	0
10	F3	0	0	**10**	0	0	0	0
10	F4	0	0	0	**10**	0	0	0
10	F5	0	0	0	0	**10**	0	0
10	F6	0	0	0	0	0	**10**	0
10	F7	0	0	0	0	0	0	**10**
20	F1	**14**	0	0	0	0	0	0
20	F2	2	**17**	0	0	0	0	0
20	F3	0	1	**19**	0	0	0	0
20	F4	3	0	1	**19**	0	0	0
20	F5	0	0	0	0	**20**	1	0
20	F6	0	0	0	0	0	**18**	0
20	F7	1	1	0	0	0	1	**19**
30	F1	**27**	0	0	0	0	0	0
30	F2	0	**30**	0	0	0	0	0
30	F3	0	0	**30**	0	0	0	0
30	F4	0	0	0	**29**	0	0	0
30	F5	0	0	0	0	**30**	0	0
30	F6	3	0	0	0	1	**29**	0
30	F7	0	0	0	0	0	1	**28**
85	F1	**85**	0	5	2	0	0	0
83	F2	0	**82**	0	0	0	1	2
37	F3	0	0	**32**	0	0	1	1
83	F4	0	0	0	**81**	0	0	1
56	F5	0	0	0	0	**55**	0	0
57	F6	0	1	0	0	1	**54**	0
32	F7	0	0	0	0	0	1	**23**

From the Tables 1-3 it is evident that for smaller sample sets the classification accuracy will be nearing or equal to 100%. Classification performance suffers for larger data sets. Table 4 summarizes the classification performance for each stage.

Table 4. Summary of Classification for Each Stage

Total number of input samples	Classification accuracy										
	Stage 1		Stage 2		Stage 3						
	Healthy	Faulty	Engine	Exhaust	F1 VS	F2 CK	F3 FC	F4 TC	F5 ML	F6 SL	F7 ES
140	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
280	1.0000	0.9928	0.9873	1.0000	0.7000	0.8500	0.9500	0.9500	1.0000	0.9000	0.9500
420	1.0000	0.9952	1.0000	0.9888	0.9000	1.0000	1.0000	0.9666	1.0000	0.9666	0.9333
866	1.0000	0.9976	0.9965	0.9720	1.0000	0.9879	0.8648	0.9759	0.9821	0.9473	0.8518

Legend: VS: Valve setting; CK: Cylinder kit; FC: Faulty crank; TC: Timing chain; ML: Muffler leakage; SL: Silencer leakage; ES: Excess smoke

Since the classification performance is appreciable for sample sets of sizes 30 each with seven fault types, the work can be implemented in service stations of moderate sizes, where around 200 vehicles are serviced everyday.

4.4. Discussion

Working in stages helps the mechanics to assess the faults stepwise and take suitable repair measures. Normally, the younger naïve mechanics detect the faults. After some years of expertise they will be able to identify the subsystem. As he acquires more expertise, he will be able to locate the faults. The work attempted to automate these traits of mechanics.

The proposed methodology works in three stages. The first stage classifies the sound samples of the motorcycles into healthy and faulty. The second stage classifies the faulty samples into engine and exhaust. The third stage identifies the exact part under faulty subsystem. The energy distribution among the wavelet packet subbands is unique to individual fault types. Hence they may be used acoustic fingerprint of fault signatures. The proposed approach yields 100% classification accuracy when 10 samples of each type of fault are used. The approach is suitable for small or medium garages and service stations. Results are satisfactory with more than 85% accuracy at each stage.

5. Conclusion

The investigation successfully classified the motorcycles into healthy and faulty in the first stage, identified the faulty subsystem in the second stage and localized the fault source in the last stage. Minimum classification accuracy of 85% was observed when uneven number of samples is used. The riders and the mechanics in service stations can be benefited by the findings. The work finds applications in fault source localization of machinery, vehicles, musical instruments based on acoustic signals. The present work leaves scope for further exploration of fault source localization internal to subsystems of motorcycles.

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