FAULT DETECTION OF MOTORCYCLES USING THE SLOPES OF THE ESTIMATED PSEUDOSPECTRUM OF THE PRODUCED SOUNDS

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ABSTRACT

The service experts assess the condition of the vehicles based on the produced sound. To benefit both, the riders and the experts, the fault diagnosis process needs to be automated. The paper presents a methodology for fault detection of motorcycles, which uses the slopes of the eight pseudospectral segments as features. The computed features are classified into healthy and faulty using artificial neural network (ANN) classifier. The experiments are conducted to prove the effectiveness of the proposed method. The results are satisfactory with an average accuracy of 85%. The study can be extended to localize the sources of the faults in subsystems. The proposed work finds applications in fault detection of machines, musical instruments, electronic gadgets and the like.

KEYWORDS

Automotive Fault Diagnosis; Sound Signal Processing; Estimated Pseudospectrum; Artificial Neural Network

1. INTRODUCTION

Motorcycles are the most preferential means of travel by reasonably middle-class population of India, due to their affordability, fuel economy, road conditions and manoeuvrability. Society of Indian Automobile Manufacturers (SIAM) has forecast a growth of 6 to 8 percent for the two-wheeler market in 2013-14 [1]. The sound patterns generated by the vehicles give a clue of the faults. Automated fault diagnosis systems are useful for assessing the condition of vehicles in remote places, places of scarce expertise and in service stations for preliminary fault detection. The sound of a moving vehicle helps the rider to know the status of the vehicle, whereas the sound of a stationary vehicle with running engine helps the mechanic to assess its working condition.

Non-speech sound signal processing is a challenging task due to lack of sound alphabet. Vehicle classification based on sound is more difficult due to variations in speed, working condition, road condition, surrounding environment etc. Most of the faults leave a trace of the clue before they turn severe. The problem of motorcycle fault detection is significant since it helps the rider to know the condition of the motorcycle, before the fault turns severe. In this work, the slopes of the

estimated pseudospectral segments are used as features input to ANN for classification. This approach exploits the variations in pseudospectral curve. The pseudospectrum is divided and analyzed in eight regions to form a slope vector of length eight. The computed slope vector is used as a feature vector input for classification.

The state-of-the-art related to the proposed study is analyzed and the studied literature is organized into three components: engine fault diagnosis, gearbox fault diagnosis, and other applications.

A fault detection system for motorcycles based on acoustic signals is presented [2]. The approach employs the 1D central contour moments and their invariants of wavelet subbands and DTW classifier. The mechanisms of engine front noise generation and the corresponding countermeasures of a diesel engine use sound intensity method [3]. Continuous wavelet transform and ANN are employed to develop a mechanical fault diagnosis system for a scooter engine platform [4]. Empirical mode decomposition (EMD) and wavelet packet backpropagation neural network are used for engine fault diagnosis [5].

A methodology for fault diagnosis of Massey Ferguson gearbox is presented using root mean square (RMS) and power spectral density (PSD) [6]. Detection of the vibration signals of a gearbox with early fatigue tooth crack is approached by employing adaptive wavelet filter [7]. An approach for the classification of the working condition of gear is discussed [8]. The approach decomposes the vibration signals into a finite number of intrinsic mode functions (IMFs) and then establishes the autoregressive (AR) model of each IMF component and finally generates the corresponding autoregressive parameters. The work considers the autoregressive parameters and the variance of remnant is regarded as the fault characteristic vectors and uses them as input parameters of SVM classifier.

Condition monitoring application uses features such as magnitude of the signal, natural logarithm of the magnitude and Mel-frequency cepstral coefficients (MFCC) [9]. The features are input to various pattern classifiers. The fault detection alternatives for induction machines are compared 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 [10]. A multi-resolution wavelet analysis is used with a neural network for the fault analysis of industrial robots [11]. Wavelet analysis of accelerometric signals is applied for detection of wheelflat faults in railway [12]. Simple time domain and frequency domain features are employed as inputs for neural network model for classifying motorcycles into bikes and scooters [13]. A structure for monitoring the state of a turbocharger and supervising the air pressure in vehicle wheels is demonstrated [14]. The structure involves fuzzy inference mechanism based on neural units. The approach combines both the adaptive feature of neural networks and the transparency of fuzzy systems. Continuous wavelet transform (CWT) is used for machine fault detection based on sound. The sound purified with CWT is used to extract the feature sound from the noisy signal. The extracted feature sound helps to diagnose the machine correctly, even if the sound has a low SNR. A denoising method based on the wavelet technique is illustrated for diagnosis of machines [15]

Wavelet-based approaches yield better results, due to better time-frequency resolution [7, 15 and 20]. Since the existing approaches employ different databases recorded in different environments and use denoising, it is hard to compare the findings of our work with the reported works. Table 1 summarizes the wavelet-based works involving sound signal processing.

Table 1. A comparison of wavelet-based works

Sl. No.	Type of work	Article	Features	Classifier	No. of Classes	Accuracy
1.	AC	[16]	HLA, DWT, STFT, PCA	k-NN, MPP	4	k-NN: 85% MPP: 88%
2.	AC	[17]	CWT	MLNN	6	95-100%
3.	FD	[18]	DB-20 wavelets	ANN	2	70-100%
4.	FD	[11]	DWT	-	6	45-100%
5.	FV	[4]	CWT	ANN	5	95%
6.	FV	[2]	DB4 & moments	DTW	2	81-100%
7.	FV	[12]	DWT	FFNN	2	94-100%
8.	VC	[19]	DWT	MLNN, PNN	4	MLNN: 71% PNN: 73%
9.	VC	[20]	DWT	MPP	2	98.25%

Legend: AC – Audio classification; ANN - Artificial neural network; CWT – Continuous wavelet transform; DBn – Daubechies wavelet of the order n; DWT – Discrete wavelet transform; FD – Fault diagnosis; FFNN- feedforward neural network; FV – Fault diagnosis of vehicle; HLA – Harmonic line association; k-NN – k-Nearest neighbour classifier; MLNN – Multilayer neural network; MPP - Minimum distance approach; PCA – Principal component analysis; PNN – Probabilistic neural network; STFT – Short time Fourier Transform; VC – Vehicle classification

From the literature survey, it is apparent that reasonable amount of research is reported for various applications of sound signal analysis. Since no work is reported on fault detection of motorcycles using pseudospectrum, the study is taken up.

The remainder of the paper is organized into 3 sections. The proposed methodology of the work is presented in Section 2. The experimental results are discussed in Section 3. Finally, Section 4 concludes the work.

2. PROPOSED METHODOLOGY

The methodology proposed for fault detection of motorcycles employs the MUSIC algorithm [23] to estimate the pseudospectrum. The slopes of the first five segments of the estimated pseudospectrum are used as features input to the ANN classifier for classification of the sound sample into healthy or faulty motorcycle. The overview of the proposed methodology is depicted in Figure 1. It comprises five stages namely, sound acquisition, segmentation, pseudospectral estimation, feature extraction and classification.

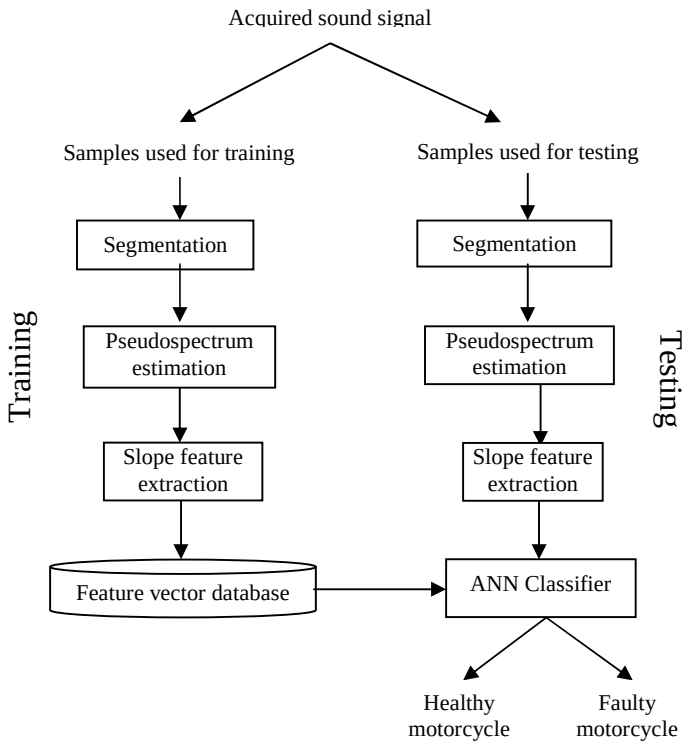

Figure 1. Block diagram of the proposed methodology

2.1. Sound signal recording

Recording of the sounds produced by the motorcycles is carried out in authorized service stations, under the supervision of expert mechanic. Sony ICD-PX720 digital voice recorder is used for recording. The motorcycle is held in idling state while recording the sound signals. The signals recorded with 44.1 kHz sampling frequency are quantized with 16 bits. The automotive guidelines suggest the sampling rate of 9 kHz to 30 kHz as ideal for recording. However, this range of frequency is ideal for recording in anechoic chamber. Since the objective is to handle the real-world signals, a higher sampling frequency of 44.1 kHz is used, which helps in capturing the minor variations.

The recording environment influences the classification performance. Other factors affecting the performance include variations in models, the age of the vehicles, maintenance, signal denoising etc. Noise produced by surrounding objects also has significant impact on the recording. So we need a clear 5 meter radius from the motorcycle where recording is carried out. Figure 2 shows the environment during the recording the motorcycle sounds. The recorder is held 500 mm from the centre line of the exhaust end, and at an angle of about 45° measured from the centre line of the exhaust end, but at least 200 mm above the ground. The 500 mm is critical, as an 80 mm error either way will result in around one decibel increase or decrease in sound level. The start of the engine and the throttle are controlled by the expert mechanic at the same time.

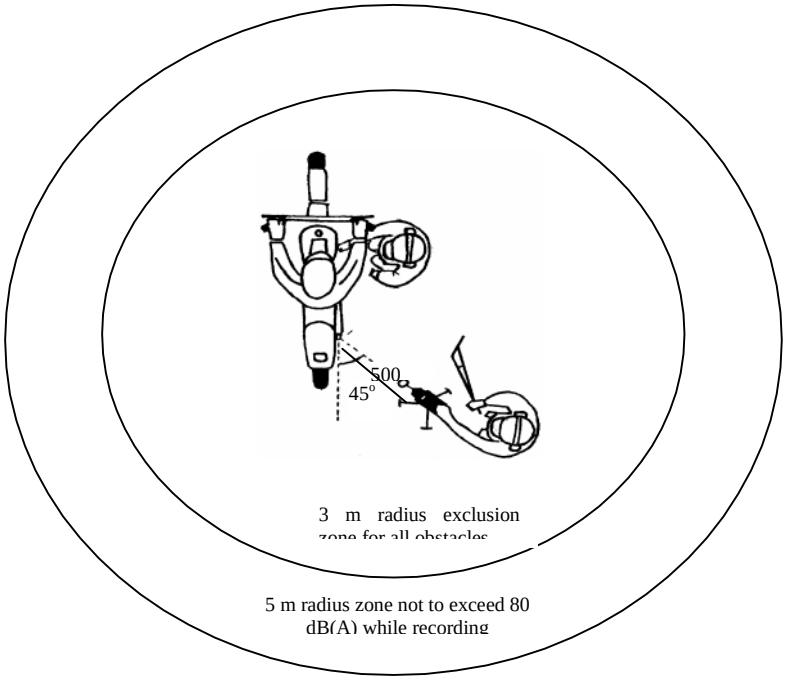

Figure 2. Recording environment

2.2. Segmentation of sound signals

The acquired sound signals are segmented into samples of one-second duration each, for uniformity in processing. A segment begins at the local maxima within 50 ms duration and runs for one second. The next segment begins at local maxima in the next 50 ms duration.

2.3. Feature extraction from pseudospectra

The features are extracted from the pseudospectral estimation of the signal. The entire pseudospectrum in the range of normalized frequencies is divided into eight regions. The slope of the spectrum in each region is computed, resulting in eight-valued vector.

2.3.1. Pseudospectrum estimation

Multiple Signal Classification (MUSIC) algorithm is used for estimating the pseudospectrum of the sound signals. The pseudospectrum is calculated using estimates of the eigenvectors of a correlation matrix associated with the input data. The MUSIC estimate is given by the Equation (1).

$$P_{music}(f) = \frac{1}{e^H(f)\left(\sum_{k=p+1}^{N} v_k v_k^H\right)e(f)} = \frac{1}{\sum_{k=p+1}^{N}\left|v_k^H e(f)\right|^2} \qquad \cdots(1)$$

where N is the dimension of the eigenvectors and v_k is the kth eigenvector of the correlation matrix of the input signal. The integer p is the dimension of the signal subspace, so the eigenvectors v_k used in the sum correspond to the smallest Eigen values. The vector $e(f)$ consists of complex exponentials, so the inner product $v_k^H e(f)$ amounts to a Fourier transform. In the eigenvector method, the summation is weighted by the Eigen values λ_k of the correlation matrix is as given in Equation (2).

$$P_{ev}(f) = \frac{1}{\left(\sum_{k=p+1}^{N} \left| v_k^H e(f) \right|^2 \right) / \lambda_k} \qquad \cdots (2)$$

The function relies on the singular value decomposition (SVD) matrix in the signal case, and it uses the eig function for analyzing the correlation matrix. Figure 3 shows the average pseudospectra of sound signals of healthy and faulty motorcycles.

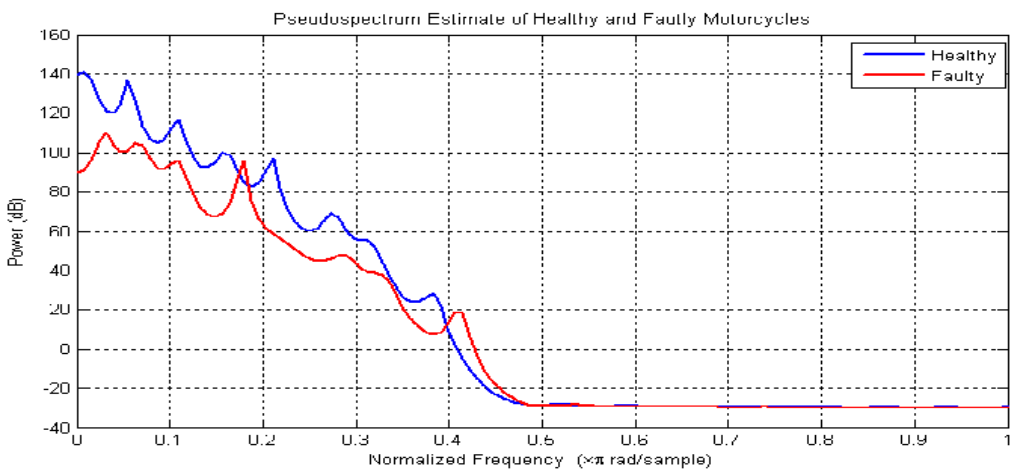

Figure 3. Spectra of sound signatures of healthy and faulty motorcycles

The spectral peaks decrease monotonically for healthy vehicles and no irregular variations are found in their spectra. But, in case of spectra of faulty motorcycles, the degraded harmonicity, non-monotonous decrease in spectral peaks and spurious peaks at higher frequencies are observed. The overall power appears to be the same but the variations in spectrum can be observed for the normalized frequency below $0.45 \times \pi rad / samples$.

2.3.2 Slope of a spectral region

The spectral regions are formed in the normalized frequency domain. The computed pseudospectral estimate has 129 values. The curvature that runs in the said region is considered for computing the slope. The slope of the pseudospectrum is computed over the partitioned regions. First eight regions are considered for feature calculation. Figure 4 depicts the computation of slope of spectral region. The slope of the spectral region is computed by considering the maximum and minimum values of the estimated pseudospectral values, S, in each region. The slope of each region is computed using Equation (3).

$$Slope = 20\log10\left(\frac{\max(S)-\min(S)}{pos\max - pos\min}\right) \qquad \cdots(3)$$

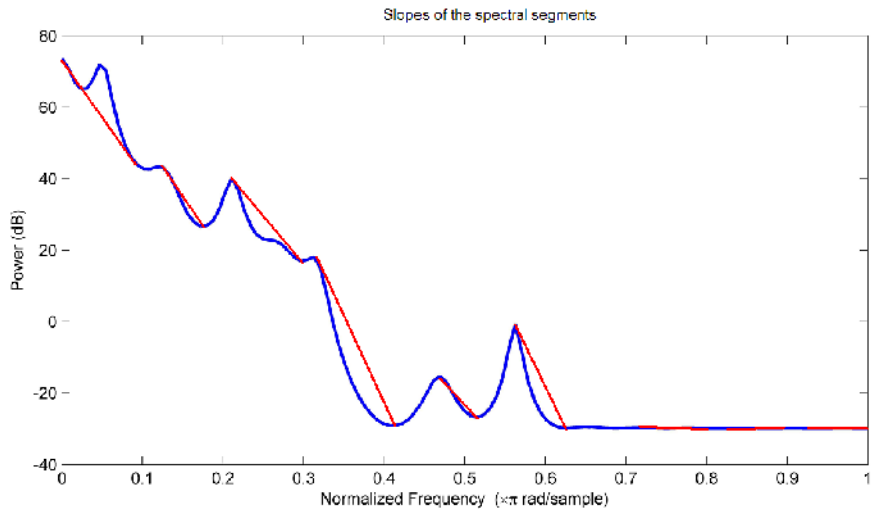

Figure 4. Spectral regions considered for computing the slope

Figures 5 to 8 show the separability of the features in the first four regions, for healthy and faulty motorcycle sound samples. It can be observed that the slopes differ for healthy and faulty motorcycles, in these regions.

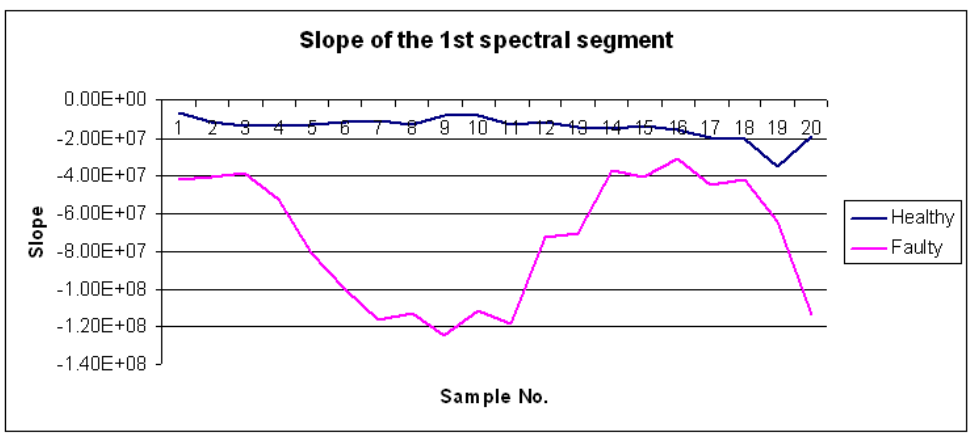

Figure 5. Slopes of the first spectral regions

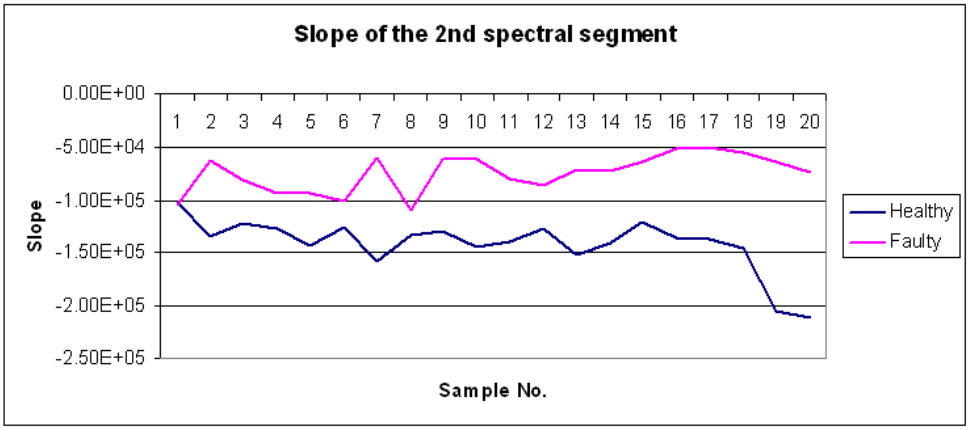

Figure 6. Slopes of the second spectral regions

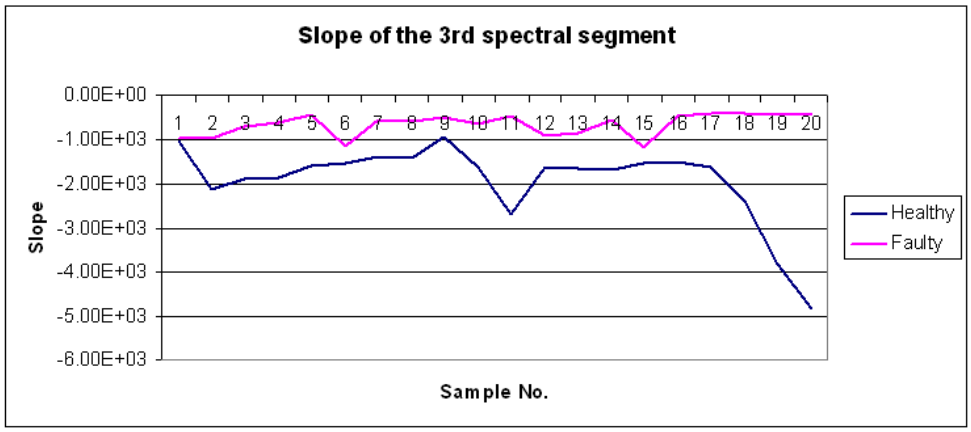

Figure 7. Slopes of the third spectral regions

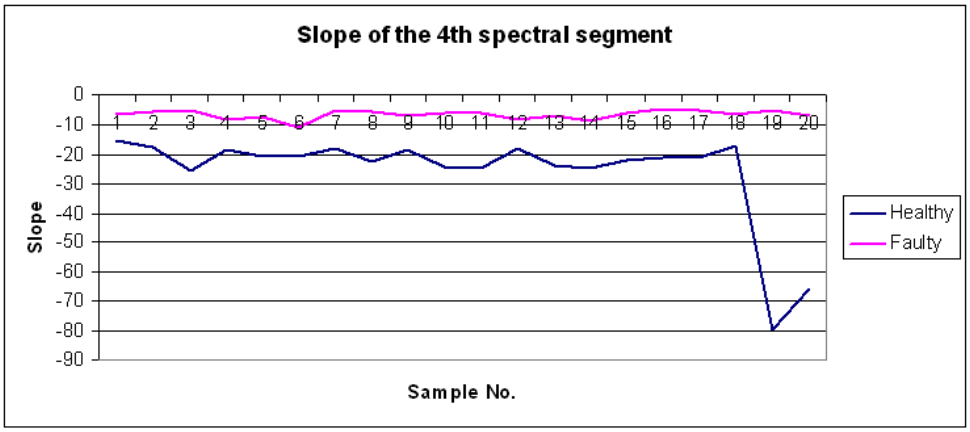

Figure 8. Slopes of the fourth spectral regions

2.3.3. ANN classifier

ANN classifier is a better option for problems with scope for approximation. The computed feature values for the current problem exhibit slight variations. Hence the ANN classifier is chosen. Figure 9 depicts the overview of the architecture of the ANN classifier. The eight features extracted based on the slopes of the pseudospectrum, are input to the neural network with four input nodes. The two output nodes correspond to the two-bit output vector indicating the health condition of the motorcycle. The hidden layer contains ten nodes. The neural network is trained using backpropagation-learning algorithm.

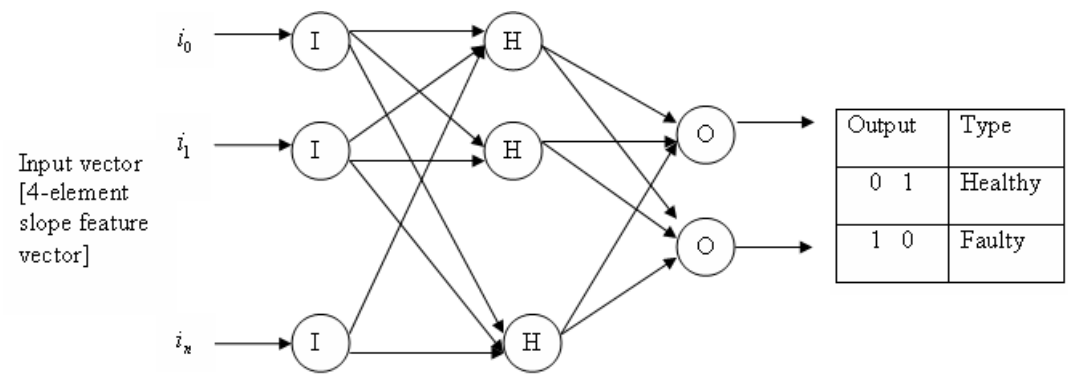

Figure 9. Architecture of the ANN

For smaller training sets, normally the error will be within the set limits. In such cases if testing is carried out on the same samples used for training, the classification accuracy will be appreciable. For larger training sets, since it takes long time to train the ANN, the training is terminated before the goal is met. In such cases, the classification performance suffers. During testing, the stabilized weights are reloaded and the test vector is given as input. The optimal number of hidden layer neurons is chosen using the criterion given in Equation (4) discussed by [21, 22]:

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

where, n=number of hidden layer neurons, C=constant yielding optimal performance, d=number of features, and N=number of rows in the training sample matrix Validation set is carried out to design the ANN for optimal performance. The ANN exhibits optimal performance for minimum mean squared error (MSE). The MSE is plotted with varying number of hidden neurons. Figure 10 shows the validation MSE is used to decide the number of nodes in the hidden layer. Since the minimum MSE is observed when 10 nodes are used in the hidden layer, the hidden layer of the designed ANN contains 10 nodes.

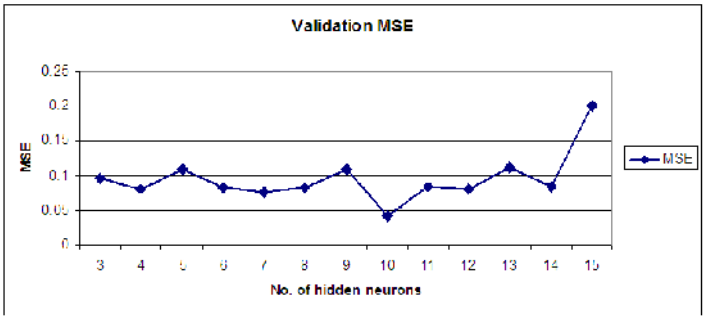

Figure 10. Validation MSE for varying number of hidden layer neurons

3. RESULTS AND DISCUSSION

Motorcycles of four popular Indian brands, namely Hero Honda (presently known as Hero Motocorp), Honda motors, TVS motors, and Bajaj motors Ltd., are considered. The database contains a total of 500 samples which includes 250 samples of healthy motorcycles and 250 samples of faulty motorcycles. The performance of the built neural network is analyzed for different combinations of training, validation and testing sets. Table 2 shows the results of classification of the individual training, validation and test sets. The classification performance is observed to decrease with increase in the size of the test set. The results of testing with the training set are obviously better than those with the validation and test sets.

Table 2. Results of classification of training, validation and test sets

No. of samples			**Combined results of classification for training, validation and test samples (Total of 500 samples)**								
			Training			**Validation**			**Testing**		
Train	**Valid**	**Test**	**TP**	**TN**	**Acc**	**TP**	**TN**	**Acc**	**TP**	**TN**	**Acc**
150	175	175	67	74	0.9400	77	79	0.8914	76	78	0.8800
175	150	175	80	82	0.9257	67	69	0.9067	73	82	0.8857
175	175	150	71	81	0.8686	71	81	0.8686	60	67	0.8467
200	125	175	82	88	0.8500	43	52	0.7600	65	77	0.8114
200	150	150	80	90	0.8500	54	65	0.7933	51	64	0.7667
200	175	125	84	95	0.8950	69	82	0.8629	42	57	0.7920
225	100	175	97	103	0.8889	36	41	0.7700	72	77	0.8514
225	125	150	93	102	0.8667	43	53	0.7680	62	64	0.8400
225	150	125	95	104	0.8844	56	67	0.8200	43	55	0.7840
225	175	100	105	107	0.9422	64	83	0.8400	41	45	0.8600
250	100	150	106	116	0.8880	31	41	0.7200	55	64	0.7933
250	125	125	103	111	0.8560	41	52	0.7440	40	59	0.7920
250	150	100	108	118	0.9040	58	66	0.8267	33	40	0.7300
275	100	125	120	120	0.8727	34	37	0.7100	45	50	0.7600
275	125	100	129	127	0.9309	54	57	0.8880	44	42	0.8600
300	100	100	126	143	0.8967	34	43	0.7700	35	43	0.7800

Legend: TP-True Positive; TN-True Negative; Acc-Accuracy

The classification accuracy degrades with increase in number of samples in the database. Finally, a database with 500 samples (250 samples of healthy and 250 samples of faulty) yielded 68.4% and 82.8% respectively for healthy and faulty motorcycles. Further the partitioning into training, validation and testing sets has also affects the classification accuracy. The classification performance depends on the size of the data sets and hence the results are summarized in Table 3.

Table 3. Impact of the size of the database on the classification performance

Classification accuracy	**Size of the database**									
Size of the database	**N=100**		**N=200**		**N=300**		**N=400**		**N=500**	
Condition	**Healthy**	**Faulty**	**Healthy**	**Faulty**	**Healthy**	**Faulty**	**Healthy**	**Faulty**	**Healthy**	**Faulty**
Minimum	98	96	90	94	88.7	82	89	88.5	68.4	82.8
Maximum	100	100	100	98	96	95.3	97	97.5	90.8	94.8
Average	99.96	99.47	98.33	97.10	92.90	92.47	93.26	93.07	78.66	89.15

The average classification accuracy is over 92%. Hence the approach is reliable for a service station, where around 150 vehicles are serviced a day. The samples recorded in real-world environments have an SNR of about 4.9. The experiment is extended for signals with different SNRs. Signals with SNR ranging from 0 dB to 10 dB are used for training and testing. The results of testing with different SNR are summarized in Table 4. Training and testing are carried out over the signals with the same SNR values.

Table 4. Classification accuracy for different SNRs

SNR in dB	**True Positive**	**False Negative**	**True Negative**	**False Positive**	**Accuracy**
0 dB	163	87	127	83	0.5800
1dB	159	91	138	112	0.5940
2 dB	177	73	137	113	0.6280
3 dB	166	84	165	85	0.6620
4 dB	166	84	166	84	0.6640
5 dB	184	66	188	73	0.7440
6 dB	195	55	187	63	0.7640
7 dB	202	28	197	53	0.7980
8 dB	218	32	196	54	0.8280
9 dB	222	28	211	39	0.8660
10 dB	228	22	204	46	0.8640

Naturally, the classification accuracy increases with increase in SNR of the signals. But the results are over 75% for signals with SNR of 6. Hence the choice of the features and the classifier is justified

4. CONCLUSION

The presented work classifies the motorcycles into healthy and faulty based on the slopes of the estimated pseudospectral regions. The samples are drawn from sound signals of healthy and faulty motorcycles of different makes and models. The results are consistent, with average classification accuracy over 78.64% in case of healthy and 89.15% in case of faulty motorcycles. Since it takes considerable time for estimating the pseudospectrum and training the ANN, the methodology is not appropriate for on-ride fault diagnosis. The work finds many applications including fault diagnosis of machinery, electronic gadgets, musical instruments and vehicles based on the sound. The work leaves scope for further investigation of localization of faults in vehicles.

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