Integration of Pseudospectral Segments of Sound Signals for Fault Location in Motorcycles

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Abstract

Motorcycles generate dissimilar sound patterns under different working conditions. Generally, the experienced mechanics in authorized service stations take test rides to hear the sounds produced to diagnose the faults. The presented work attempts to locate the faults in motorcycles based on the sound. The features are extracted using pseudospectra of sound signals. Integration is performed for estimating the areas under different segments of the spectral curve. Manhattan distance is used for comparing the test feature vectors with reference feature vectors for classification. The results are over 85% for fault location experiment with combination of 4 faults and over 90% for combinations of 3 faults and 2 faults. The proposed work can be extended to consider some more faults of motorcycles. The proposed work finds applications in surveillance, fault diagnosis of vehicles, machinery, musical instruments and the like.

Keywords: *Fault location, pseudospectral analysis, Manhattan distance, integration*

1. Introduction

The sound patterns generated by the vehicles convey information necessary for fault diagnosis. The different sound sources in motorcycles include rotating parts, tyre friction, crank, piston, timing chain, push rod and clutch plate. The garage mechanics in service stations diagnose the faults in vehicles based on the sounds produced during test rides. Automated fault diagnosis systems are essential when the vehicle is in remote places or in places of scarce expertise. In this work, the faults in different parts of motorcycles are considered for analysis. Different faults being addressed are unset valve, faulty crank, faulty cylinder kit, muffler leakage, silencer leakage and misaligned timing chain. Motorcycles dominate the Indian automobile market, accounting for nearly 77% of vehicle sales (Courtesy: India-Reports on February 20, 2010). The two-wheeler sales are projected to exceed 10 million units by 2012-13.

The proposed work attempts to extract the features from the pseudospectrum. The pseudospectral estimation is carried out over the sound signals produced by the motorcycles. The estimated pseudospectrum is divided into eight segments. The areas under the spectral segments are computed using the trapezoidal rule of integration. The extracted features of the sound signals of a fault type are averaged to compute the reference feature vector. The test feature vectors are extracted in the same manner and are compared with the reference feature vectors using Manhattan distance. The smallest of the distances indicates the type of the fault. The proposed work finds applications in traffic census of the vehicles, traffic rule observance, machine fault detection and location, automatic acoustic surveillance etc. The work leaves scope for further investigation of faults from various subsystems of engines of motorcycles.

The literature survey is carried out to know the state-of-the-art in the related areas. To the best of our knowledge, almost negligible amount of work is reported for the fault diagnosis and source location of motorcycles. Hence, the proposed work. The studied literature is organized into four perspectives: Engine fault diagnosis, Gearbox fault diagnosis, medical diagnosis, and other applications. Accordingly, the following works are cited.

The 1D central contour moments and their invariants of approximation coefficients of DWT are used as feature inputs for DTW classifier for determining the health condition of motorcycles [1]. The sound intensity method is used to identify the noise sources of engine front of a diesel engine [2]. A continuous wavelet transform (CWT) algorithm is combined with an ANN and generalized regression for analyzing fault signals in a scooter fault diagnosis system [3].

RMS and Power Spectral Density (PSD) of Massey Ferguson gearbox are calculated to detect different faults [4]. An adaptive wavelet filter based on Morlet wavelet is used for detection of symptoms from vibration signals of a gearbox with early fatigue tooth crack [5]. Vibration signals are decomposed into a finite number of intrinsic mode functions and then the AR model of each IMF component is established; finally, the corresponding autoregressive parameters and the variance of remnant are regarded as the fault characteristic vectors and used as input parameters of SVM classifier to classify the working condition of gear [6].

Heart sounds processing stages are formalized and algorithms are proposed to enable computers to approximate these steps, and the effectiveness of each step in extracting relevant information from actual patient data is investigated [7]. Heart sound analysis employs time-frequency distribution (TFD) analysis and Mel frequency cepstrum coefficient (MFCC) [8]. Multi-resolution wavelet transform is used for electrocardiogram (ECG) feature extraction system [9].

A condition monitoring application employs features such as magnitude of the signal, natural logarithm of the magnitude and MFCC, which are used as input to various pattern classifiers [10]. The fault detection alternatives for induction machines are compared according to the information they require 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 [11]. A multi-resolution wavelet analysis coupled with a neural network based approach is applied for fault diagnostics of industrial robots [12]. The diagnostic method for detection of wheel flat faults in railway diagnostics is based on the wavelet analysis of accelerometric signals [13]. An acoustic signature based method employs simple time domain and frequency domain as inputs for neural network model for classifying motorcycles into bikes and scooters [14]. Engine fault diagnosis uses empirical mode decomposition (EMD) and wavelet packet BP neural network [15].

A novel structure modeling the fuzzy inference mechanism based on neural units combines both the adaptive feature of neural networks and the transparency of fuzzy systems for monitoring of the state of a turbocharger and supervision of air pressure in vehicle wheels [16]. A de-noising method based on the wavelet technique is used in feature sound extraction for diagnosis of machines [17].

[21] focus on automobile failure detection and diagnostic accuracy. The authors propose a new fault diagnosis of maximizing fuzzy dependability based on fuzzy rough set theory. This method could evaluate vehicle faults according to the dependency degree of condition attribute and calculate the probability of vehicle faults in line with fuzzy dependency degree. [22] classify the vehicles broadly into two, three wheelers and heavy vehicle based on their acoustic signatures. A source filter model of engine sound is used to derive suitable features. The performance of formant based features is compared with that of Mel-frequency cepstral coefficients (MFCC) via a k-NN classifier on a manually labeled database of traffic sounds. [23] present an information fusion approach for ground vehicle classification based on the emitted acoustic signal. The first set of features aims to represent internal sound production, and a number of harmonic components. The second set of features is extracted based on a computationally effective discriminatory analysis, and a group of key frequency components. A modified Bayesian fusion algorithm, which takes advantage of matching each specific feature set with its favored classifier. [24] develop an algorithm for fault diagnosis in vehicle engines using sounds techniques. The fault under test is compared with the faults in the database according to their correlation, normalized mean square error, and formant frequencies values. The best match is considered the detected fault. [25] propose a method for traffic information extraction of vehicle acoustic signal based on wavelet packet analysis is proposed. It uses db5 wavelet function to decompose the acoustic signal by three-layer wavelet packet. A threshold of classification is proposed based on the analysis of the data. [26] investigate STG fault diagnosis using both vibration and acoustic emission (AE) sensors. Gear fault features were extracted from vibration signals using a Hilbert-Huang Transform (HHT) based algorithm and from AE signals using AE analysis, respectively. These fault features were used input to a K-nearest neighbor (KNN) algorithm for fault detection.

Table 1 summarizes the studied literature in terms of features, classifiers and performance. To the best of our knowledge, no reported work attempts to analyze the spectral trace of a sound signal for fault source localization application. The work presented in this paper is an extension of our earlier work [1]. In the earlier work, the aim of the study was limited to high level fault detection, i.e., only to detect whether a given motorcycle is healthy or faulty based on the sound produced. But the present work localizes the fault and indicates the type of the fault. The performance is analyzed for recognition of a fault among two, three and four faults. The performance of our approach is comparable with the best of the reported works.

Table 1. Summary of the Literature Survey

Reference	Features	Classifier	Accuracy
1.	DB4 central and contour	DTW	81-100%
3.	CWT	ANN	95%
6.	EMD-IMFs	SVM	100%
7.	Wavelets	k-means clustering	61-89%
8.	B-Distribution	ANN	80%-90%
9.	DB4 and DB6	QRS detector	99.18%
10.	FFT, log of FFT and MFCC	SVM and MLP	SVM 98.5 % MLP 97.14%
11.	DWT	Feedforward NN	90%
12.	DWT	Feedforward NN	45%-100%
13.	DWT	-	94%-100%
14.	ZCR, STE, RMS, Csd and CMean	ANN	72% for bikes 77% for scooters
15.	EMD, IMFs	Wavelet packet BP Network	N/A
16.	Knowledge-base parameters	ANN	MLP 80% Neuro-fuzzy 90%
21.	Fuzzy dependency degree	Maximization	N/A
22.	MFCC and formants	k-NN	68% - 96%
23.	Harmonic components, Key frequency components	Bayesian-based decision level fusion	73.44% to 84.24%
24.	Formant frequencies	Best match	N/A
25.	Wavelet packets with DB5	Thresholding	92%
26.	Vibration signals using a HHT	k-NN	95% to 100%

Legend: ANN - Artificial neural network ; BP – Backpropagation; CMean –Mean of the spectral centroid; Csd – Standard deviation of spectral centroid; CWT – Continuous wavelet transform; DBn – Daubechies wavelet of the order n; DTW – Dynamic time warping; DWT – Discrete wavelet transform; EMD-Empirical mode distribution; FFT- Fast Fourier transform; HHT- Hilbert-Huang Transform; HLA – Harmonic line association; k-NN – k-Nearest neighbor classifier; IMF – Intrinsic mode function; MFCC- Mel frequency cepstral coefficients; MLNN – Multilayer neural network; MLP – Multilayer perceptron; MPP - Minimum distance approach; N/A – Not available; PCA – Principal component analysis; PNN – Probabilistic neural network; QRS complexes - Ventricular contractions show as a series known as the QRS complex; RMS – Root mean square; STE – Short time energy; STFT – Short time Fourier Transform; SVM – Support vector machine; ZCR –Zero crossing rate;

From the literature survey, it is evident that reasonable amount of research is reported at the wider range of applications, ranging from fault classification in machines to cardiac sound analysis. Since there is no work reported on fault source location of motorcycles based on their sound patterns, we have taken up a study. The rest of the paper is organized into 3 sections. The proposed methodology, along with a brief on tools and techniques is discussed in Section 2; the experimental results in Section 3. The Section 4 concludes the work.

2. Proposed Methodology

The sound signals of the motorcycles are recorded in authorized service stations in real-world environment, under the supervision of the expert mechanics. The acquired sound signals are segmented into one-second samples for uniformity in processing. Pseudospectra are estimated from the segmented sound samples and are used to generate the features. The generated pseudospectral curve is partitioned into eight parts. The area under each pseudospectral part is computed. Eight parts of the pseudospectrum yield eight features. The reference feature vectors of different fault types are computed by averaging the respective feature vectors. Manhattan distance is computed between the reference feature vectors and the test feature vectors. The smallest of the distances indicates the type of the fault. The overview of the methodology is depicted in figure 1. It comprises of five stages namely, sound signal acquisition, segmentation, pseudospectral analysis, feature extraction and classification.

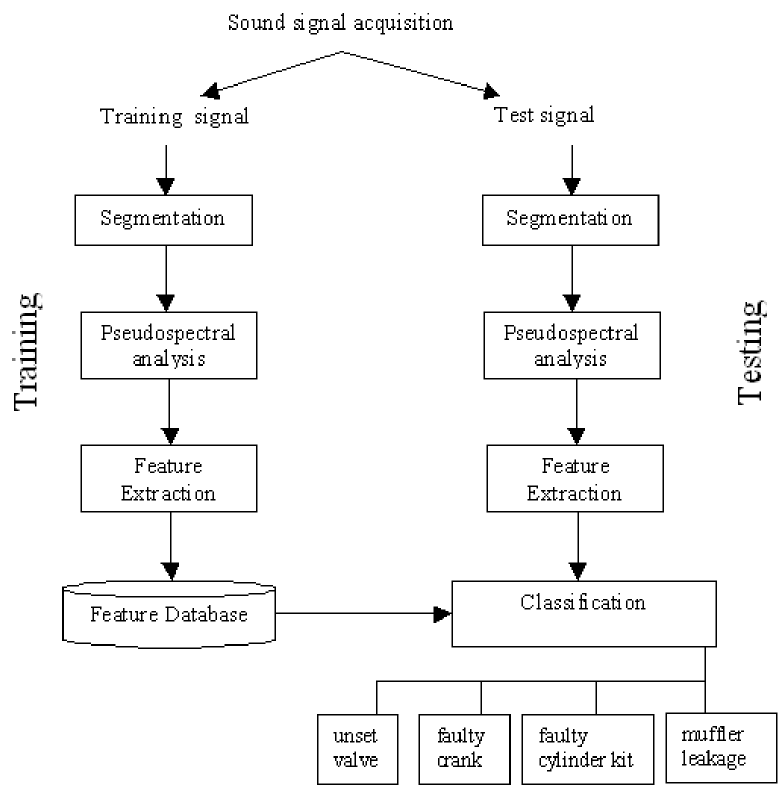

Figure 1. Block Diagram of the Proposed Method

2.1. Acquisition of Sound Samples

The sound signals of the motorcycles are recorded using Sony ICD-PX720 digital voice recorder, with sampling frequency of 44.1 kHz, under idling state of the motorcycle. The recording is done in service stations with the help of an expert mechanic in a service station. The healthy vehicles selected are less than one year old, not run more than 6000 km and regularly serviced. During testing phase vehicles having faults are chosen with the help of service mechanic. The recorder is held closer to the engine. The recording environment has disturbances from human speech, sound of other vehicles being serviced, air-compressor and auto-repair tools. The motorcycles having faulty crank, damaged timing chain, unset valve, muffler leakage, silencer leakage, and faulty cylinder kit are considered in this work.

A brief description of the faults under consideration for this work is given below:

Valve setting: For smooth functioning of engine, correct opening and closing of valves is necessary. This ensures smooth power delivery and low noise from the engine. Any deviation of even 5 to 10 degrees in valve opening/closing will cause considerable rise in peak combustion chamber pressures, leading to change in sound from the engine.

Crank fault: It may occur due to wear and tear of either oil ring, first ring or second ring.

Cylinder kit: It is caused by problems in piston or piston ring. It reduces the pick up of the vehicle and causes excess smoke.

Muffler Leakage: The exhaust gas coming out of combustion chamber passes through the tail pipe, along which to reduce the noise, a component named muffler, is employed. The main function of muffler is to reduce the noise. Due to the reactive gases in the residual exhaust, which are at high temperature mixed with water vapor, creates an ideal ambiance for corrosion reactions. This results in minute holes in the muffler and changes the firing sound coming out of engine.

2.2. Segmentation

The 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 is considered as a segment. The next segment begins at local maxima in the next 50 ms duration from the end of the previous segment.

2.3. Feature Extraction

The feature extraction is carried out over the segmented samples. Pseudospectrum of the sound segment is estimated and partitioned into eight parts. Trapezoidal rule is used to integrate the pseudospectral parts. Reference feature vectors are computed by averaging the respective feature vectors. Subsections 2.3.1, 2.3.2, and 2.3.3 discuss the pseudospectrum estimation, integration of the pseudospectrum, and Manhattan distance respectively.

2.3.1. Pseudospectrum Estimation

We use the pmusic function of MATLAB for pseudospectral estimate of the sound signals. The pseudospectrum is calculated using estimates of the eigenvectors of a correlation matrix associated with the input data x. [S, w] = pmusic(x, p) implements the MUSIC (Multiple Signal Classification) algorithm and returns S, the pseudospectrum estimate of the input signal x. p is the signal subspace dimension and w is a vector of normalized frequencies (in rad/sample) at which the pseudospectrum is evaluated.

The MUSIC estimate is given by the formula

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

where N is the dimension of the eigenvectors and vk 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 eigenvalues and also span the noise subspace. The vector $e(f)$ consists of complex exponentials, so the inner product $v_k^H e(f)$ amounts to a Fourier transform. The second form is preferred for computation because the FFT is computed for each v_k and then the squared magnitudes are summed.

In the eigenvector method, the summation is weighted by the eigenvalues λ_k of the correlation matrix:

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

The function relies on the SVD matrix decomposition in the signal case, and it uses the eig function for analyzing the correlation matrix.

Figure 2 shows the spectra of sound signals of healthy and unhealthy motorcycles.

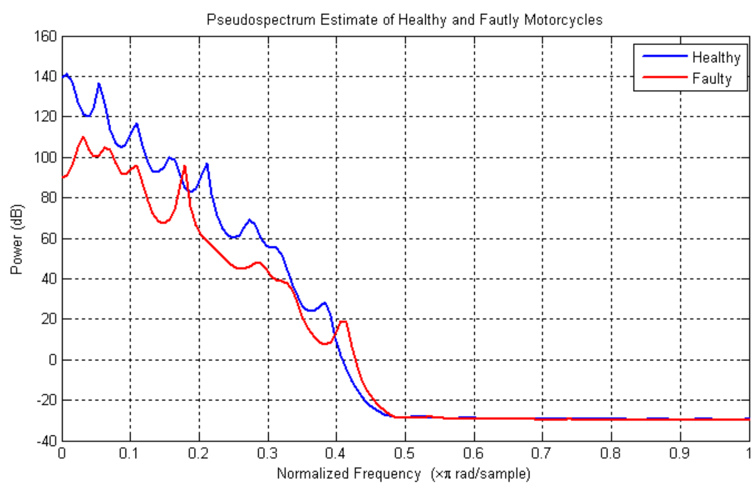

Figure 2. Spectra of Sound Signatures of Healthy and Faulty Motorcycles

From the spectra of the sound signals of the motorcycles we can observe that for healthy vehicles the spectral peaks decrease monotonically and no irregular variations in the spectrum. But, in case of unhealthy motorcycles, the degraded harmonicity, non-monotonous decrease in spectral peaks and spurious peaks at higher frequencies, are observed. Figures 3 and 4 show the spectra and logarithmic plot of the estimated pseudospectra, respectively. The work exploits the spectral variations in the estimated pseudospectra, computes the areas under the spectral segments formed as shown in Figure 5. The computed areas under the curves are used as the feature vector.

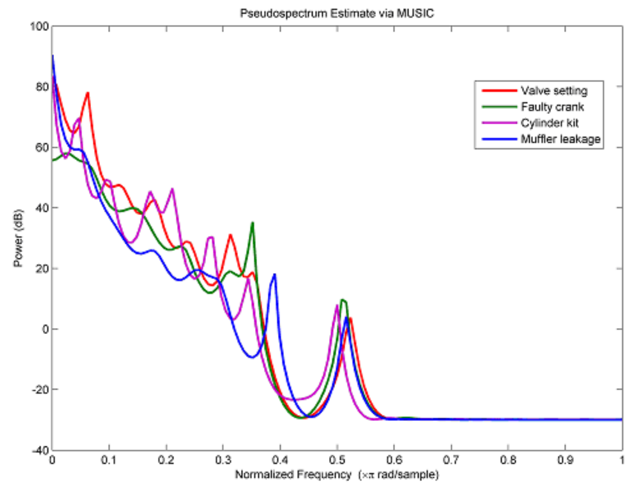

Figure 3. Estimated Pseudospectra of the Faults

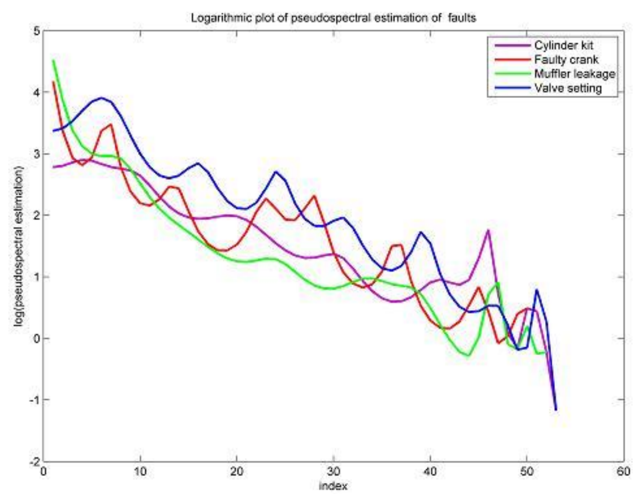

Figure 4. Logarithmic Plot of Pseudospectral Estimates of Faults

The pseudospectrum estimate of the sound samples has 129 values. *Pmusic* function of MATLAB is used with 16 complex sinusoids. The feature vector is computed as the vector of areas under the curve segments of the spectrum. Non-uniform spans for the curve segments are used for computing the areas. The spans are computed over the segments spanning the feature values 1-2, 3-4, 5-8, 9-16, 17-32, 33-64 and 65-129 of the estimated pseudospectrum.

2.3.2. Trapezoidal Rule for Integration

The trapezoidal rule (also known as the trapezoid rule or trapezium rule) is an approximate technique for calculating the definite integral. The trapezoidal rule works by approximating the region under the graph of the function f(x) as a trapezoid and calculating its area. It follows that

$$\int_a^b f(x)dx \approx (b-a)\frac{f(a)+f(b)}{2} \qquad \cdots(3)$$

For various classes of rougher functions (ones with weaker smoothness conditions), the trapezoidal rule has faster convergence in general than Simpson's rule. Moreover, the trapezoidal rule tends to become extremely accurate when periodic functions are integrated over their periods. The segmentation of the spectral curve is as depicted in Figure 5.

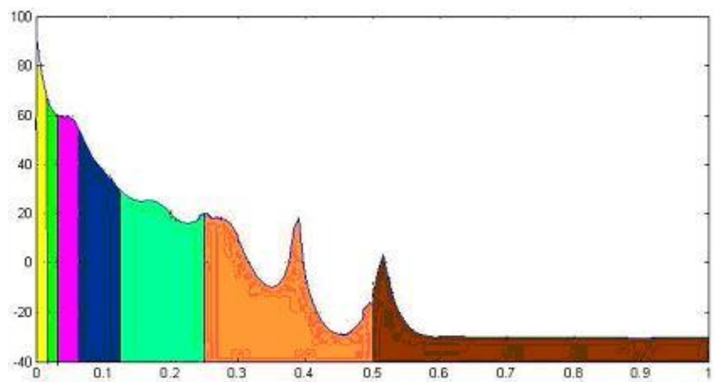

Figure 5. Spectral Spans for Integration

The areas under the segmented spectral curves of the faults differ from each other. They indicate the variations in lower frequency regions. Table 2 shows the average values of integration for different types of faults.

Table 2. Average Feature Values of Integration of Spans for Different Types of Faults

	Average integration vectors						
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7
F1 (Valve setting)	3490.8	4200.5	13704	3475	1010.3	104.71	9.0633
F2 (Faulty Crank)	131.42	153.21	747.34	607.83	106.41	117.21	8.8245
F3(Cylinder kit)	4238.2	3514.1	5710.8	2130.3	1062	102.84	9.0563
F4 (Muffler Leakage)	7065.2	3551.1	2240.4	687.8	279.06	73.068	8.955

2.3.3. Manhattan Distance

The distance between two points measured along axes at right angles. In a plane with p1 at (x1, y1) and p2 at (x2, y2), it is |x1 - x2| + |y1 - y2|. The same is expressed as

$$\sum_{k=1}^{n}(x_k - y_k) \qquad \cdots(4)$$

where, *x* and *y* are vectors of length n.

3. Results and Discussion

In this work, the faults in motorcycles of different models of Hero Honda are considered. The models considered are Passion plus, Extreme, Street 100, CD 100, CD Dawn, CD Deluxe, CBZ, Splendour, Splendour plus, Super splendour, all from Hero Honda. Honda Activa and Hero Honda Pleasure are the scooter models included for study. Different faults being addressed are miss-set valve (VS), faulty crank (FC), faulty cylinder kit (CK), muffler leakage (ML), silencer leakage (SL) and misaligned timing chain (TC).

Experiment 1. Combination of 4 Faults

In this experiment, we have tested with 174 samples of different motorcycles, covering the mentioned four faults. Out of these 18 samples are misclassified, reslting in an overall error of 0.1034. Misclassification is mainly with cylinder kit problem, which normally results in other faults. Table 3 gives the confusion matrix for the combination of four faults.

Table 3. Confusion Matrix for the Combination of 4 Faults

Combi4	VS	FC	CK	ML	Classification accuracy
VS	**43**	0	9	0	0.8269
FC	0	**30**	0	0	1.0000
CK	6	0	**28**	3	0.7568
ML	0	0	0	**55**	1.0000
Overall classification performance					**0.8966**

The average of the feature vectors serves as the reference feature vector for comparison for each fault. While testing, the pseudospectrum of the test sample is computed; its integral values of different regions are computed and saved as feature vector. The test feature vector is compared against the reference feature vectors. The classification accuracy for each fault is shown in the last column. The overall classification accuracy is 0.8966.

The experiment is repeated with different distance measures. Manhattan distance has yielded the better results compared to dynamic time warping and Bhattacharyya distance. DTW is computationally complex. Manhattan distance calculation is computationally efficient and simple. Hence it is more suitable for real-time testing. Table 4 compares the performance of these three distance measures.

Table 4. The Classification Performance of the Three Distance Measures

			No. of samples correctly classified		
Sl. No.	Fault	No. of samples	DTW	Bhattacharyya	Manhattan
1.	Valve setting (VS)	52	43	32	**43**
2.	Faulty crank (FC)	30	30	29	**30**
3.	Cylinder kit (CK)	37	25	27	**28**
4.	Muffler leakage (ML)	55	53	32	**55**

Manhattan distance of the test feature vector is computed against each of the reference feature vectors. The smallest of the distances indicates the fault class. The testing is carried out first considering all the four faults. In the second experiment, combinations of three faults are considered. In the third experiment, combinations of two faults are considered. The results are satisfactory. Given below are the confusion matrices of the results of these experiments.

Experiment 2. Combinations of 3 Faults

When combinations of three faults are considered for analysis, the classification performance is moderate. It is better than that for the combination of four faults. Normally a vehicle has two faults at a time. Possibility of motorcycles with more than two faults is a rare case. But even when a single fault is present in a motorcycle, it is necessary to locate the exact fault. In these experiments the individual faults are located, by comparing the feature vectors against the reference feature vectors. The confusion matrices for the combinations of three faults are given in Table 5. The classification accuracy depends also on the combination of the faults being considered.

Table 5. Confusion Matrices with Combinations of 3 Faults

Combi3-1	VS	FC	CK
VS	43	0	9
FC	0	30	0
CK	6	0	31

Combi3-2	VS	FC	ML
VS	51	1	0
FC	0	30	0
ML	0	0	55

Combi3-3	FC	CK	ML
FC	30	0	0
CK	0	34	3
ML	0	0	55

Combi3-4	VS	CK	ML
VS	43	9	0
CK	6	28	3
ML	0	0	55

The best classification results are obtained for the second combination, where only one sample is misclassified, yielding the overall classification accuracy of 0.9927.

Experiment 3. Combinations of 2 Faults

Combinations of two faults naturally yielded better results compared to the combinations involving three and four faults. This can be attributed to the easier separability resulting in smoother classification. Table 6 lists the confusion matrices for the combinations of two faults.

Table 6. Confusion Matrices with Combinations of Two Faults

Combi2-1	VS	FC
VS	51	1
FC	0	30

Combi2-2	VS	CK
VS	43	9
CK	6	31

Combi2-3	VS	ML
VS	52	0
ML	0	55

Combi2-4	FC	CK
FC	30	0
CK	0	37

Clear separability of the features of fault signatures yields better classification accuracy. The best performance is exhibited for combinations 3, 4, 5 and 6, yielding 1.0000 for both the faults for these combinations. It shows that these faults are clearly distinguishable. Further these experiments are carried out on the sound signals without denoising. The denoising is intentionally avoided to test the suitability of the methodology for real-world environments of authorized service stations.

Table 7. Summary of the Overall Classification Performance for Combinations of Two, Three and Four Faults

Combination	a	b	c	d	(a+d)/tot	d/(c+d)	a/(a+b)	d/(b+d)
	TN	FP	FN	TP	Accuracy	Sensitivity	Specificity	Precision
2-1	30	1	30	51	0.9878	1.0000	0.9677	0.9808
2-2	31	9	31	43	0.8315	0.8776	0.7750	0.8269
2-3	55	0	55	52	1.0000	1.0000	1.0000	1.0000
2-4	37	0	37	30	1.0000	1.0000	1.0000	1.0000
2-5	55	0	55	30	1.0000	1.0000	1.0000	1.0000
2-6	55	0	55	34	1.0000	1.0000	1.0000	1.0000
3-VS	229	12	19	137	0.9219	0.8782	0.9502	0.9195
3-FC	269	1	0	90	0.9972	1.0000	0.9963	0.9890
3-CK	246	18	18	93	0.9040	0.8378	0.9318	0.8378
3-ML	216	6	0	165	0.9845	1.0000	0.9730	0.9649
4-VS	113	6	9	43	0.9123	0.8269	0.9496	0.8776
4-FC	126	0	0	30	1.0000	1.0000	1.0000	1.0000
4-CK	128	9	9	28	0.8966	0.7568	0.9343	0.7568
4-ML	101	3	0	55	0.9811	1.0000	0.9712	0.9483

Legend: TP – True positive; FP – False positive; TN – True negative; FN – False negative;

Higher specificity and sensitivity are desirable for reliable fault diagnosis. From the summary of the results tabulated in Table 6, it is found that the sensitivity and specificity of classification are above 0.82 in most of the cases. Exceptions of these values below this are 4-CK and 2-2. This can be attributed to the intricacies of the cylinder kit. The sound generated in the cylinder kit leads to other faults. Hence the confusion is obvious, which resulted in smaller values for specificity and sensitivity.

4. Conclusion

Motorcycle fault detection based on the sounds produced is a common trait of the experienced mechanics. Automation of this trait is a challenging but essential job. The work presented is an attempt to automate the fault location in motorcycles. Four types of faults are considered, which generate different sound patterns and hence result in distinct pseudospectral variations. The integration of pseudospectral spans of the sound samples is used as features. Manhattan distance is employed for classification. The work leaves scope for the detection of presence of multiple faults in motorcycles. It finds applications in acoustic based fault localization in machinery, cardiac signals, musical instruments, and the like.

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