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Acoustic signal based detection and localisation of faults in motorcycles

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Abstract: Vehicles produce dissimilar sound patterns under different working conditions. The study approaches detection and localisation of faults in motorcycles, by exploiting the variations in the spectral behaviour. Fault detection stage uses chaincode of the pseudospectrum of the sound signal. Fault localisation stage uses statistical features derived from the wavelet subbands. Dynamic time warping classifier is used for classification of samples into healthy and faulty in the first stage. In essence, the same classifier classifies the faulty samples into valve-setting, muffler leakage and timing chain faults in the second stage. Classification results are over 90% for both the stages. The proposed study finds applications in surveillance, fault diagnosis of vehicles, machinery, musical instruments etc.

1 Introduction

Sound patterns produced by machinery, human body, vehicles and the like, differ under different working conditions. The research areas like automatic vehicle recognition, classification and fault diagnosis are drawing more attention in the research community. Motorcycles dominate the Indian automobile market with nearly 77% of the vehicle sales. Society of Indian Automobile Manufacturers (SIAM) has forecast the two-wheeler segment to register a growth of 6–8% in 2013–14 [1]. This increase in sales of motorcycles demands for expert mechanics for fault diagnosis. Expert mechanics diagnose the faults in motorcycles based on the generated sound patterns. Signal processing techniques are required to automate this trait of mechanics. Automation of fault diagnosis based on acoustic signatures is considered a challenging task. Hence, the expertise of the mechanics needs to be automated. The automated fault detection systems are significant in remote areas where the expertise is scarce. It also helps the service station experts in preliminary fault analysis and further repair measures.

This paper addresses a problem of fault detection and fault source localisation of motorcycles based on the sound signals. It is highly desirable to work on the signals recorded in noisy environment. Fault source localisation is very essential for proper troubleshooting. The work presented uses the chaincodes of the pseudospectra as features and dynamic time warping (DTW) classifier for fault detection. Statistical features derived from the subbands of wavelets and DTW classifier for fault localisation. The primary objectives of the work include a study of the spectral behaviour of the sound signals of motorcycles for automated fault detection and fault source localisation.

The work presented in this paper is an extension of our earlier work [2]. In the earlier work, the aim of the study was limited to fault detection, but the present work indicates the type of the fault. Literature survey is carried out to know the state-of-the-art in automated fault diagnosis. A fault detection system for motorcycles based on acoustic signals is presented [2]. The approach employs the one-dimensional (1D) central contour moments and invariant contour moments of coefficients of wavelet subbands and DTW classifier. A motorbike engine fault diagnosis system is discussed [3], which uses entropy of db4 wavelet transform for feature extraction and a functional link neural network for classification. A mechanical fault diagnosis system is developed [4] for a scooter engine platform, using continuous wavelet transform and artificial neural network (ANN). A system for detection of the vibration signals of a gearbox is proposed [5], which employs adaptive wavelet filter.

A methodology for fault diagnosis of the Massey Ferguson gearbox is presented [6], which uses root mean square and power spectral density. The mechanisms of engine front noise generation and the corresponding countermeasures of a diesel engine are proposed [7]. These mechanisms use sound intensity method. A structure for monitoring the state of a turbocharger and supervising the air pressure in vehicle wheels is demonstrated [8]. The approach uses fuzzy inference mechanism based on neural units to combine both the adaptive feature of neural networks and the transparency of fuzzy systems. A methodology based on wavelet transform for gear fault localisation is proposed [9], which uses acoustic emission sensors for split-type gearbox.

A model based on wavelet-transform and ANN is illustrated for the localised gear tooth defect recognition

[10]. A multi-resolution wavelet analysis coupled with a neural network is applied for the fault analysis of industrial robots [11]. A denoising method based on the Morlet wavelet is presented for the feature sound extraction [12]. A scheme for extracting the sound of vehicle engines is discussed with different types of failure [13]. Independent component analysis is used for the feature extraction, fuzzy self-organising feature map and model-based fuzzy procedures for diagnosis of plant operation [14].

A methodology focuses on automobile failure detection and diagnostic accuracy based on maximising fuzzy dependability [15]. This method evaluates vehicle faults according to the dependency degree of condition attribute and calculates the probability of vehicle faults according to the fuzzy dependency degree. The vehicles are broadly classified into two, three wheelers and heavy vehicle based on their acoustic signatures [16]. Features are derived using a source filter model of engine sound. The performance of formant-based features is compared with that of Mel-frequency cepstral coefficients (MFCC) via a k-nearest neighbour (NN) classifier is presented [17]. An information fusion approach is used for ground vehicle classification based on the emitted acoustic signal. The first set of features represents internal sound production and a number of harmonic components. The second set of features is based on discriminatory analysis, and a group of key frequency components. A modified Bayesian fusion algorithm is used for classification. An algorithm is developed for fault diagnosis in vehicle engines [18]. The fault under test is compared with the faults in the database according to their correlation, normalised mean square error and formant frequencies values. The best match is considered as the detected fault. A method is proposed for traffic information extraction of vehicle acoustic signal based on wavelet packet analysis [19]. It uses db5 wavelet to decompose the acoustic signal by the wavelet packet. A threshold of classification is proposed based on the analysis of the data.

Table 1 compares some of the works from the studied literature in terms of features, classifiers and performance. The reported works use techniques like wavelets, fuzzy classification and variants of ANNs. Much emphasis is given to the fault classification of machines and robots. To the best of our knowledge, almost negligible amount of work has gone into the fault diagnosis of motorcycles, based on their sound patterns. It is difficult to present a comparison with our work, because of differences in databases and recording environments, feature extraction methods, classifiers and noise levels of the signals.

From the literature survey, it is evident that a fair amount of research is reported covering the signal processing techniques to fault classification in machines, vehicles and gearboxes. Since there is no work reported on fault source localisation of motorcycles based on their sound patterns, we have taken up a study.

Rest of the paper is organised into three sections. The proposed methodology, along with a brief on tools and techniques is discussed in Section 2; the experimental results in Section 3. Section 4 concludes the work.

2 Proposed methodology

The methodology consists of two stages: fault detection and fault localisation. The sound signals of motorcycles are segmented into samples of 1 s duration for uniformity in processing. Features are computed over the segmented signals. Fig. 1 depicts the block diagram of the proposed methodology.

Fault detection is the first stage of the work. It identifies a motorcycle as healthy or faulty based on the given sound sample. The samples identified as faulty are subjected to further classification into one of the three types of faults: valve-setting (VS) problem, muffler leakage (ML) and

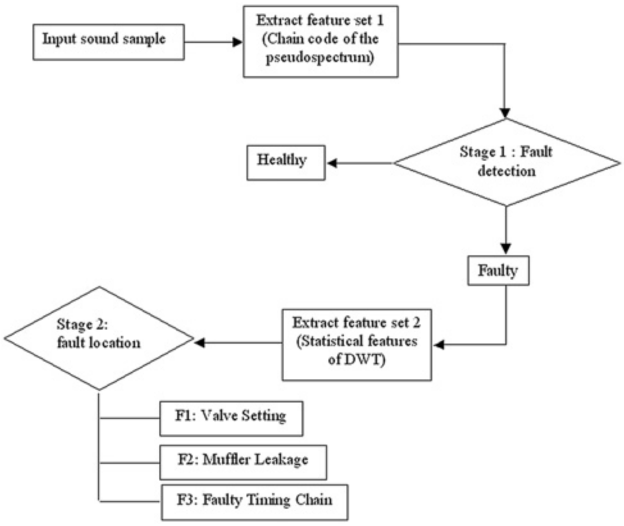

Fig. 1 *Block diagram of the proposed methodology*

Table 1 Summary of the literature survey

References	Features	Classifier	Accuracy
[2]	DB4 central and contour	DTW	81–100%
[4]	CWT	ANN	95%
[8]	knowledge-base parameters	ANN	multilayer perceptron (MLP) 80% neuro-fuzzy 90%
[11]	discrete wavelet transform (DWT)	feedforward NN	45–100%
[15]	fuzzy dependency degree	maximisation	N/A
[17]	MFCC and formants	k-NN	68–96%
[18]	harmonic components and key frequency components	Bayesian-based decision level fusion	73.44–84.24%
[19]	wavelet packets with DB5	thresholding	92%

ANN – artificial neural network; DBn – Daubechies wavelet of the order n; DTW – dynamic time warping; DWT – discrete wavelet transform; HHT – Hilbert–Huang transform; k-NN – k-nearest neighbour classifier; MLP – multilayer perceptron and N/A – not available.

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faulty timing chain (TC). A brief description of the fault types considered in this work follows.

Valve Setting (VS): 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 5–10° in valve opening/closing will cause considerable rise in peak combustion chamber pressures, leading to change in sound from the engine.

Muffler Leakage: the main function of muffler is to reduce the noise. Owing to the reactive gases in the residual exhaust, which are at high temperature mixed with water vapour, creates an ideal ambiance for corrosion reactions. This results in minute holes in the muffler and changes the firing sound coming out of engine.

Timing Chain: It is a semi-major part of the engine. The main function of TC is to operate the valves. Loose chain vibrates and alters the VS, resulting in change in sound.

2.1 Segmentation

The acquired sound samples are segmented into samples of one second duration each for uniformity in processing. A segment begins at the local maxima in the first 50 ms duration. The portion of the signal of one second duration, beginning from the local maxima after a given segment is considered as the next segment.

2.2 Feature extraction

The features selected are chaincodes of the pseudospectral estimation for fault detection stage. The extracted features are input to DTW classifier in the first stage. The sound signals labelled as faulty are subjected to the second stage, that is, fault localisation. The second stage uses the statistical features extracted from the DB4 wavelet subbands. The features extracted during the second stage are input to DTW classifier, which compares the test feature vectors with the reference feature vectors of different fault types. The nearest match is indicative of the fault type.

2.2.1 Pseudospectral estimation: The approach analyses the spectral variations between healthy and faulty motorcycle sound patterns. The pseudospectrum is the frequency decomposition of the mean of the time-changing variance. The pseudospectrum is calculated using estimates of the eigenvectors of a correlation matrix associated with the input data. The details of using the multiple signal classification (MUSIC) algorithm in signal processing are discussed [20–23]. The MUSIC estimate is given by (1)

$$P_{\text{music}}(f) = \frac{1}{\mathrm{e}^{\mathrm{H}}(f)\left(\sum_{k=p+1}^{N} \boldsymbol{v}_k \boldsymbol{v}_k^{\mathrm{H}}\right)\boldsymbol{e}(f)} = \frac{1}{\sum_{k=p+1}^{N} \left|\boldsymbol{v}_k^{\mathrm{H}}\boldsymbol{e}(f)\right|^2} \quad (1)$$

where N is the dimension of the eigenvectors and $\boldsymbol{v}_k$ 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 $\boldsymbol{v}_k$ used in the sum corresponds to the smallest eigenvalues. The vector $\boldsymbol{e}(f)$ consists of complex exponentials, so the inner product $\boldsymbol{v}_k^{\mathrm{H}}\boldsymbol{e}(f)$ amounts to a Fourier transform. In the eigenvector method, the summation is weighted by the eigenvalues λ_k of the correlation matrix, as shown in (2)

$$P_{ev}(f) = \frac{1}{\left(\sum_{k=p+1}^{N} \left|\boldsymbol{v}_k^{\mathrm{H}}\boldsymbol{e}(f)\right|^2\right)/\lambda_k} \quad (2)$$

Fig. 2 shows the typical pseudospectra estimated using the sound signals of healthy and faulty motorcycles.

For the sound signals of healthy motorcycles, the spectral peaks decrease monotonically and no irregular variations are observed in the spectrum. However, in case of faulty motorcycles, the degraded harmonics, non-monotonous decrease in spectral peaks and spurious peaks are observed at higher frequencies. It can be attributed to the uneven operation of engine cycles in presence of faults. The average pseudospectra of the sound signals representing different faults are shown in Fig. 3.

From Fig. 3, it is observed that the average pseudospectra differ for different faults up to a normalised frequency of $0.45 \times \pi$ rad/sample and beyond this normalised frequency the power of the spectrum is observed to be steady for all

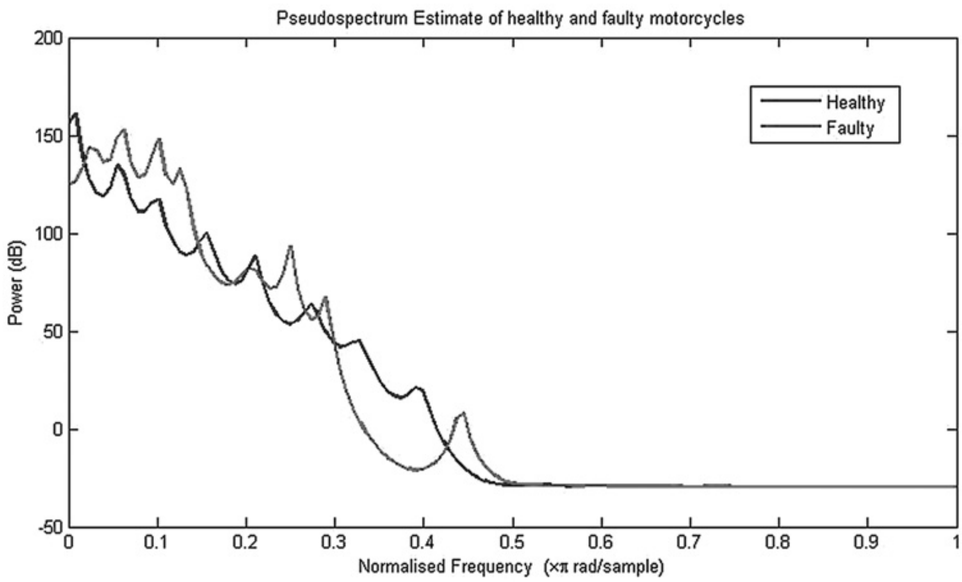

Fig. 2 *Pseudospectra of sound signals of healthy and faulty motorcycles*

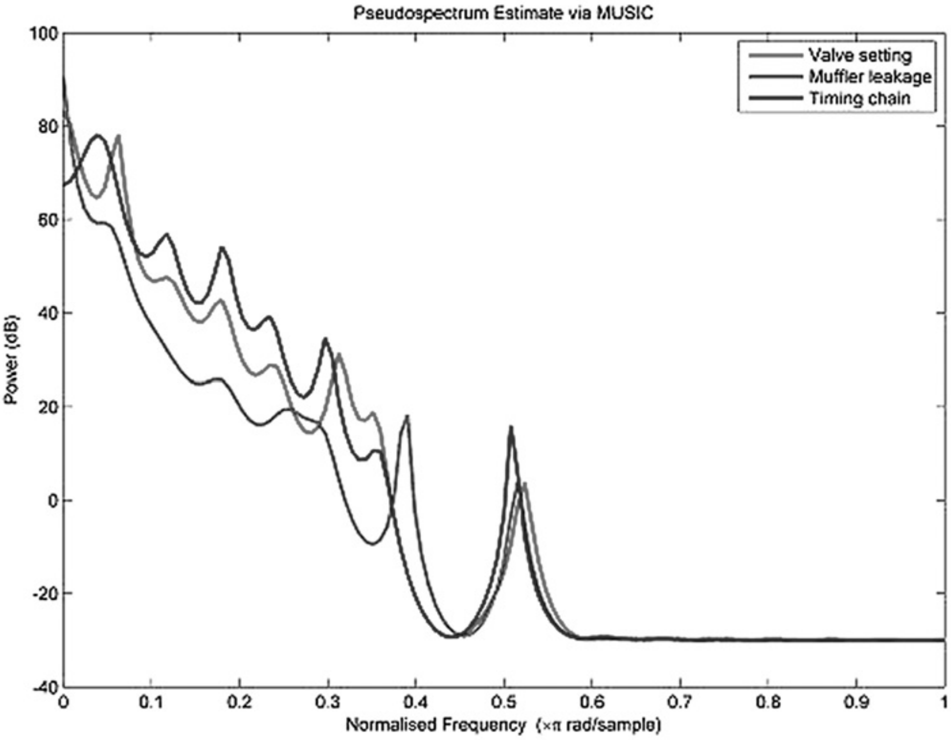

Fig. 3 *Average pseudospectra of different faults*

the faults. The portion of the chaincode of the signal up to this point in the pseudospectral plot is considered for feature computation.

2.2.2 Chaincode of a spectral segment: The eight-directional chaincode convention is used in defining a pseudospectral segment. It is observed that the pseudospectral segments vary in the directions of 0 (right), 1 (top-right) and 7 (bottom-right). The gradient changes of estimated pseudospectral vector are traced to construct the chaincode. The process is summarised as in (3)

$$\mathrm{CC}(i) = \begin{cases} 0 & \text{if } (\mathrm{pse}(i) = \mathrm{pse}(i+1)) \\ 1 & \text{if } (\mathrm{pse}(i) < \mathrm{pse}(i+1)) \\ 7 & \text{if } (\mathrm{pse}(i) > \mathrm{pse}(i+1)) \end{cases} \tag{3}$$

where $\mathrm{CC}(i)$ is the chaincode at position i, pse is the coefficient of the estimated pseudospectrum and $1 \le i \le 128$, since the estimated pseudospectrum consists of 129 coefficients. The reference feature vector for healthy motorcycle samples is constructed by computing the mode of the chaincodes.

2.2.3 Daubechies DB4 type wavelets: Daubechies DB4 [24] type wavelets are used to compute the feature vectors of faulty motorcycle samples. DB4 wavelet is chosen because of its near optimal time-frequency localisation properties. The sound signals of the faulty motorcycles are decomposed into approximation and detailed coefficients. The approximation coefficients are decomposed at every stage yielding the coefficients for the next subband. Decomposition is carried out into eight subbands. The statistical features are computed for each subband, which are used for classification.

2.2.4 Statistical features of wavelet subbands: The construction of reference feature vectors through averaging across the subbands is difficult as the number of approximation coefficients in each subband varies. Different statistical features are derived from the wavelet decomposition to form the feature vector. The feature vector consists of the mean of the first subband, the median of the second subband, variance of the third subband, standard deviation of the fourth subband, minimum of the fifth subband, maximum of sixth subband, mode of the seventh subband and harmonic mean of the eighth subband. For a specific type of fault, the average of these features forms the reference feature vector.

2.3 Classification

The classification is approached using DTW algorithm [25], which computes an optimal warping path between two time series and the distance between them. The algorithm is used for recognition of isolated musical patterns [26], environmental sound [27] and speech recognition [28]. The algorithm finds an optimal match by warping the sequences to determine a measure of their similarity. DTW matches the patterns independent of non-linear variations. The chaincodes are not uniform in length after removing the trailing zeros. Hence, DTW is adjudged as suitable classifier. It matches the patterns independent of non-linear variations. The two numerical sequences $(a_1, a_2, \ldots, a_n)$ and $(b_1, b_2, \ldots, b_m)$ are considered. The local distances between the elements of the two sequences are calculated. It results in a matrix of distances of size $(n \times m)$

$$\boldsymbol{d}_{ij} = \left|a_i - b_j\right|, \quad i = 1, \ldots, n \quad j = 1, \ldots, m \tag{4}$$

The local distance matrix is used to compute the minimal distance matrix between the two sequences, using a dynamic programming approach and the optimisation

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criterion, as given in (5)

$$a_{ij} = \boldsymbol{d}_{ij} + \min(a_{i-1,j-1},\ a_{i-1,j},\ a_{i,j-1}) \qquad (5)$$

where a_{ij} is the minimal distance between the subsequences $(a_1, a_2, \ldots, a_n)$ and $(b_1, b_2, \ldots, b_m)$. A warping path is obtained through minimal distance matrix from a_{11} element to element a_{nm}, consisting of those a_{ij} elements that have formed the a_{nm} distance. The global warp cost of the two sequences is defined as given in (6)

$$\text{GC} = \frac{1}{p}\sum_{i=1}^{p} w_i \qquad (6)$$

where w_i are those elements that belong to the warping path and p is the number of such elements.

DTW algorithm is very useful for isolated words recognition in a limited dictionary. Using dynamic programming ensures a polynomial complexity to the algorithm, $O(n^2 v)$, where n are lengths of the sequences and v is the number of words in the dictionary. The $O(n^2 v)$ complexity may not be satisfactory for a larger dictionary. However, DTW is an easy to implement algorithm; open to improvements, very much suitable for applications that require simple word recognition such as telephones, car computers and security systems.

3 Results and discussion

The sound samples are recorded under the supervision of expert mechanics in service stations. Sony ICD-PX720 digital voice recorder is used for recording the sound samples. The acquired sound signals are sampled with sampling frequency of 44.1 kHz and quantised with 16 bits. Motorcycle engine runs in an idling condition and throttle is controlled by the expert mechanic. Recording environment has common disturbances from speech, sounds of the vehicles, air-compressor and auto-repair tools. Recorder is held closer to the engine to minimise the effects of the surrounding noise. Fig. 4 depicts the environment for recording the motorcycle sounds [29]. Recorder is held 500 mm from the centreline 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 1 dB change in the sound level.

Healthy motorcycles are less than 1 year old, not crossed 6000 km and regularly serviced. However, no restriction is imposed for faulty motorcycles. Following are the results of fault detection and fault localisation experiments.

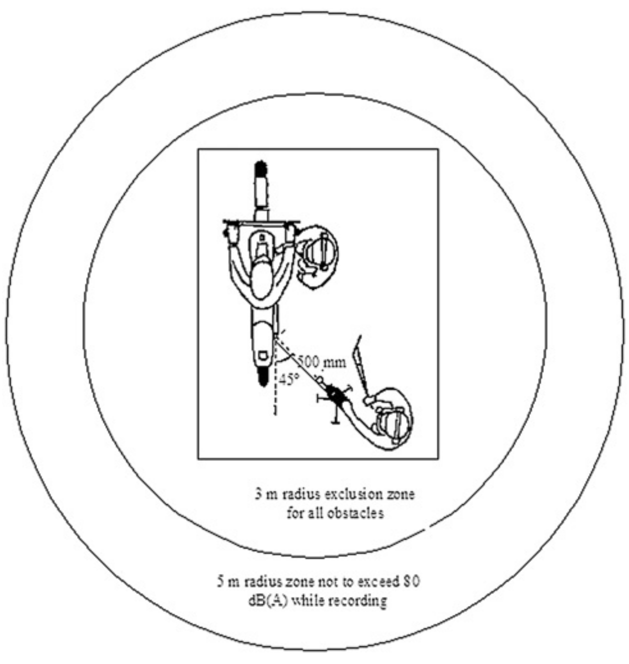

Fig. 4 *Recording environment*

3.1 Fault detection

For the fault detection stage, the samples of motorcycles of different makes and models are considered. However, for the second stage, that is, fault localisation, only the sound samples of motorcycles manufactured by Hero Honda (Now Hero Motocorp) are used. The sample set consists of 210 samples of healthy and 210 samples of faulty. The sizes of the training and test sets are varied from 10 to 200 in steps of 10. The number of samples used for testing is (210-N), where N is the number of samples used for training. Fig. 5 shows the results of fault detection.

3.2 Fault localisation

Fault localisation identifies the exact type of the fault. The faults chosen are from two different subsystems, namely engine and exhaust. VS and TC problems are engine subsystem faults and ML is related to the exhaust subsystem. Test results on combination of three faults are shown as confusion matrix in Table 2. The test results are shown for sample sets of size 10 for each type of fault. The experiment of fault localisation is repeated with different combinations of fault types and different sizes of test sample sets.

From observing the confusion matrices given in Table 2, it can be observed that the lowest classification accuracy is 0.9143. The proposed approach yields better performance for the signals with smaller signal-to-noise ratios of about 4.9. Signals are not denoised since the garage mechanics diagnose the faults based on the noisy signals in the real-world environment.

Testing is performed with increasing sizes of the samples sets. The size of each test sample set is varied from 20 to

Fig. 5 *Performance of the classifier for fault detection*

Table 2 Confusion matrix for TC, VS and ML

Seventy test samples of each fault	TC	VS	ML
TC	**66**	4	0
VS	1	**68**	1
ML	0	6	**64**

Table 3 Results of classification for increasing test sample sizes

N (no. of samples of each type of fault)	Accuracy	Sensitivity	Specificity	Precision	FPR	FNR
20	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000
30	0.9833	1.0000	0.9677	0.9667	0.0323	0.0000
40	0.9625	0.9512	0.9744	0.9750	0.0256	0.0488
50	0.9400	0.9074	0.9783	0.9800	0.0217	0.0926
60	0.9417	0.9077	0.9818	0.9833	0.0180	0.0923
70	0.9500	0.9200	0.9846	0.9857	0.0154	0.0800

70. If the test sample size is n, the n samples of each fault type are included. Table 3 shows the classification performance when the samples of ML fault are used for testing, against faulty VS and faulty TC samples.

Given

a = true negative, that is, correct rejections
b = false positive, that is, false alarms
c = false negative, that is, misses and
d = true positive, that is, hits
total = $(a + b + c + d)$.

The evaluation parameters used are defined as follows

Accuracy = $(a + d)$ / total.
Sensitivity = $d / (c + d)$.
Specificity = $a / (a + b)$.
Precision = $d / (b + d)$.
False positive rate (FPR) = $b / (a + b)$.
False negative rate (FNR) = $c / (c + d)$.

Table 3 shows the parameters for evaluation of performance.

It is evident from these results that the sensitivity and specificity are high, which are desirable for reliable classification.

4 Conclusion

Fault detection and localisation in motorcycles is performed based on the sound patterns produced. The chaincodes of the pseudospectra are used as features with DTW classifier used for fault detection. The statistical features of wavelet subbands are used as features for fault localisation. Same classifier are used for fault localisation stage. Results are over 90% for both fault detection and fault localisation stages. The work leaves scope for further investigation of fault localisation in subsystems of automotives. It finds applications in troubleshooting of electronics gadgets, machines, vehicle fault recognition and vehicles for physically challenged.

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