SUPPORT VECTOR MACHINE CLASSIFIER FOR ENGINE MISFIRE DETECTION USING EXHAUST SOUND QUALITY

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This paper proposes a novel non-contact-based technique to detect engine misfiring using sound quality metrics of the sound waves measured near the exhaust to train a support vector machine (SVM) classifier. This method was tested on a four-stroke, four-cylinder SI engine run on a wide range of load torques, 20 to 50 Nm, and wide range of speeds, 1260 to 3340 rpm, where at every test condition a cylinder was misfired intermittently. 52 sound signals were measured near the exhaust, containing 26 pairs of no misfiring condition and its corresponding one cylinder misfiring condition. The key sound quality metrics namely, Zwicker Loudness, Roughness and Fluctuation Strength of the exhaust sounds were used to train and test an SVM classifier. The algorithm correctly classified misfiring signals and correct signals with 95.2% training accuracy, 90% test accuracy, and 0.01 s computation time. Thus, exhaust sound quality metrics can successfully predict misfiring of an SI engine using SVM. The proposed technique could be advantageous over existing misfire detection techniques, as this method does not require an in-cylinder, engine-attached or exhaust-attached measurement, thus eliminating the need for costly, high maintenance and less durable sensors. Further, the presented method is computationally faster and robust over wider torque and speed range than most existing techniques.
Keywords: cylinder, misfire, load, speed, loudness, roughness, fluctuation strength

1. Introduction

On-board fault diagnosis and monitoring of an IC engine is an important activity required to ensure vehicle's optimum performance and minimum load on the environment, by minimising emissions. Misfiring in a spark ignition (SI) engine is a leading cause of sudden power drops and increased emissions [1-2]. Over the years, many techniques have been developed to detect engine misfire. The current widely used techniques measure one or more of the following physical quantity to detect misfire: a) instantaneous crankshaft angular velocity (engine speed) [3-8], b) in-cylinder (combustion chamber) pressure [8], c) exhaust gas pressure [8], d) engine vibrations [8-9], and e) ignition signal [10-11]. These methods use in-cylinder sensors or engine block attached sensors that are costly as they have to withstand very high temperatures and pressures. Further, the in-cylinder sensors are subject to wear and tear due to presence of very high temperature and pressure and exhaust fumes inside the cylinder. The engine block-attached sensors get disconnected due to engine vibrations especially at high engine speeds and need to be inspected and fixed from time to time. Many existing misfire detection algorithms are computationally expensive as they employ complex signal processing techniques [4, 7]. Machine learning algorithms for classifying the misfiring signals has gained popularity in recent years [1, 2, 10, 11] because of their high misfiring prediction accuracy and less computation time. However, machine learning algorithms are highly condition dependent. Most of these techniques have been shown to work only for low load and/or low speed conditions [1, 9, 11].

If sound waves emitted from a vehicle's exhaust are measured just outside the exhaust then this will have the advantage of being a non-contact based method and hence any cheap and low maintenance sensor can be used for this purpose. Sound quality metrics are widely used to understand subjective response of a human ear to a sound, but no research has suggested or used these metrics for engine misfire diagnostics as yet. This paper proposes a novel non-contact-based technique to detect engine misfiring using the sound quality metrics of the sound waves measured near the exhaust to train a support vector machine (SVM) classifier for predicting future misfires. This method attempts to overcome some of the limitations of the current misfiring detection methods. An experiment is conducted to test this method for predicting misfires in a 4-stroke 4-cylinder SI engine.

2. Theory

2.1 Sound quality for misfire detection

Sound quality is defined as the perceptual responses to the sound of a product [12]. Human ear sensitivity to sound is strongly dependent on frequency, being more sensitive in the middle frequencies (250 to 12,500 Hz) while sounds of lower or higher frequencies are perceived much lower than their actual sound pressure level (SPL) ([13]). Sound quality metrics, also known as psychoacoustic metrics have been devised to quantify how a human ear perceives sounds, therefore these metrics correlate well with the human ear frequency-related filtering of a sound signal. Previous research shows that exhaust sound quality metrics correlate with the operating characteristics of an engine [14]. Thus, it is quite probable that the exhaust sound quality metrics may provide useful information about an engine fault, specifically about the occurrence of a cylinder misfire. This paper proposes that sound quality metrics are important features that classify misfiring of an engine. Experiments were conducted to support this claim, and are described in section 3 and 4. The most widely used metrics for automotive exhaust sound quality analyses are Loudness, Roughness, and Fluctuation Strength [14], as described below [13].

2.1.1 Loudness

The "loudness" metric quantifies the human ear perception of sound volume, or the physical strength or amplitude of the sound. The loudness of a sound is expressed in the SI units of 'sones' ([13]). Calculation of the loudness of non-tonal sounds requires use of the 'critical-band width'. Critical bandwidth is a measure of the frequency resolution of the ear. The standard algorithm for calculating loudness is prescribed in the standards ISO 532B and is given in equation (1). In this algorithm the sound signal is represented in 1/3 octave spectrum and then combined into critical bands, and a spectral masking is applied. The resultant spectrum is a graph of specific loudness 'N′' versus critical band rate 'z' (in Barks). Integrating this spectrum over differential critical band rate gives the total loudness N of a sound signal as follows [18]:

$$\mathrm{N} = \int_0^{24\ \mathrm{Bark}} \mathrm{N}'\mathrm{dz}\ \mathrm{sones} \tag{1}$$

2.1.2 Roughness

The "roughness" metric is the human ear perception of roughness or unevenness (annoying quality) of a sound. More specifically, roughness quantifies the perception of rapid (15-300 Hz) amplitude modulation of a sound and is measured in the units of asper ([13]). The roughness of 1 asper corresponds to the roughness perception of a 60 dB, 1 kHz tone that is 100% amplitude modulated at a modulation frequency of 70 Hz. Roughness R of a sound in terms of the modulation frequency f_{mod}, and masking depth ΔL_E as a function of critical-band rate z is calculated as [13] follows:

$$\mathrm{R} = 0.3\,\frac{\mathrm{f_{mod}}}{\mathrm{kHz}} \int_0^{24\ \mathrm{Bark}} \frac{\Delta \mathrm{L_E}\,(\mathrm{z})\mathrm{dz}}{\mathrm{dB/Bark}}\ \mathrm{asper} \tag{3}$$

2.1.3 Fluctuation Strength

The "fluctuation strength" metric quantifies the loudness modulations at low frequencies that are discernable individually. More specifically, it quantifies slower amplitude modulation of sounds (up to 20 Hz). Fluctuation strength is expressed in units of vacil, where a fluctuation strength of 1 vacil corresponds to a 60dB, 1 kHz tone 100% amplitude modulated at 4 Hz. Fluctuation strength F of non-tonal noises is calculated using following equation [13] in terms of modulation factor m, modulation frequency f_{mod}, and level of the broad-band noise, L:

$$F = \frac{5.8(1.25m-0.25)[0.05\left(\frac{L}{dB}\right)-1]}{(\frac{f_{mod}}{5\ Hz})^2+\left(\frac{4\ Hz}{f_{mod}}\right)+1.5}\ \text{vacil} \tag{4}$$

2.2 SVM classifier for engine fault diagnosis

Support Vector Machine (SVM) is a supervised machine-learning technique that is gaining popularity in engine fault diagnosis. This algorithm has been found to be computationally quicker and more accurate [1, 10, 11, 15] than some other machine learning techniques such as decision tree [2], residual generation, and statistical pattern recognition [4]. The main advantage of SVM is that it can accurately classify faults in a complex system where the faulty signals may not be linearly separable from correct signals or they may follow a complex separation relationship [16]. An SVM is a soft margin classifier which makes the algorithm more adaptive to new testing data sets. For the proposed classification problem, the nature of relationship between the exhaust sound quality metrics and engine misfiring is not known, but it is expected to be non-linear. This is because previous fault detection algorithms have shown that faulty signal and no-fault signals tend to be non-linearly separable based on the features extracted from engine speed or engine vibration signal [1, 10, 11, 15, 17]. Therefore, for the proposed problem at hand, SVM was tuned using a radial basis function [16], which is a commonly used kernel to fit non-linear data.

3. Experimental Setup

A four-stroke 4-cylinder spark ignition engine was used as the test engine. Table 1 gives the specification of the engine. The engine was loaded using an eddy current absorption type dynamometer; make- E-50LC, rated power 50hp@1600 rpm. Figure 1 shows the engine test rig. The test engine and dynamometer set-up were located inside the engine test room whereas the exhaust port and coolant water tanks were located outside the room. Details of setup are in authors' previous paper [18]. A computerized control panel was connected to the engine that monitored the instantaneous values of the engine operating parameters such as engine rotational speed, engine torque, air intake, fuel weight, and water flow rate collected through various sensors attached to the engine test rig. The sound signals were measured near the exhaust using Brüel and Kjær Type 4189 microphones as shown in Figure 2. These signals were stored via Brüel and Kjær PULSE Analyzer at a sampling frequency of 65536 Hz.

The test engine was turned on and a desired load torque was applied. The engine was run at a set constant speed with all cylinders firing and signals were recorded for 60 s. Keeping the engine running, one cylinder was misfired by switching off the electric power to the cylinder spark plug and the signals were recorded for another 30 s, then the cylinder was switched on and the signals was recorded for another 30 s. This process was repeated 26 times for the [torque, speed] conditions as listed in Table 2. Thus, 52 sound signals near the exhaust, containing 26 sets of correct signals and their corresponding misfiring signals were acquired. The engine was not able to run at the lower speed(s) with increasing torque, therefore signals at those conditions could not be obtained.

Table 1: Test engine specification

Make	Maruti Suzuki Eeco
Body	Aluminium
Cubic Capacity	1196 cc
Fuel	Petrol
Fuel distribution	Multi-point Injection
Coolant	Water
No. of cylinders	4
No. of valves	16
Cylinder Bore	0.071 m
Stroke	0.0755 m
Connecting Rod Length	0.12 m
Compression Ratio	9.9
Engine Management	32 bit
Rated Power	73 bhp @ 6000 rpm
Rated Torque	101 Nm @ 3000 rpm

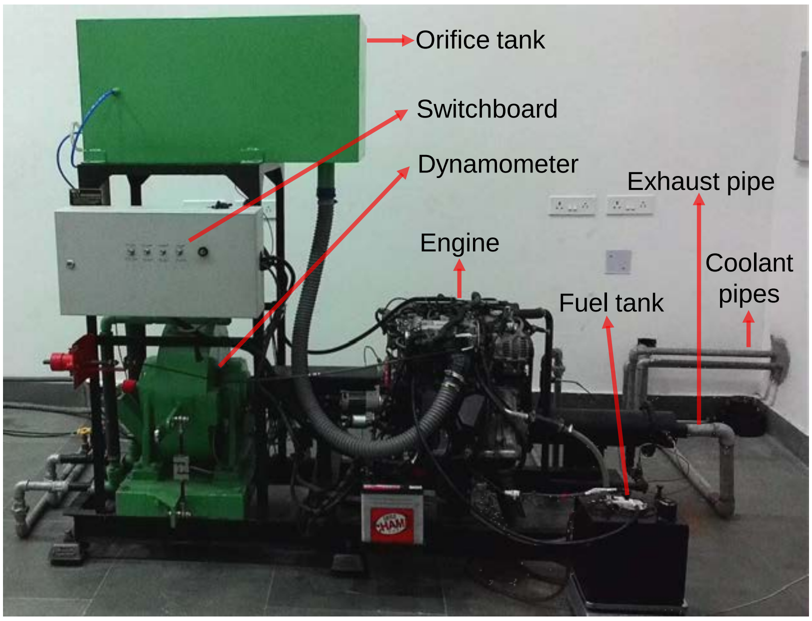

Figure 1: Engine test rig

Figure 2: Signal measurement at the exhaust

Table 2: List of 26 experimental conditions

Load Torque	**Engine Speed (in rpm)**							
20 Nm	1260	1540	1800	2100	2390	2700	3060	3320
30 Nm	-	1530	1800	2100	2390	2700	3030	3340
35 Nm	-	-	1800	2100	2400	2700	3030	-
40 Nm	-	-	-	2090	2390	2700	3040	3340
50 Nm	-	-	-	-	-	-	-	3340

4. Results and Discussions

4.1 Classification based on exhaust sound quality

The data sets were split into 42 training data sets (21 correct, 21 misfiring signals) and 10 test data sets (5 correct, 5 misfiring signals). It was ensured that the test data covered the full torque and speed range. The test data contained correct and misfiring signals corresponding to [35 Nm, 1800 rpm], [30 Nm, 2100 rpm], [40 Nm, 2390 rpm], [50 Nm, 3340 rpm], and [20 Nm, 2700 rpm]. The code for classifying the engine misfiring was written in Python 2.7.10, using packages 'pandas' and 'numpy' for data manipulation, and 'sklearn' for classification. The classification algorithm used was svm from scikit learn (package sklearn). Firstly, the sound signals were processed in Brüel and Kjær PULSE Sound Quality to obtain Stationary, Mean and Instantaneous Loudness (in sones), Roughness (in asper) and Fluctuation Strength (in vacil). These metrics were entered as features into the SVM classifier that was tuned using k-fold cross-validation technique with k=4 [19]. Table 3 shows the result of classification. The developed method correctly classified all misfired signals, leading to a 100 % accuracy in misfire detection. However, it also classified one correct signal as misfiring. Overall, using SVM, the exhaust sound quality metrics correctly classified correct signals and misfiring signals with 95.2% training accuracy and 90 % test accuracy in 0.01 s. Thus, the exhaust sound quality metrics successfully predict an engine's cylinder misfiring using SVM with high accuracy and high computational efficiency.

Table 3: Classification of misfiring and correct signals using exhaust sound quality

Features used	Training Accuracy	Testing accuracy	Computation time
Stationary loudness Mean loudness Fluctuation Strength Roughness Mean instantaneous loudness	95.2%	90 %	0.01 s

4.2 General discussions and future recommendations

It is found that the stationary loudness, mean loudness, fluctuation strength, roughness and mean instantaneous loudness of exhaust sounds are highly sensitive to cylinder misfiring. Thus, these features predict misfiring with 100% accuracy and overall classify the correct signals and misfired signals with 90% accuracy. Existing misfire techniques are system-dependent and have been usually shown to perform well only under low load and low torque conditions [1, 9, 11]. Our proposed method has been tested to be robust over a wide range of load torques, from 20 Nm to 50 Nm, and wide range of engine speeds, from 1260 rpm to 3340 rpm. Results indicate that the method is torque independent, for example, it correctly predicted misfiring at 50 Nm torque without being trained on any signal recorded at 50 Nm. Thus, exhaust sound quality metrics successfully classify misfiring of an SI engine. The proposed technique has high potential in engine fault diagnosis. Future experiments will be done to test if this method can classify both the presence of a misfire and the location of misfire, i.e. which cylinder misfired.

5. Conclusions

This paper proposes a novel non-contact-based technique to detect engine misfiring using the sound quality metrics of the sound waves measured near the exhaust to train an SVM classifier. This method was tested on a four-stroke, four-cylinder SI engine over a wide range of load torques (20 to 50 Nm) and wide range of speeds (1230 to 3340 rpm). Results show that the sound quality metrics namely, stationary, mean and mean instantaneous loudness, fluctuation strength, and roughness are highly sensitive to cylinder misfire. These metrics correctly predicted misfiring with 100% accuracy, but correctly classified the correct and misfired signals with 90% accuracy in 0.01 s computation time over the entire load torque and speed range. The proposed method is a drastic improvement over existing misfiring methodologies as it does not require a contact-based measurement; thus eliminating the need for costly, difficult to maintain, and less durable sensors. Moreover, the proposed method is computationally faster and robust. A classifier based on this method integrated with any affordable microphone could be a cheap misfiring prediction device. This device could be used for end-of-the-line testing at assembly plants, at automotive workshops, or at homes.

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