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Vibration analysis to detect and locate engine misfires

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***Abstract* - Vibration analysis is used to detect faults and anomalies in machinery and other mechanical systems that produce vibrations during operation. The study aimed to develop an algorithm that can detect and locate engine faults in automobiles by analyzing vibrational data produced during engine operation. Analysis was done on one type of engine fault – Spark Ignition Engine misfire. To detect anomalies in the vibrational pattern (waveform), analysis was carried out in both time and frequency domains. To obtain vibrational data an AVR – 32 (Arduino) based data acquisition device was built, and analysis was carried out in MATLAB using scripts and functions. The developed algorithm isolates frequency components in the waveform that corresponds to engine faults and converts them into numerical quantities that are then compared with computed ranges. The algorithm was able to identify the presence of a misfire in the engine and could locate the cylinder in which the misfire occurs with significant accuracy.**

Keywords - locating engine misfires, vibration analysis

I. INTRODUCTION

Vehicle engine faults need to be detected to prevent damage to components of the vehicle, maintain driver and passenger comfort as well as prevent catastrophic failure during its operation. The heart of any automobile is its engine. Modern-day engines are complex machines that are controlled by computers and rather intimidating for the usual mechanic to work on. Engine faults can be categorized into faults that can be identified visually, with the use of onboard diagnostics (OBD) scanner, and by listening to the sound generated by the engine. Faults that are identified by listening, requires expert knowledge, and experience. It can be difficult for a new and inexperienced mechanic to correctly identify a fault by listening to the engine sound. Even experienced mechanics can incorrectly diagnose faults leading to unnecessary expenses and rework. It is therefore imperative that a system is introduced which can correctly identify engine faults by analyzing engine sound/vibrations. After identifying the problem, the mechanic will then have to locate it. This is done through trial and error and involves the removal of electrical connections and engine components. Therefore, having a system that locates the problem is also vital. This study aims to develop an algorithm to accurately detect engine misfires and locate the cylinder where it occurs by analyzing vibrations generated during operation. Vibration analysis is widely used to detect failures and faults in industrial machinery but is seldom used to detect vehicular faults.

An algorithm is proposed in [1] where engine faults are identified using sound recordings. Sound recognition techniques are used in the detection algorithm mentioned in [2]. The proposed algorithm uses three criteria to decide on the fault. A mini microphone is used to record sounds at different engine rotational speeds in [3]. Engine faults are then identified using a model built in MATLAB. All the above-mentioned research is based on sound analysis and has a common problem of eliminating excessive noise from the recorded sound wave. Further, the effectiveness of capturing all vibrations emitted from the engine is questionable as the microphone only captures waves that reach it through an air medium. Both issues can be mitigated if the vibrations are recorded using an accelerometer that is placed on a suitable/effective position on the vehicle frame/engine. This method is used in [4] to acquire vibrations generated from the engine. Using a 3-axis accelerometer it is possible to measure the vibrations in all 3 planes. Variations in signal parameters between the normal engine and the fault engines are then identified. A 3-axis accelerometer is used along with a data acquisition device in [5] to acquire vibrations to detect faults in induction motors.

A simple but powerful data acquisition device can be fabricated using Arduino as mentioned in [6]. The Arduino platform is used to acquire vibrational data from a 3-Axis digital accelerometer. However, post-processing of the vibrational data must be done on a computer or Field Programmable Gate Array (FPGA). Another such Arduino-based data acquisition device is used in [7] to measure free vibrations on a wind turbine blade. A more powerful alternative to the Arduino platform is discussed in [8] where a Raspberry Pi single-board computer (SBC) is used. The main advantage of using an SBC is the ability to perform the data acquisition as well as the post-processing in the same device. However, SBCs are relatively more expensive than microcontrollers and the post-processing algorithm can be implemented in an FPGA which has a smaller form factor.

Vibration analysis to determine piston scuffing fault in Internal Combustion engines is appraised in [9]. It was shown that piston scuffing fault caused an increase in maximum, root means square, mean, skewness, kurtosis, and impulse factor of the engine vibration in the frequency band of 2.4–4.7 kHz [9]. The development of an algorithm that can determine faults by assessing nuances between normal and abnormal waveforms is presented in [10] where analysis is done to determine tool wear and condition in high-speed milling. Here reconfigurable infinite impulse response (IIR) band-pass digital filter and statistical techniques [10] are used for processing and analyzing vibrational signals. The vibrations are analyzed after converting the signal into a time-frequency domain with the use of Continues Wavelet Transform (CWT). In the developed algorithm, arithmetic means value, and the sum of absolute values of the digitally filtered vibration signal is utilized as reference value to set up a healthy tool threshold. A comparison between a set healthy tool threshold and the sum of absolute values of the digitally filtered vibration signal is the basis for the decision-making algorithm. This algorithm can indicate faults in real-time which is advantageous. Another real-time fault detection algorithm is presented in [11] where vibrational analysis is done to identify faults in industrial machinery. Here, Fast Fourier Transform (FFT) is used to convert the wave from the time-domain to the frequency-domain. The use of CWT or FFT greatly depends on the nature of the waveform as FFT does not consider time-domain characteristics whereas CWT allows the assessment of characteristics that vary with time. For example, the effectiveness of both CWT and FFT to distinguish abnormalities in EEG signals is assessed in [12]. It was found that since EEG signals are non-stationary (characteristics change with time) CWT is more suitable than FFT for spectral analysis. To arrive at a conclusive decision, it is therefore imperative to use both methods to analyze waveforms and see what is most effective in determining engine faults.

Signal analysis techniques to locate engine faults (misfire) are being discussed in [13]. In this study, time-domain features such as the peak-to-peak value (PP), root mean square value (RMS) are used to identify and isolate the misfiring cylinder of an engine. Experiments showed that as the engine rotational speed is changed, the features that can be used to detect and locate the cylinder also change. Therefore, the performance of the features in isolating faults is dependent on the engine rotational speed.

Vibration analysis is used in many instances to detect anomalies and faults in mechanical systems. Extensive research has been done on detecting engine faults through vibration analysis. However, locating faults have been only discussed in [13]. Here, analysis is performed exclusively in the time domain. In this study, waveforms will be analyzed in both frequency and time domains. The developed algorithm isolates fault signals to detect and identify engine faults.

II. METHODOLOGY

A. Theory

A digital 3 -axis accelerometer (ADXL 345) was chosen as the sensing device. The data acquisition device was made using the Arduino platform. The algorithm for analyzing the signal was created in MATLAB using scripts and functions. Signal analysis is predominantly done in the frequency domain using the Fast Fourier Transform (FFT) as the waveforms emitted from the engine are stationary signals when considered for a long enough period.

FFT is an algorithm that calculates the Discrete Fourier Transform in a numerically efficient way. The benefit of using the FFT algorithm is that it is an order $n\log(n)$ operation, where n is the number of discrete data points. For large data sets, this is favorable as FFT is almost linear scaling in n as the effect of $\log(n)$ is less significant as n gets large. The FFT algorithm is standard and comes as a built-in feature in MATLAB.

At the early stages of the research, waveforms were analyzed using a Spectrogram that utilizes a Gabor transform. Spectrograms can be used to assess a waveform in both time and frequency domains. For example, when a signal is transformed from the time domain to the frequency domain using the FFT it would yield a plot that shows the constituent frequencies of that waveform and their magnitudes. However, it is not possible to observe when these frequency components occur in the waveform. The Gabor transform allows us to compute the spectrogram which is a time-frequency plot that shows which frequencies are active in each period of a waveform. The Spectrogram is computed by convolving a Gaussian wavelet with the Fourier transform while the Gaussian window is moved across the original waveform. This yields a frequency plot weighted by the Gaussian window.

B. Experimentation

A normal running engine produces vibrations due to the combustion that occurs in the cylinder and other moving parts in the engine. The constituent frequencies of this vibrational signal will be constant at a particular rotational speed of the engine. If a misfire is induced in one of the cylinders, the vibrational signal will change significantly due to the unbalanced combustions in the cylinder. Additional frequency components will be observed in the signal and thus the issue could be identified. Further, the magnitude of these newly induced frequencies and their distribution will be assessed to find a correlation between waveform characteristics and the misfiring cylinder. If successful, the misfiring cylinder can be located. The vibrations were captured using a 3 – Axis digital accelerometer (ADXL345) and acquired by a Data Acquisition Device (built using the Arduino platform) through I^2C communication protocol. The received data is then transmitted via Serial communication (UART) to a computer. The Arduino board is interfaced with MATLAB which is installed in the computer. The received data is then written to a spreadsheet by a MATLAB script. This data contains the acceleration values in the X, Y, and Z axes and the time stamps at which readings were taken. The sampling rate ranges from 450 Hz to 500 Hz which was deemed satisfactory as it would give a maximum measurable frequency of 225 Hz (In a 4 stroke 4-cylinder engine at 2000 RPM, combustion occurs at a frequency of 66.67 Hz). The recorded data can then be loaded to the MATLAB environment for further analysis.

1) Experiment 01

A series of preliminary tests were carried out to check the feasibility of the research and to develop the algorithm. The objectives of the experiment are as follows,

- Determine whether the waveform produced is stationary.
- Observe whether misfires can be detected through waveform analysis.

The experiment was carried out on a 2002 Toyota Corolla 1.5L 4 stroke 4-cylinder engine (1NZ-FE) using just one accelerometer positioned between the left-most (1st cylinder) and the 2nd cylinder. The accelerometer was fixed to the engine block rigidly with the use of a stud and bolt connection.

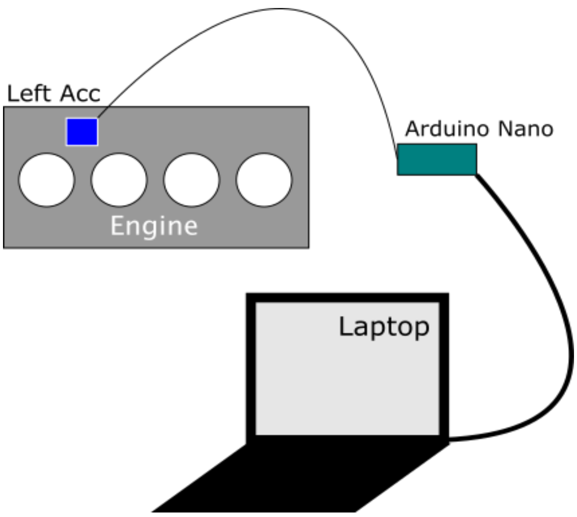

Fig 1: Test setup for experiment 01

A misfire was induced in the first cylinder by disconnecting the electrical connection to its ignition coil. Readings were then taken at idling speed and at 2000 RPM. The procedure was repeated for misfires in each cylinder and finally for the normal (no misfire) scenario.

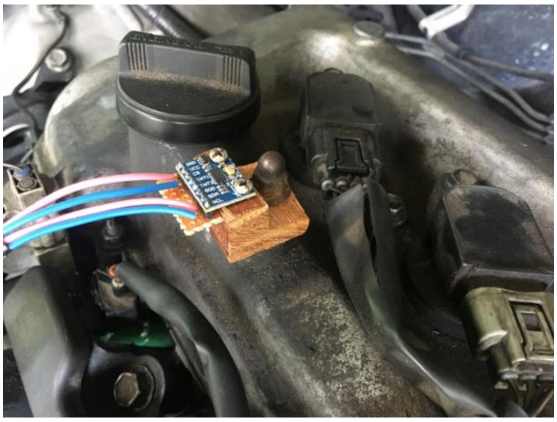

Fig 2: Accelerometer fixed rigidly to the engine block.

The obtained waveforms were then analyzed using a preliminary algorithm that was coded in MATLAB.

2) Experiment 02

The second set of experiments were carried out on the same engine at idle speed (around 1000 rev/min). Readings were taken from two accelerometers at two different locations to see if and how the waveforms change with the location of the accelerometer.

Objectives of the experiment are as follows,

- To see if the magnitudes of the additional frequencies (explained in future sections) have any correlation with the position of the misfiring cylinder.
- To assess the reproducibility of the vibrational waveforms.

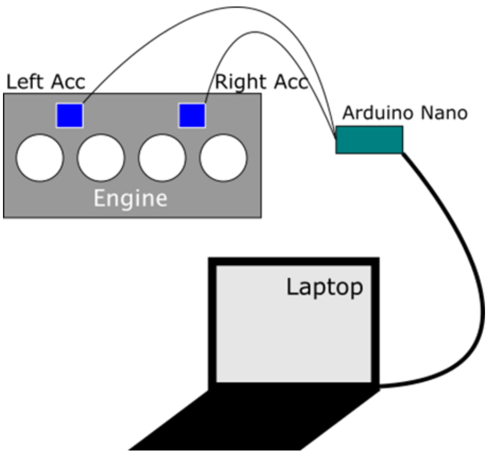

Fig 3: Test setup for experiment 02

As in the 1st experiment, readings were taken for 5 scenarios (normal, misfires in cylinders 1,2,3, or 4). Readings were taken by both accelerometers simultaneously. In this experiment, only the Y-axis readings were taken from both accelerometers because upon analyzing data obtained in the 1st experiment it was clear that significant differences in the waveforms in different scenarios were observed only in the Y-axis readings. The procedure was repeated trice.

Measurements were obtained from two locations to see if the results could be used to locate the misfiring cylinder.

Fig 4: Updated data acquisition device with 2 accelerometers

C. Results

1) Experiment 01

A total of 30 waveforms were obtained in the first experiment. The breakdown of those waveforms are as shown in Tbale I. To demonstrate the differences in the obtained waveforms Fig 5 to Fig. 9 are presented.

TABLE I. RESULTS BREAKDOWN

Scenario	**X axis**	**Y axis**	**Z axis**	**Total**
Idle				
Normal	1	1	1	3
1st cylinder misfire	1	1	1	3
2nd cylinder misfire	1	1	1	3
3rd cylinder misfire	1	1	1	3
4th cylinder misfire	1	1	1	3
2000 RPM				
Normal	1	1	1	3
1st cylinder misfire	1	1	1	3
2nd cylinder misfire	1	1	1	3
3rd cylinder misfire	1	1	1	3
4th cylinder misfire	1	1	1	3
Total	10	10	10	30

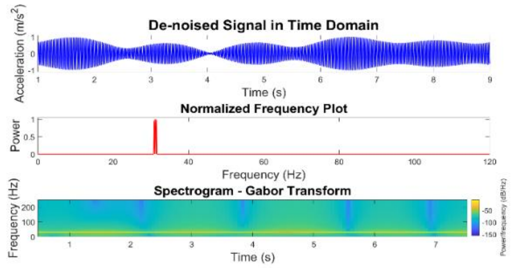

Fig 5: Y-Axis Readings - Normal at Idle

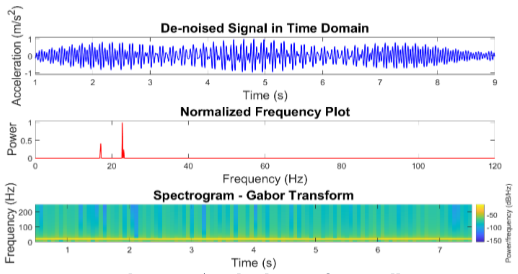

Fig 6: Y-Axis Readings - 1st Cylinder misfire at Idle

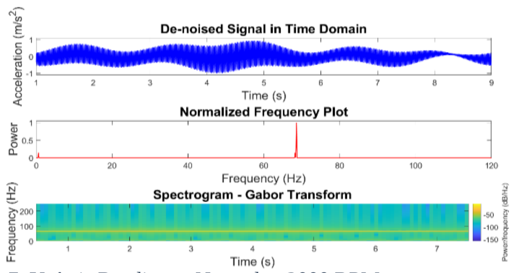

Fig 7: Y-Axis Readings - Normal at 2000 RPM

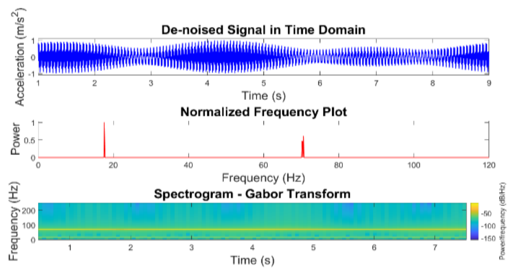

Fig 8: Y-Axis Readings – 2nd Cylinder misfire at 2000 RPM

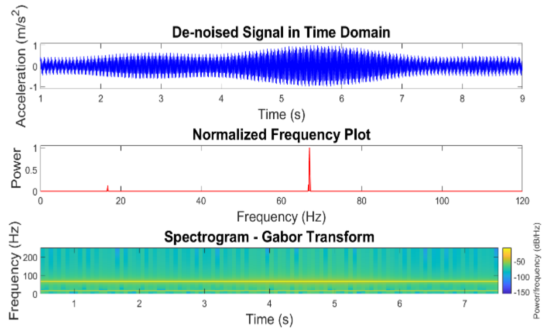

Fig 9: X-Axis Readings – 3rd Cylinder misfire at 2000 RPM

2) *Experiment 02*

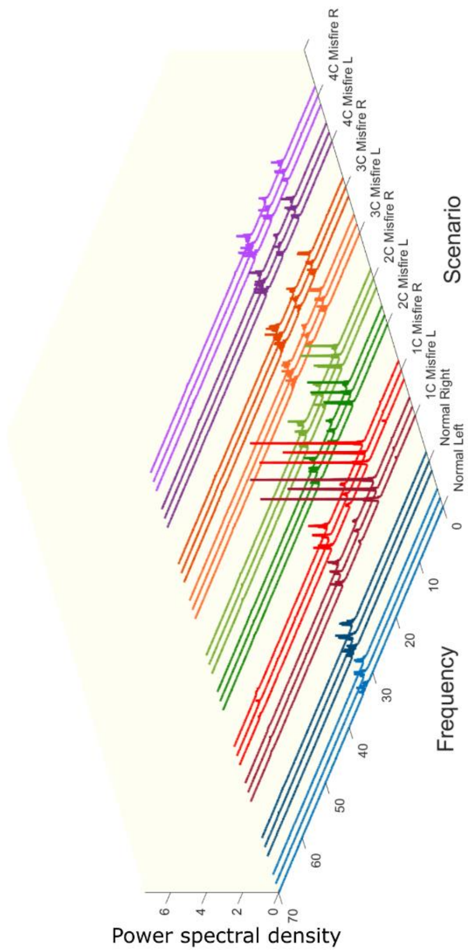

Fig 10: Power spectral density vs Frequency of different engine conditions.

The 3D plot shown in Fig 10 contains the frequency spectrum of all the waveforms obtained by both accelerometers. Note that for each scenario and accelerometer, 3 frequency distributions are plotted. This is because measurements were repeated 3 times for each scenario.

D. Analysis and Discussion

1) Experiment 01

Fig 5 to Fig. 9 shows the denoised waveform in the time domain, frequency spectrum, and spectrogram of some of the waveforms. To validate that the signals received are stationery, the waveforms were analyzed in the time- frequency domain using a spectrogram (Gabor Transform).

The horizontal line in the spectrogram indicates that the signal does not change with time, thus is stationary. After converting the signal to the frequency domain using the FFT, the noise was removed by eliminating low power frequency components. In all waveforms, a clear spike was observed in the frequency spectrum at a frequency similar to that of the frequency of combustion (spark frequency) at that particular engine speed. For instance, in Fig 7,8 and 9 a spike is present at around 68-69 Hz which is the frequency of combustion at 2000 RPM. At normal conditions (no misfire), the only frequency component that was present in the waveform corresponds to the spark frequency. This was later validated through multiple tests.

When a misfire is induced in one of the 4 cylinders, extra frequency components appear. As shown in Fig 8, when a misfire is induced in the 2nd cylinder an additional spike appears at 17.63 Hz. This new frequency component was observed in all misfiring scenarios in the Y-Axis at 2000 RPM. At idle speed, additional frequency components were only visible in some misfire scenarios. Further in all scenarios where this frequency appeared, it was similar to the combustion frequency of a single cylinder (single-cylinder spark frequency). For instance, at 2000 RPM, a cylinder experiences a spark every 2 rotations of the crankshaft, thus at a frequency of 16.67 Hz. The presence of this additional frequency component could therefore be considered as an indicator for a misfire. However, locating the cylinder is not possible through this analysis.

2) Experiment 02

As the waveforms were validated to be stationary signals from experiment 01, analysis was performed exclusively in the frequency domain. Four key regions were identified where frequency components would appear. These regions are,

a) Single cylinder spark frequency region
b) Engine crank rotational frequency region
c) Intermediate frequency region
d) Engine spark frequency region

The frequency distributions of the obtained waveforms are shown in the 3D plot (Fig 10). Frequency spikes were observed in the spark frequency region as observed in Experiment 01. Whenever there was a misfire, additional spikes were observed in the Single spark frequency region, Engine crank rotational frequency (Crank frequency) region, and intermediate frequency region. From these three regions, the crank frequency region showed the most variance in power of the frequency components. Therefore, the single spark frequencies of each waveform were isolated using a MATLAB script for further analysis.

Fig 11 shows the average power values (with associated uncertainties) of the crank frequencies in each scenario. The two points in each region show the means of the power values obtained from the left accelerometer and right accelerometer, respectively. From Fig.11 it is possible to distinguish the normal running condition, 1st cylinder misfire and 2nd cylinder misfire as their power ranges do not overlap with others. However, it is difficult to distinguish the 3rd cylinder misfire case from the 4th cylinder misfire case by only assessing the mean power values as their power ranges overlap. Therefore, a different approach had to be taken for the analysis. The graph in Fig 12 shows the means of RMS values of the vibrational signals.

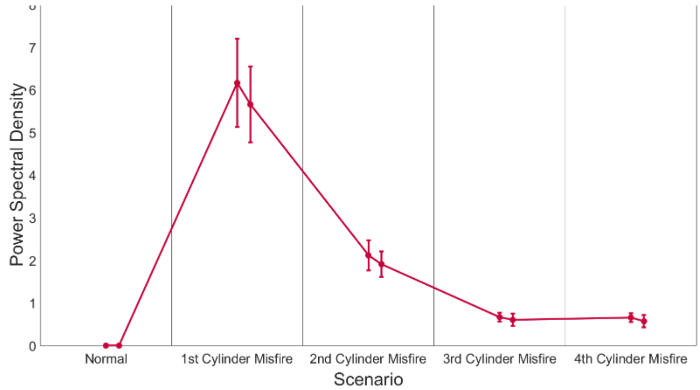

Fig 11: Mean Power vs misfire scenario

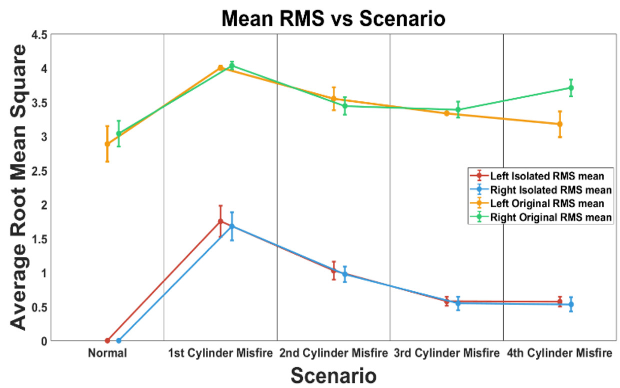

Fig 12: Mean RMS values vs misfire scenario

The green and orange points show the mean RMS of the original waveforms (without processing) of different misfire scenarios. The red and blue points are the mean RMS values of the same waveforms where all other frequency components except the crank frequency are filtered out (only the crank frequency component exists). The mean power variation also shows the same pattern. However, RMS was selected over PSD as it required less computation. As expected under normal conditions the RMS values of the isolated signals (filtered signals) are zero as the single spark frequency does not exist in the original waveform. In other cases, the RMS values are non-zero for the isolated signals. The mean RMS values show a similar trend to the mean power values shown in Fig 11. Similarly, normal, 1st cylinder misfire, 2nd cylinder misfire can be differentiated by just observing the RMS range of the isolated waveforms (-1.5σ and 1.5σ). To differentiate the 3rd and 4th cylinder misfiring cases from each other the RMS ranges of their respective original signals must be used. Specifically, the signal obtained from the right accelerometer. There is a clear difference between the mean RMS values of the original right accelerometer signals of the 3rd and 4th cylinder misfiring scenarios. Further, the ranges were chosen to avoid their RMS ranges from overlapping while yielding an acceptable level of accuracy (87%). Under these conditions, the misfiring engine can be located by the following methodology shown in Table III.

TABLE II. MEAN RMS VALUS AND RANGE OF RMS VALUES

Range between -1.5σ to 1.5σ accounts for 86.64% of readings										
	Normal		***1st Cylinder Misfire***		***2nd Cylinder Misfire***		***3rd Cylinder Misfire***		***4th Cylinder Misfire***	
	Mean	Range (+1.5σ - 1.5σ)	Mean	Range (+1.5σ - 1.5σ)	Mean	Range (+1.5σ - 1.5σ)	Mean	Range (+1.5σ - 1.5σ)	Mean	Range (+1.5σ - 1.5σ)
Mean RMS of isolated Right Accelerometer Signal (IRMS)	3.0392	3.2273 2.8511	4.0363	4.0931 3.9795	3.4454	3.5741 3.3167	3.3912	3.5097 3.2727	3.7106	3.8326 3.5886
Mean RMS of original Right Accelerometer Signal (ORMS)	0	0 0	1.6781	1.8823 1.4739	0.9751	1.0884 0.8618	0.5469	0.6468 0.4470	0.5317	0.6364 0.4270

TABLE III. IDENTIFICATION ARGUMENTS

	Isolated Signal RMS		**Original Signal RMS**
Normal	0		
1st Cylinder misfire	(1.4739 - 1.8823)		
2nd Cylinder misfire	(0.8618 - 1.0884)		
3rd Cylinder misfire	(0.4470 - 0.6468)	AND	(3.2727 - 3.5097)
4th Cylinder misfire	(0.4270 - 0.6364)	AND	(3.5886 - 3.8326)

Since only the waveforms that were obtained by the right accelerometer were used for the identification there is no need for a system with two accelerometers for data acquisition for this engine model and this engine fault.

III. CONCLUSION

Vibrations transmitted through the vehicle structure were recorded using an accelerometer connected to a data acquisition device. A low-cost data acquisition device was built using the Arduino platform. The recorded waveforms which originated from the same engine but under normal and misfiring conditions were analyzed. The analysis was done on MATLAB. Two separate experiments were carried out to obtain data to develop a method to detect engine misfires and to locate the misfiring cylinder. Frequency analysis showed that frequency components equal to the crank frequency of the engine at idling speed appear when there is a misfire in one of the cylinders. The average power of the crank frequency components can be used to differentiate normal; 1st cylinder misfire and 2nd cylinder misfire scenarios. To distinguish misfires in the 3rd and 4th cylinders assessing the power of the frequency components proved insufficient. Differentiation was possible by a combined assessment of the mean RMS values of the isolated fault signals and the original signals.

This method can be used to detect and locate an engine misfire (with about 87% accuracy) in this engine at idle speed.

This study was performed on one engine model preliminarily. The methodology can be developed, however, to detect misfires in other engine models through conducting the same tests on those engines and setting identification arguments unique to them. Currently, the methodology can only detect engine misfires under controlled conditions. That is, on an engine that does not have other faults except for misfires. This study does not assess how the existence of other faults such as damaged camshaft, knocking, faulty mounts, etc. in addition to engine misfiring, affect the performance of the methodology. In the future, the methodology may be developed to detect and locate other engine faults such as engine knocking.

Based on the conducted study, an algorithm can be developed and implemented on a device that can be used to detect and locate engine faults. Such a device will assist mechanics in accurately detecting and locating engine faults without unnecessary engine disassembly and trial and error techniques. Further, an algorithm based on this methodology may be implemented on the Engine Control Unit to detect faults and improve efficiency. For instance, engine efficiency can be improved by controlling the spark timing of individual cylinders once engine knocking is identified and located.

REFERENCES

[1] L.M.Contreras-Medina, R.J.Romero-Troncoso, J.R.Millan-Almaraz and C.Rodriguez-Donate, "FPGA Based Multiple-Channel Vibration Analyzer," IEEE, pp. 229-232, 2008.

[2] Wail.M.Adaileh, "Engine Fault Diagnosis Using Acoustic Signals," Applied Mechanics and Materials, pp. 2013-2020, 2013.

[3] M.Akin, "Comparison of Wavelet Transform and FFT Methods," Journal of Medical Systems, vol. 26, pp. 241-247, 2002.

[4] A.González, J.L.Olazagoitia and d.J.Vinolas, "A Low-Cost Data Acquisition System for Automobile," Sensors, 2018.

[5] A.K .Kemalkar and V.K.Bairagi, "Engine Fault Diagnosis Using Sound Analysis," International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT), pp. 943-946, 2016.

[6] A.Moosavian, G.Najafi, B.Ghobadian, M.Mirsalim, S.M.Jafari and P.Sharghi, "Piston scuffing fault and its identification in an IC engine by vibration," Applied Acoustics, pp. 40-48, 2015.

[7] Chomphan and Suphattharachai, "Vibration Analysis of Gasoline Engine Faults," American Journal of Applied Sciences, pp. 1166-1171, 2013.

[8] E.Ftoutou, M.Chouchane, N.Besbès and R.Ouali, "Detection of diesel engine misfire by vibration analysis in the time domain," Academia, 2020.

[9] F.Aswin and Z.S.Suzen, "Analysis of free vibration measurement by mems," in International Conference on Applied Science and Technology, 2018.

[10] M.Iwaniec, A.Holovatyy, V.Teslyuk, M.Lobur, K.Kolesnyk and M.Mashevska, "Development of Vibration Spectrum Analyzer Using," IEEE, 2017.

[11] M.Madain, A.Al-Mosaiden and M.Al-khassaweneh, "Fault Diagnosis in Vehicle Engines Using Sound Recognition Techniques," IEEE, 2010.

[12] P.Y.Sevilla-Camacho, J.B.Robles-Ocampo, J.Muñiz-Soria and F.Lee-Orantes, "Tool failure detection method for high-speed milling using," Int J Adv Manuf Technol, 2015.

[13] S.K.Shomea, U.Datta and S.R.K.Vadali, "FPGA based Signal Prefiltering System for Vibration," Procedia Technology, 2011.