Data-Driven Fault Detection of Automotive Engine Mounts Using Onboard Vibration Signals

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Abstract

With the increasing rate at which new technologies are developed and integrated into modern vehicles, their complexity and demands on reliability have grown. Hence, potential downtimes are directly correlated with high costs for both customers and manufacturers, making the need to ensure operational stability evident. Being the most crucial part of an automotive vehicle, the integrity of the drivetrain and its components have to be assured. Traditionally, this was achieved by increased loads during the design phase or regular service intervals. As these preventive measures lack the ability to assess or detect the imminent occurrence of component faults, aggregating damages and connected costs still remain inevitable, especially as direct data acquisition for such components is not possible. Due to the recent advancement of onboard functionalities of modern cars, constant and extensive sensory data is generated throughout each part of the vehicle, enabling the proactive monitoring of its condition. Caused by the mechanical and thermal loads during operation, altered mechanical properties of damaged components such as engine mounts can influence the overall vibrational behavior of the vehicle. By analyzing statistical features such as Root Mean Square, Kurtosis, and Crest Factor of the vibrational signals generated by the car's onboard sensors, this study aims to investigate them for the fault detection of engine mounts. Through the comparison of healthy and unhealthy states across different vehicles in the initial phase of engine ignition, the results show that only the Root Mean Square was able to consistently differentiate the health states, suggesting the higher energy dissipation within the fault-induced state as main indicator for detection.

Keywords

Data Analytics, Engine Mounts, Condition Monitoring, Predictive Maintenance, Vibration Analysis, RMS

1. Introduction

The engine mount serves as the main mechanical link between the engine and the chassis of the car. Usually consisting of a composite of metal and an elastomer material, its key function is to reduce noise and vibrations emitted by the internal combustion process of the engine to the chassis. To further increase the dampening characteristics, hydraulic versions exist that incorporate fluids within the structure of the engine mount. Caused by the influence of dynamic and simultaneous thermal and mechanical stress loads during the regular operation of the car, the elastomer base is exposed to damage phenomena like tearing or deformation. As the initial indications of damage are too minute to be perceived, their progression is left unnoticed until the engine mount loses the mechanical properties to sufficiently compensate the vibration generated by the engine, leading to noticeable noise and vibration production throughout the rest of the car. With these having numerous possible origins of causes and contaminants such as damage phenomena of other drivetrain components and environmental factors, the challenge of distinguishing the specific fault is further emphasized as typical production cars are not equipped with sensors for condition monitoring of engine mounts. As a consequence, the identification of engine mount faults as auch are directly linked to costly troubleshooting procedures and advanced expertise. This study aims to pinpoint the existence of engine mount faults without the need for dedicated sensors by utilizing data generated by onboard acceleration sensors during specific operational states of the vehicle. By comparing the acceleration signals with their fault-induced state through a selection of statistical features, an indicator for the detection of engine mount faults

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is established. With the Root Mean Square (RMS) feature of lateral acceleration signals showing a significant elevation in the unhealthy state during the initial phase of engine ignition across vehicles, this study finds that the increased energy dissipation from the engine to the chassis can serve as a reliable indicator for the existence of engine mount faults.

The remainder of this paper is structured as follows. Section 2 reviews related work in the field of vibration analysis and its applications, with particular attention to time-domain, frequency-domain, and time-frequency domain based methods. Section 3 describes the experimental setup, especially the data acquisition, preprocessing, and feature extraction used in this study. Section 4 presents the experimental results, analyzing statistical feature distributions across health states, test vehicles, and time windows. Finally, Section 5 concludes with a discussion of the findings, limitations followed by the potential directions for future research in Section 6.

2. Related Work

This section reviews applied vibration-based fault diagnosis techniques. Moreover, established methods for analyzing vibration signals in machinery condition monitoring are surveyed in Subsection 2.1. Subsection 2.2 highlights the novelty of this work by identifying research gaps in existing literature.

2.1. Vibration Analysis

Making up more than 82% of conducted fault diagnosis techniques across various areas of the industry, the analysis of vibrational signals is a powerful tool for the early detection of anomalous system behavior [1]. Their popularity within industry for the diagnosis of machines for a multitude of faults such as bearing damage, increased wear, and gearing misalignments is further underlined by their ease of implementation as a stoppage or disassembly of the machine is not required [2]. The basis for the diagnosis of machine condition through vibrational analysis consists of examining the amplitudes and frequencies of acceleration signals [3]. As the interpretability of the raw signals becomes increasingly difficult with more complex and interconnected systems, techniques are employed to process the signal in its time, frequency, or combined time-frequency domain specific features for fault detection [4, 5]. Being the simplest approach to the analysis of vibrations signals, time-domain based methods aim to establish a significant differentiation between vibrational signals stemming from a damaged and undamaged machine through statistical features such as RMS , Crest Factor (CF), and Kurtosis which constitute different characteristics of the signal such as overall energy, peak-to-RMS ratio, and amplitude distribution [6, 2, 7]. By applying them directly or in combination with other features, various fault diagnosis methods have been implemented for condition monitoring of rotating machines components such as gearboxes, gearings and bearings across industries [8, 9, 10, 11, 12]. As the vibrational profile of a machinery represents the sum of vibrational signals at any given time, frequency domain based analysis methods such as Fast Fourier Transform (FFT) aim to decompose the raw signal into harmonic carrier waves with their distinct amplitude and frequency [13]. Unlike time and frequency domain based approaches that assume stationary conditions, time-frequency based methods such as Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Hilbert-Huang Transform (HHT) detect non-stationary features by analyzing the signal in both time and frequency domains simultaneously [14]. With the addition of induction motors, both frequency and time-frequency domain based features find similar applications to the mentioned time based variant in the condition monitoring of rotary machines and their components [15, 16, 17, 18, 19, 20, 21].

A recent approach towards the fault detection of engine mounts through vibrational signal analysis is shown by Maulana et. al. [22]. By installing acceleration sensors on the engine mount, the data is analyzed by applying the Hilbert-Huang Transform (HHT) through a two-stage process. During the empirical mode decomposition (EMD), the initial signal is iteratively decomposed into intrinsic mode functions (IMFs). Subsequently, the Hilbert Transform is applied to each IMF to map the instantaneous frequencies and amplitudes over time. By cross-referencing peak frequencies within damaged and undamaged states, a significant increase of amplitude is observed, serving as main indicator for detection.

2.2. Novelty

Existing vibration-based approaches for engine mount fault detection, such as the HHT-based method demonstrated by Maulana et. al. [22], require dedicated acceleration sensors mounted directly or in close proximity to the engine mount for data acquisition. This particular dependency introduces practical limitations such as sensor placement sensitivity, machine disassembly for installation, and restricted scalability across vehicle fleets. Consequently, a research gap is presented for fault detection methods that leverage acceleration sensors already built into production vehicles. This work addresses this gap by exhibiting the preliminary results of a viable fault detection method for engine mounts by using sensors data extracted from the vehicle's crash module, eliminating the need for additional measurement equipment while ensuring the scalability of the approach across different vehicle platforms.

3. Methodology

In line with the aspects mentioned regarding time-domain based vibration analysis in Section 2.1, the fault detection in the context of this study aims to establish a significant differentiation between the unhealthy and healthy state based on statistical feature values, serving as a decision criterion. The following sections describe the processes involved in the acquisition, processing, feature extraction, and evaluation of the acceleration signals generated by vehicle onboard sensors for the fault detection of engine mounts.

3.1. Experimental Setup

For the generation of acceleration signals and evaluation of the approach's transferability across a selected range of vehicles, different derivatives equipped with gasoline engines and hydraulic engine mounts were used. In total three vehicles of the following vehicle types were involved in the study, further referred to as Test Vehicle 1 to 3:

- Test Vehicle 1: 5-door midsize SUV
- Test Vehicle 2: 4-door fastback Coupé
- Test Vehicle 3: 5-door Gran Coupé

Each vehicle has two engine mounts in total which are located on the lower right and left side of the engine. Furthermore, the distinction between a healthy and unhealthy state is defined as follows:

- Healthy: Both engine mounts are undamaged.
- Unhealthy: Either the left or right engine mount is damaged.

The damage is introduced to the engine mount through an incision in the elastomer membrane of the hydraulic fluid reservoir and draining it, causing a significant loss of dampening capability. The puncture damage is expected to cause higher energy dissipation from the engine to the vehicle body, especially when being subjected to high amplitude and low frequency loads [23].

To accommodate passenger safety features such as crash detection, sensor readings of the vehicle's acceleration are continuously processed by its electronic control units (ECUs) [24]. For the test vehicles involved in this study, this feature is provided by the Advanced Crash Safety Module (ACSM). Located in positions such as underneath the driver's seat as shown in Figure 1, this module processes acceleration signals within the vehicle's longitudinal and lateral axes at a sampling rate of 100 Hz.

Through the internal bus communication system, the acceleration data from the ACSM are transmitted to other components of the vehicle using the FlexRay protocol. To gain access to the raw signals at their original sampling rate, a direct tap on the FlexRay network is installed in each test vehicle. The measurement equipment used to record the signals consists of the VN7640 transceiver and CANanalyzer software by Vector. The tap is linked via a D-SUB9 connection to the FRpiggy hardware interface of the transceiver. The data is transferred to a computer running the measurement software through a USB connection. A schematic overview of the measurement setup is shown in Figure 2.

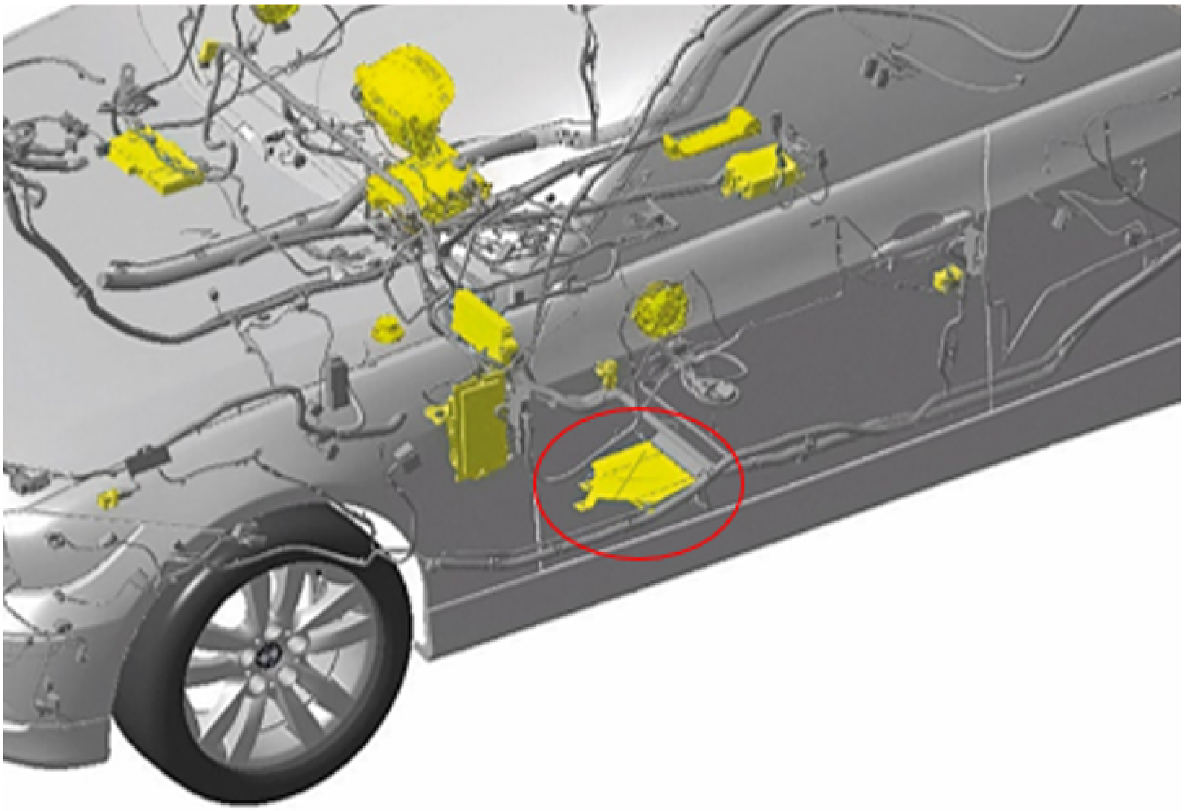

Figure 1: Exemplary overview of the ECUs (yellow) including the crash safety module or ACSM (circled red) in a vehicle produced by the car manufacturer BMW. (source: https://www.press.bmwgroup.com).

3.2. Data Acquisition

A vehicle's overall vibration behavior is influenced by various dynamic factors during its operation such as road conditions, speed, and driving maneuvers. To ensure the most optimal expressiveness of the engine mount fault on the acceleration signal, a specific and repeatable driving scenario was defined for the data acquisition. As already mentioned in 3.1, the specific engine mount fault, characterized by loss of dampening capability, is expected to cause increased transient forces from the engine to the vehicle body during operational states involving high amplitude and low frequency loads. Such a state is found during the ignition of the engine from a standstill position. Considering this state also bears the advantage of minimizing the influence of external factors mentioned in the beginning of this section.

To ensure comparability between the traces, the vehicles were driven until the engine coolant temperature reached 90 degrees Celsius prior to each recording, which started shortly before engine ignition and ended after reaching the idle state.

In total, 194 data traces have been recorded:

- Test Vehicle 1:
  - Healthy: 38
  - Unhealthy: 28
- Test Vehicle 2:
  - Healthy: 32
  - Unhealthy: 32
- Test Vehicle 3:
  - Healthy: 34
  - Unhealthy: 30

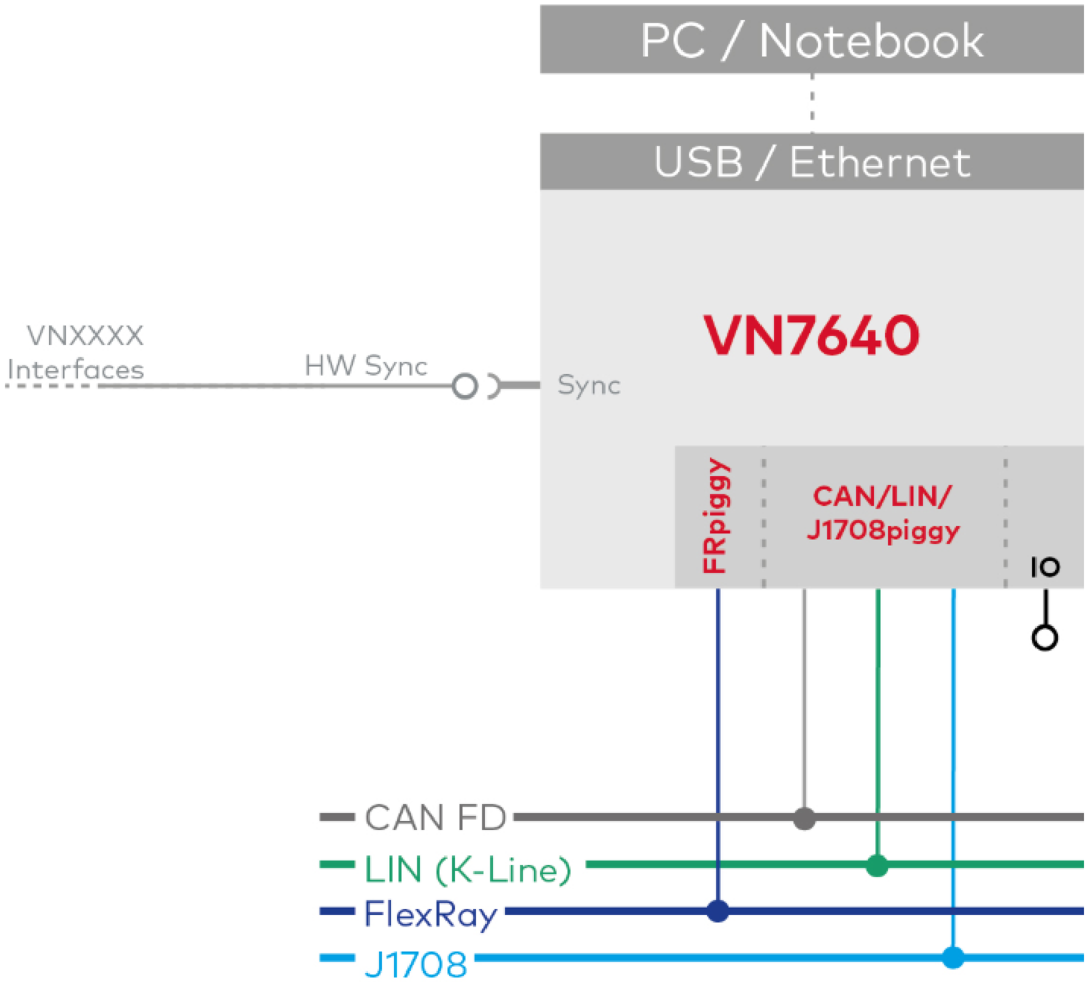

Figure 2: Measurement equipment interface with the vehicle's internal BUS communication network. (source: https://www.vector.com).

3.3. Data Preprocessing

Using the Python programming language and its libraries `asammdf` and `pandas`, the recorded traces were initially converted from their raw `.mf4` format into a more accessible `.parquet` format as instances of the `pandas.DataFrame` class.

From the reformatted data traces, longitudinal and lateral acceleration signal data is extracted along with engine crankshaft revolutions, serving as a segmentation signal. Each trace is trimmed to the timestamps where the crankshaft revolutions exceed zero, effectively placing the start the ignition at the first nonzero timestamp. The mean value of each trace is subtracted from their respective trace to remove constant offsets caused by the vehicle's tilt.

To analyze the progression of signal features over time, the traces are segmented into equally sized time windows. According to expert opinion, the ignition process, regardless of the vehicle's operational state, is confined within a predetermined time window after initial movement of the engine crankshaft, further referred to as Time Window A. The subsequent transition phase to the idle state and the idle state itself are segmented into their respective time windows, resulting in the additional Time Windows B and C. Figure 3 shows the progression of the lateral acceleration and the engine crankshaft's revolutions per minute (RPM) of a preprocessed trace with highlighted time window regions.

In Time Window A, the engine crankshaft experiences rapid acceleration from its initial minimum value, accompanied with strong oscillating and irregular acceleration readings, primarily caused by

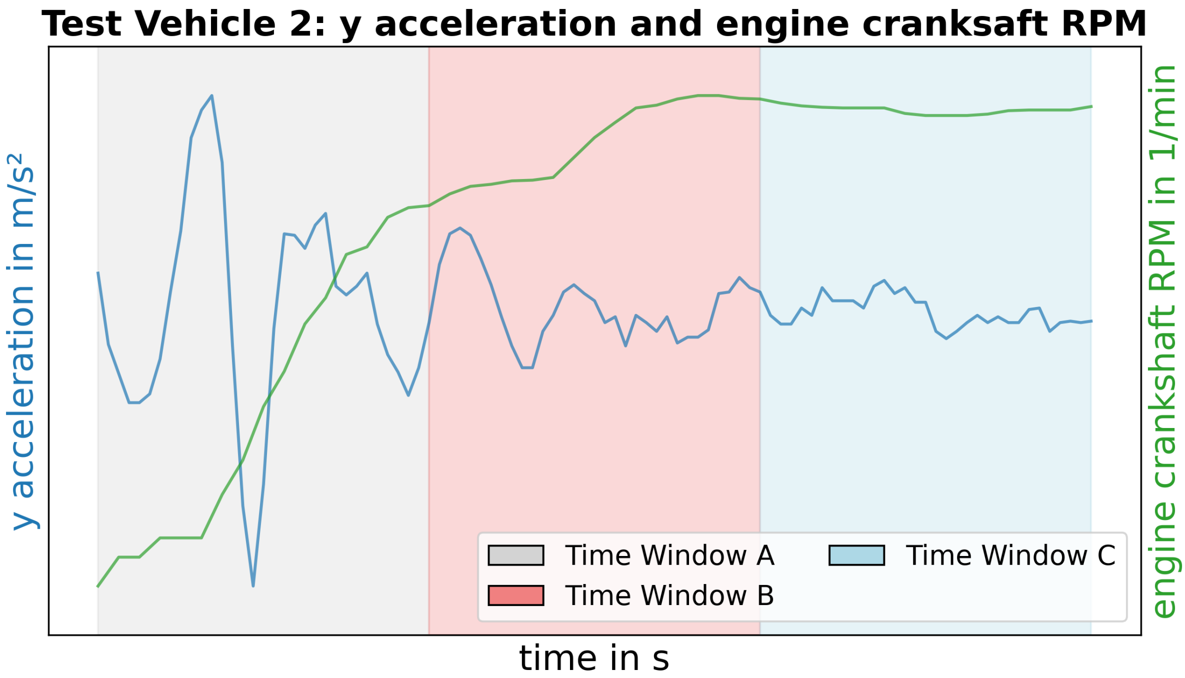

Figure 3: Segmented lateral acceleration (blue) and engine crankshaft RPM (green) of a preprocessed trace over time.

the intertial forces. With further progression into Time Window B, both signals stabilize. Engine crankshaft RPM approaches idle speed and lateral accelerations show less frantic behavior. Finally, in Time Window C, the engine reaches a near constant RPM and lateral acceleration oscillates with minimal amplitudes, indicating the idle state.

3.4. Feature Extraction

Within each segment, the following time-domain based statistical features are calculated for both the longitudinal and lateral acceleration signals, where $x[n]$ is the value of the signal at index n, $n = 0, 1, \ldots, N-1$ the sample index, and N the total number of samples in a given trace:

- Root Mean Square (RMS):

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} x[n]^2}$$

- Kurtosis:

$$\mathrm{Kurtosis} = \frac{\frac{1}{N}\sum_{n=0}^{N-1}\left(x[n]-\mu\right)^4}{\left(\frac{1}{N}\sum_{n=0}^{N-1}\left(x[n]-\mu\right)^2\right)^2}$$

$$\text{where} \quad \mu = \frac{1}{N}\sum_{n=0}^{N-1} x[n]$$

- Crest Factor:

$$\mathrm{CF} = \frac{\max\limits_{0\le n<N} |x[n]|}{\sqrt{\frac{1}{N}\sum_{n=0}^{N-1} x[n]^2}}$$

The features are calculated per segment and then aggregated by grouping over the test vehicle, health state, and time window.

4. Results

On the example of Test Vehicle 2, Figures 4 to 6 show distribution of RMS, Kurtosis, and CF features for each time window within the longitudinal (x) and lateral (y) directions of acceleration, split separately between healthy (lightgrey) and unhealthy (lightorange) states.

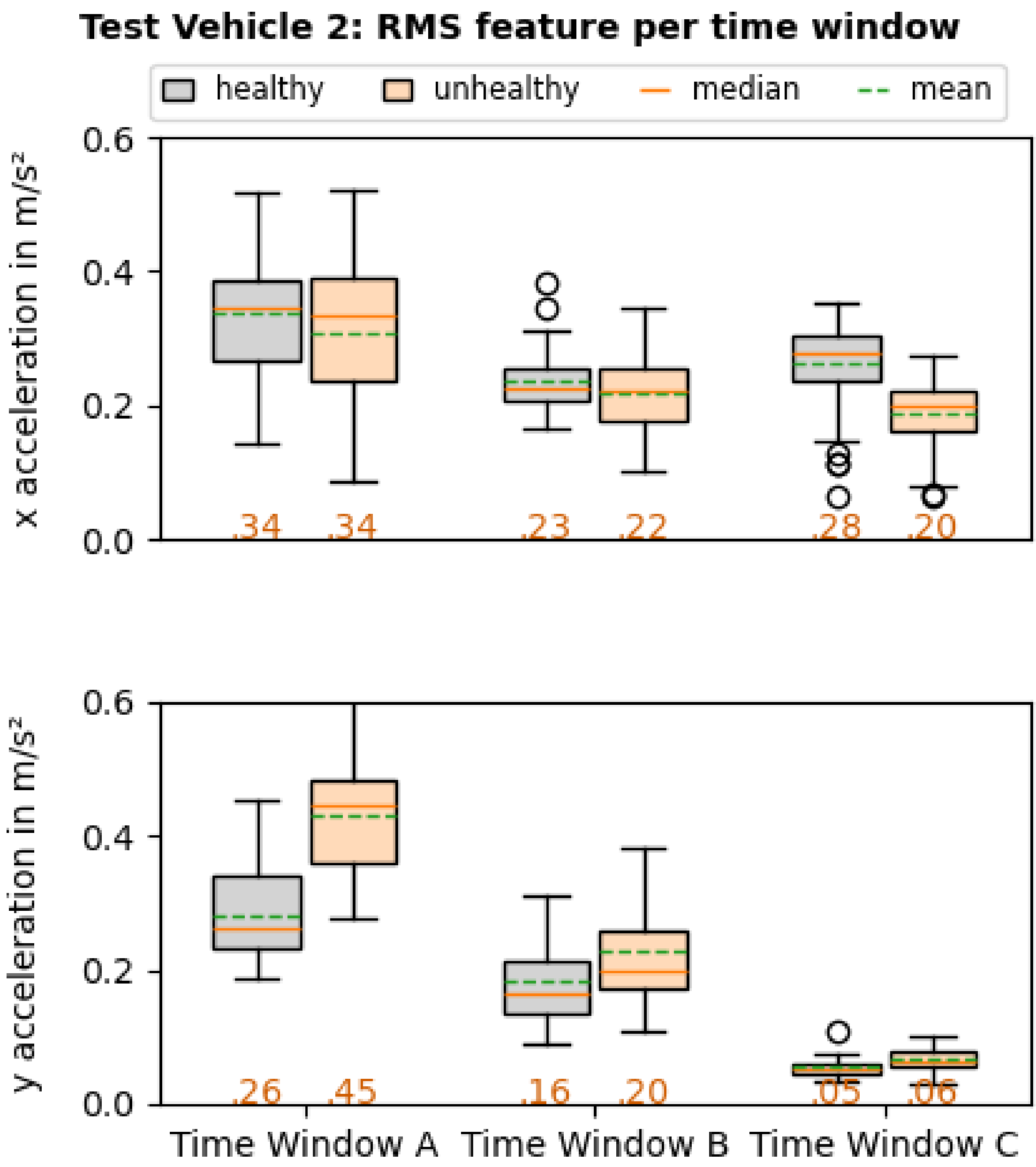

Figure 4: Box plots of RMS features grouped over x and y accelerations, health state and time window of Test Vehicle 2.

For both CF and Kurtosis features, negligible differences were observed between interquartile ranges (IQRs), mean, and median values of the health states across time windows and acceleration axes. During and after engine ignition, the fault-induced changes do not lead to a significant change in both distribution shape and peak-to-RMS ratio when compared to the healthy state. Neither metric showed sensitivity to the induced fault.

Similarly, RMS features of longitudinal acceleration show no consistent separation of IQRs, mean, and

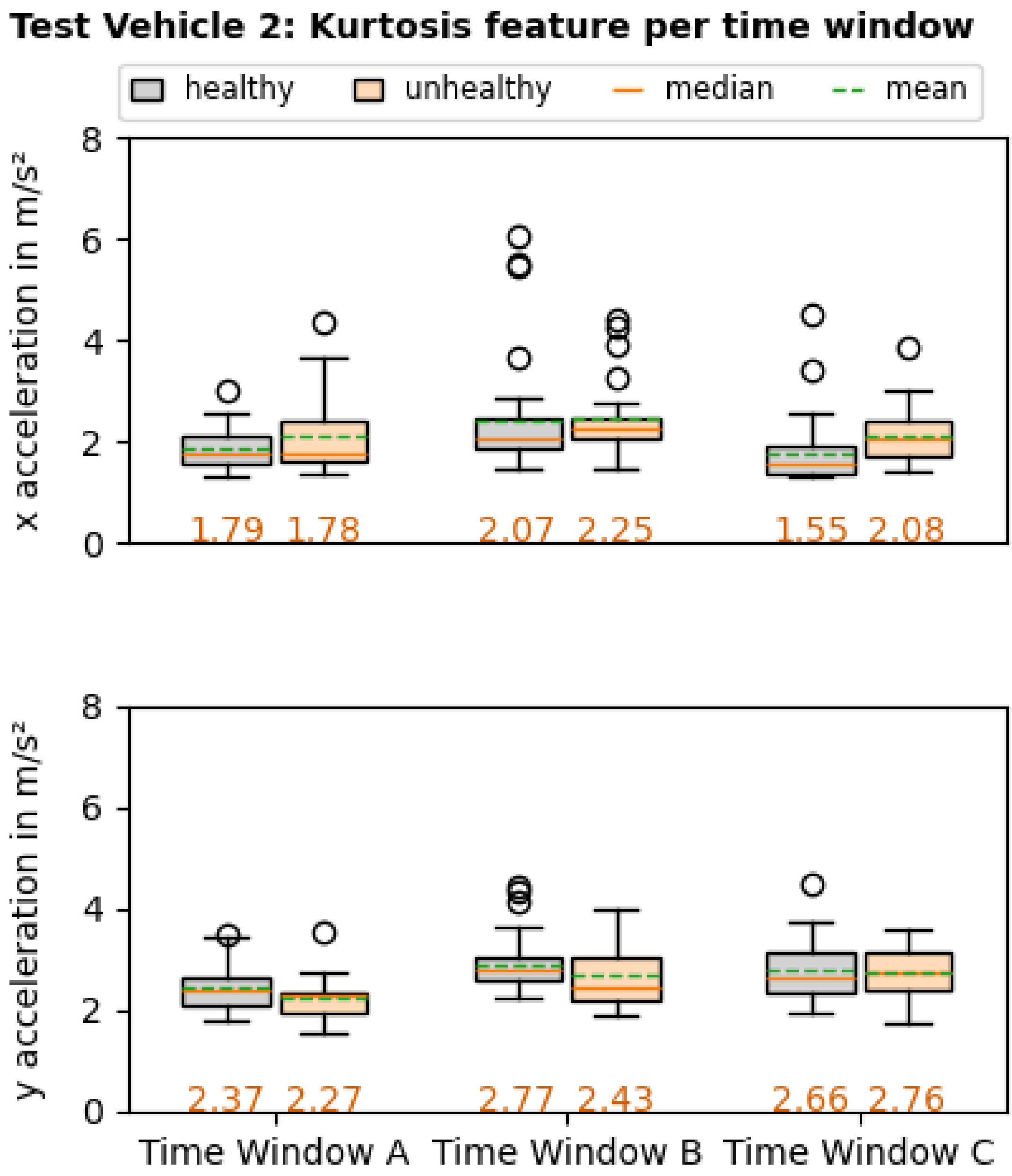

Figure 5: Box plots of Kurtosis features grouped over x and y accelerations, health state and time window of Test Vehicle 2.

median, with the exception of Time Window C which shows a lower distribution for unhealthy traces. As the engine transitions from high-amplitude, low-frequency loads to low-amplitude, high-frequency loads after ignition, this unexpected result is likely caused by inconsistent brake actuation leading to slight longitudinal vehicle movements unrelated to the engine mount condition.

A strong negative correlation between acceleration amplitude RMS and time was found in the lateral RMS features, which is consistent with previous assumptions. This observation is accompanied by a greater separation between the IQRs, median, and mean of the healthy and unhealthy states in earlier time windows, with Time Window A showing a clear and statistically significant elevation of unhealthy RMS values.

Similar to Test Vehicle 2, the bus traces from Test Vehicle 1 and Test Vehicle 3 (Figures 7 to 12) confirm the same trends across all three features. Specifically, Kurtosis and CF exhibit overlapping distributions

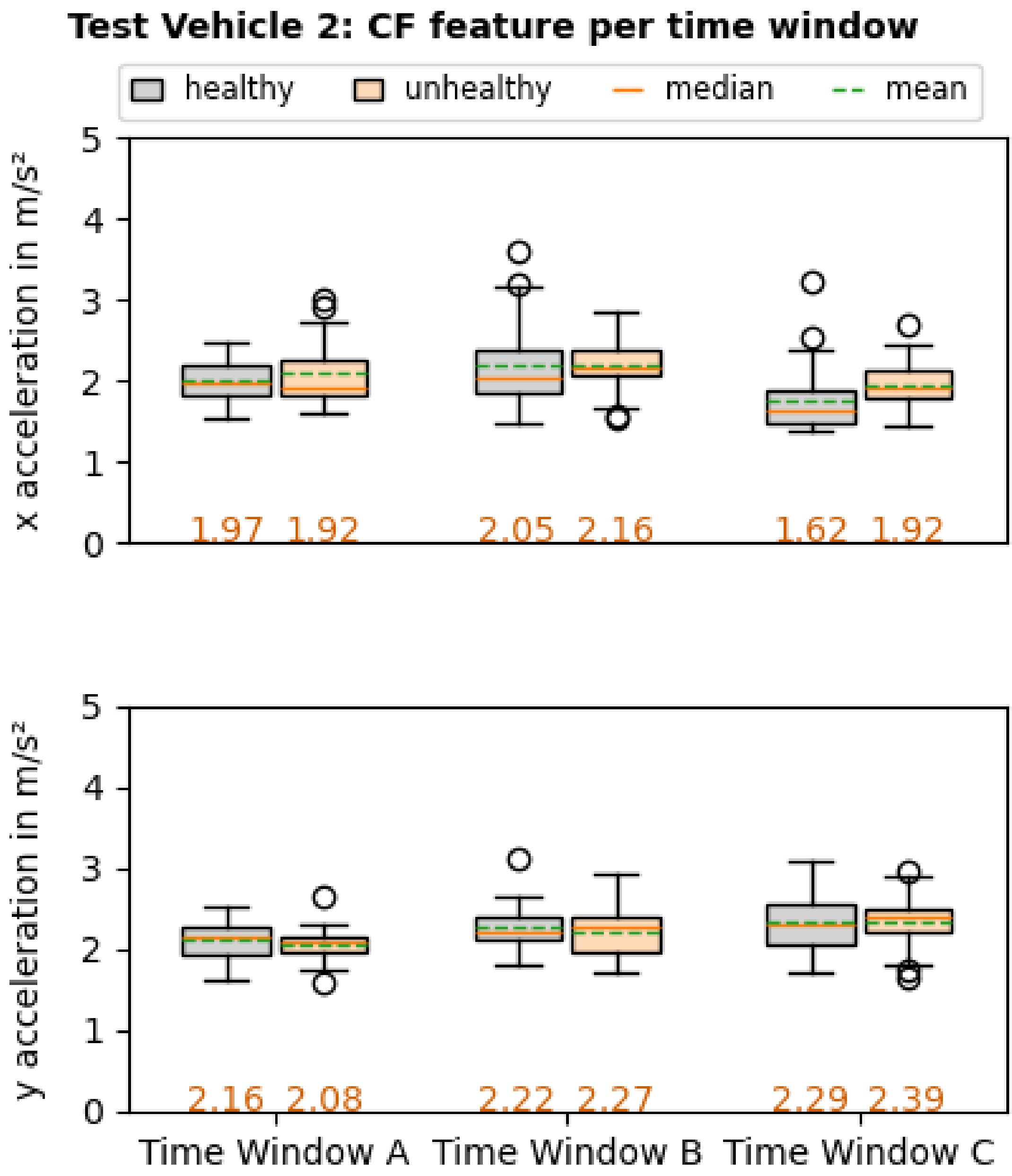

Figure 6: Box plot CF features grouped over x and y accelerations, health state and time window of Test Vehicle 2.

across health states, time windows, and acceleration axes, reinforcing the notion that these features are not sensitive to the specific fault. Conversely, the lateral RMS demonstrates consistent elevated values in the unhealthy state in Time Window A across all vehicles. Across vehicle platforms, the relative RMS median offsets varied between 25.0% (Test Vehicle 3), 27.3% (Test Vehicle 1), and 73.1% (Test Vehicle 2).

5. Conclusion

With the initial goal of detecting engine-mount faults, this study investigated the potential of using data generated by onboard acceleration sensors. By analyzing statistical features of the vibrational signals from the crash module within time windows set during and after engine ignition, the RMS features from the lateral acceleration in particular were able to show distinct differences between healthy and unhealthy engine mounts states across the considered test vehicles. No reliable fault indication could be established from the longitudinal acceleration's RMS features, reinforcing that the dominant fault-induced vibration pathway is lateral. Other statistical features such as Kurtosis and CF remained insensitive across all test vehicles, suggesting that the specific fault does not significantly impact the impulsiveness or peak-to-RMS ratio, only its overall energy. The lateral RMS features revealed a strong negative correlation over the time windows and the largest positive offset of unhealthy relative to healthy features in Time Window A. This observation aligns with the initial assumption of increased energy dissipation from the engine to the vehicle body caused by fault-induced damping loss in the engine mount during the high-amplitude, low-frequency loads, found especially within the initial phase of engine ignition. These findings suggest that readily available vehicle sensor data, leveraged by techniques from traditional vibration analysis, can serve as an effective approach for the detection of damaged engine mounts without additional measuring equipment. By comparing the lateral acceleration's RMS features to a baseline made during the early healthy states of the vehicle, it can serve as an indicator upon suspicion of a engine mount fault, reducing time and resources otherwise needed for conventional means of diagnostics.

6. Future Work

As previously mentioned in Section 4, the inconsistency of brake actuation during data acquisition likely influenced the longitudinal RMS features, causing incosistent conditions between traces. Other effects such as vehicle platforms, ambient temperature, positioning of the vehicle, battery charge state, and engine oil temperature can have an impact on the vibrational behavior of the vehicle during engine ignition. To ensure further comparability between traces, variations in these factors should be monitored and accounted for in future data acquisitions. With the advancement of computation and storage capacities of modern ECU generations, the data extraction and feature computation onboard, enabling real-time monitoring and storage by transmitting aggregated features instead of raw continuous traces. As this solution only suggests an engine mount fault based on statistical features, data-based approaches such as Machine Learning can be applied to recognize patterns in the raw timeseries data and thus detect faults on component level.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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A. Box Plots of Statistical Features of Test Vehicle 1 and 3

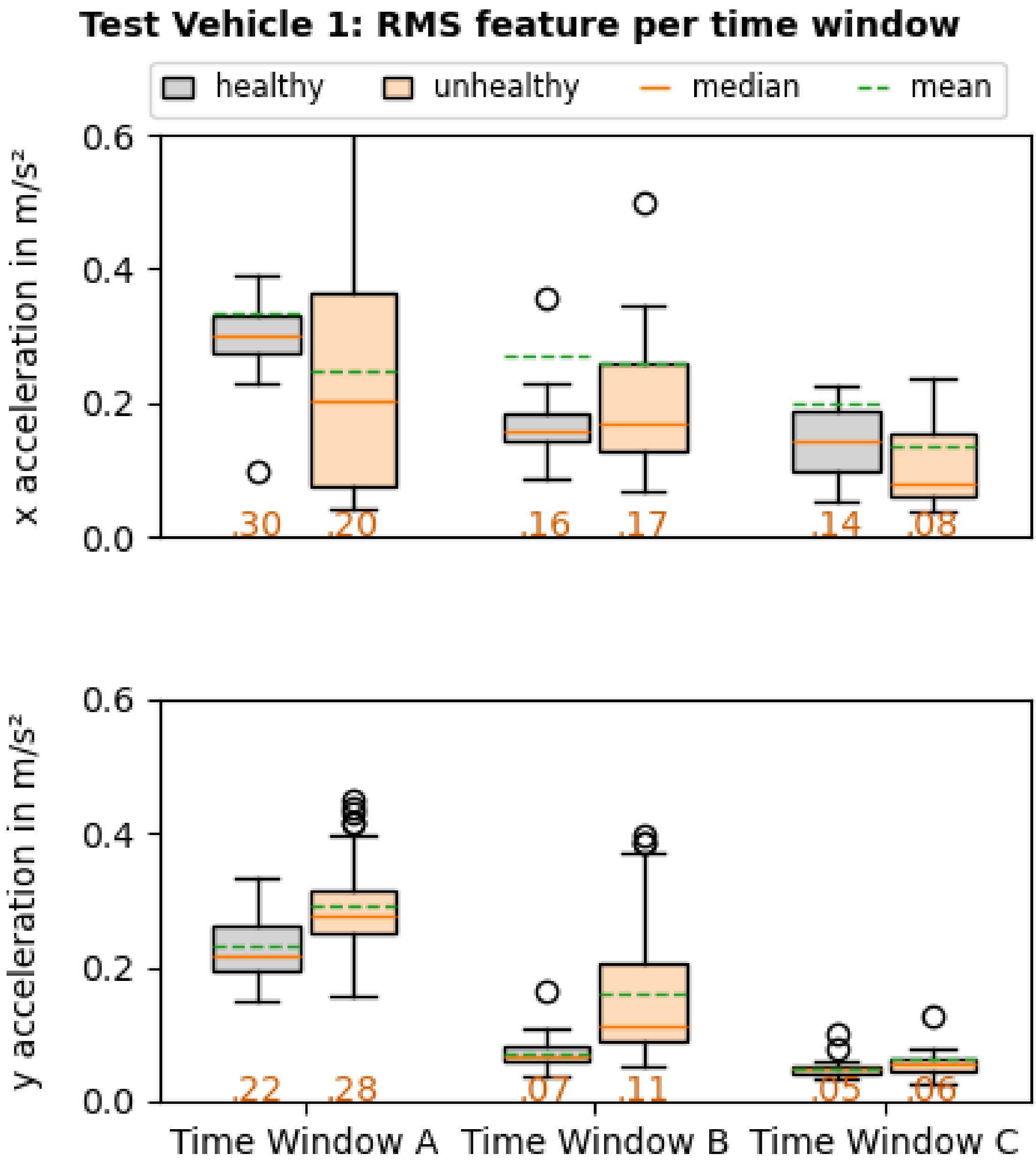

Figure 7: Box plot of RMS features grouped over x and y accelerations, health state and time window of Test Vehicle 1.

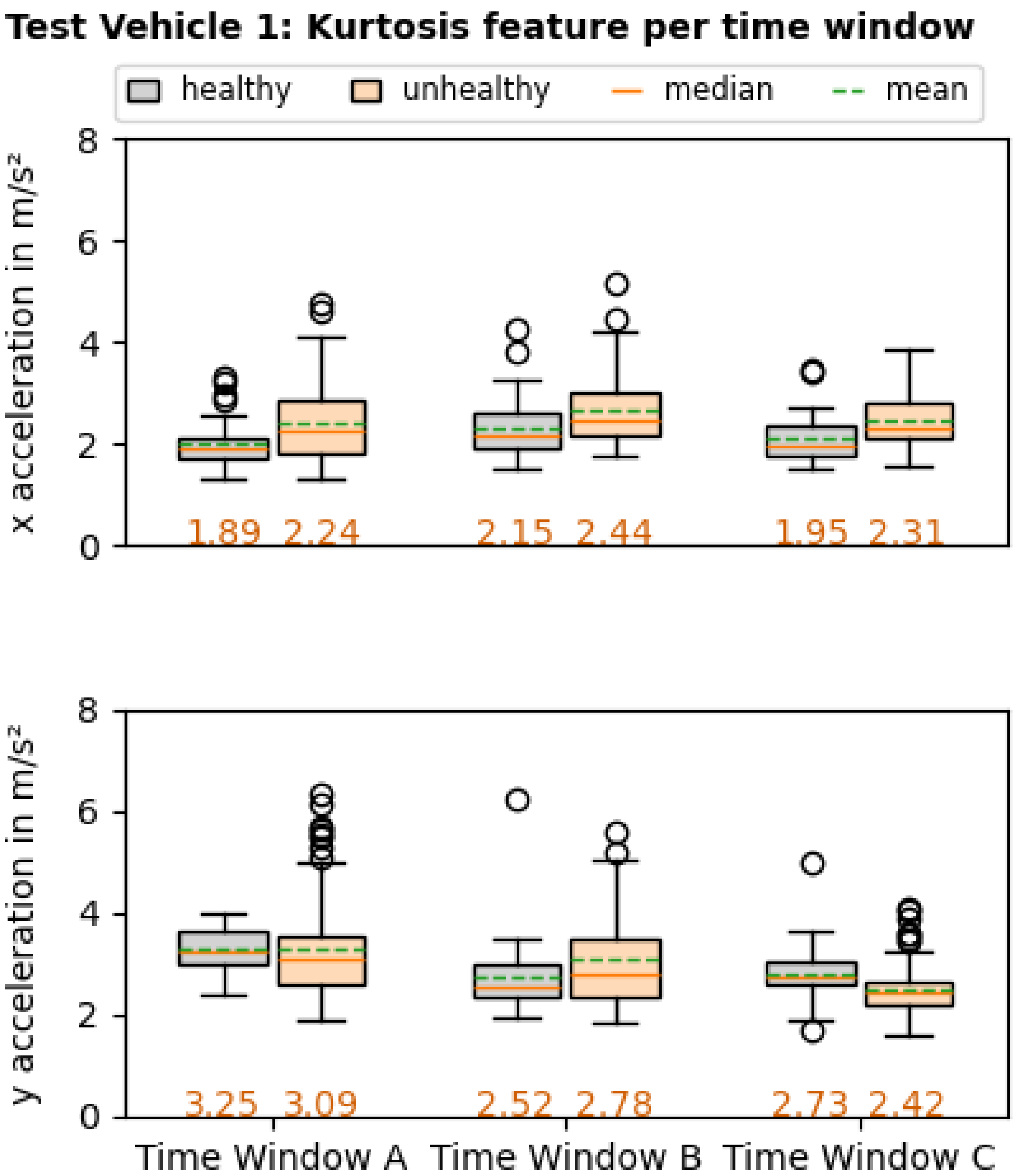

Figure 8: Box plot of Kurtosis features grouped over x and y accelerations, health state and time window of Test Vehicle 1.

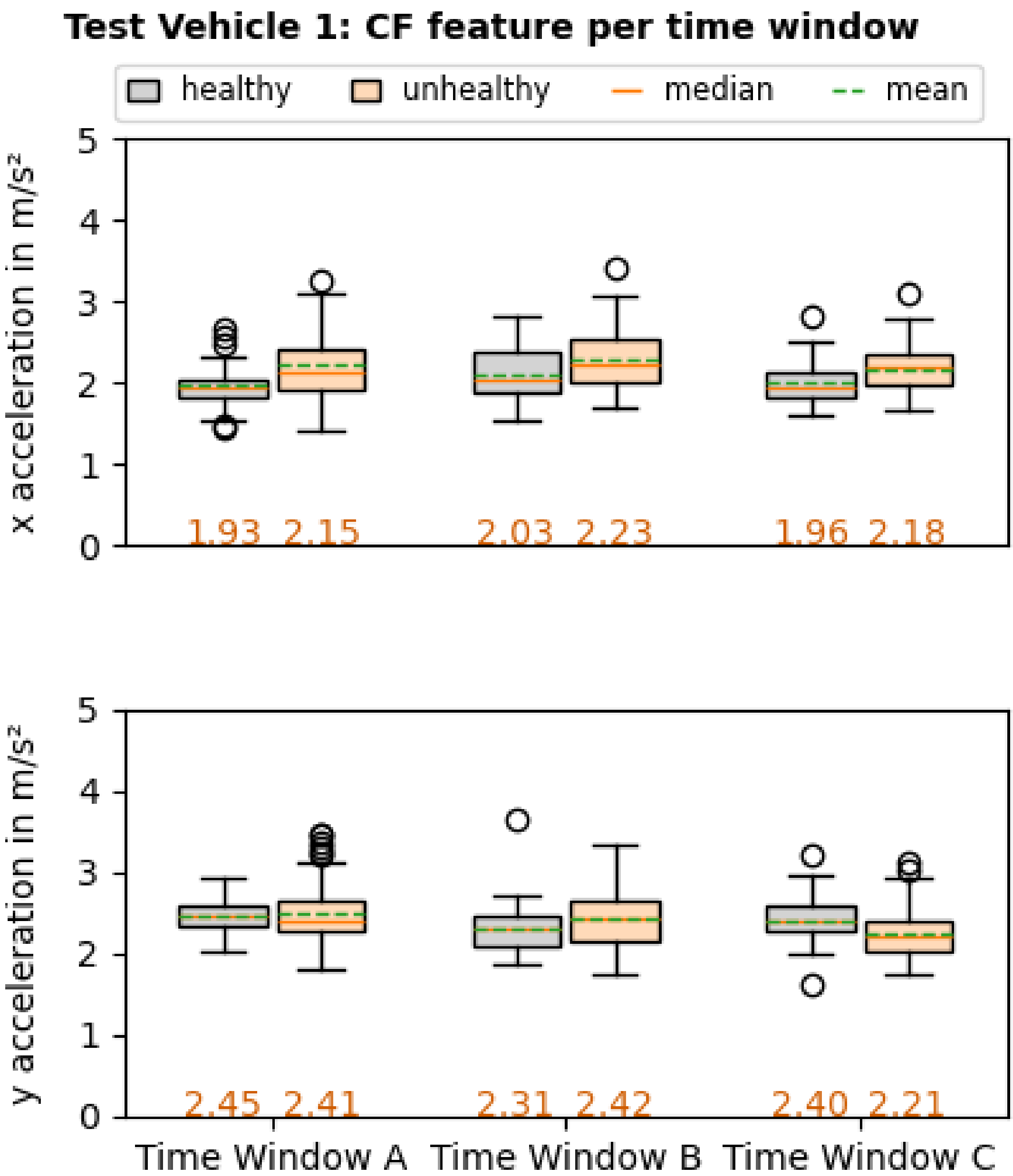

Figure 9: Box plot of CF features grouped over x and y accelerations, health state and time window of Test Vehicle 1.

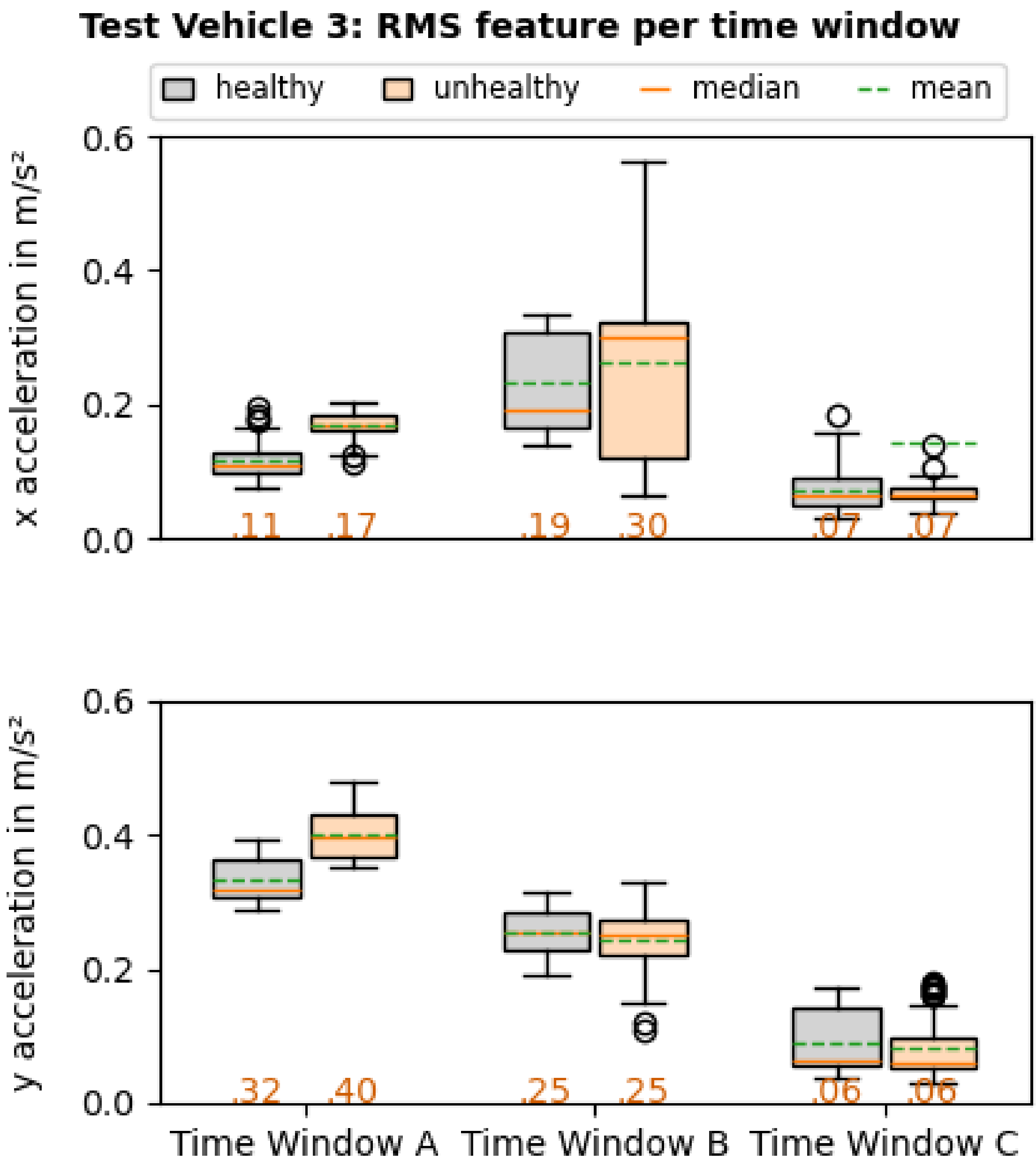

Figure 10: Box plot of RMS features grouped over x and y accelerations, health state and time window of Test Vehicle 3.

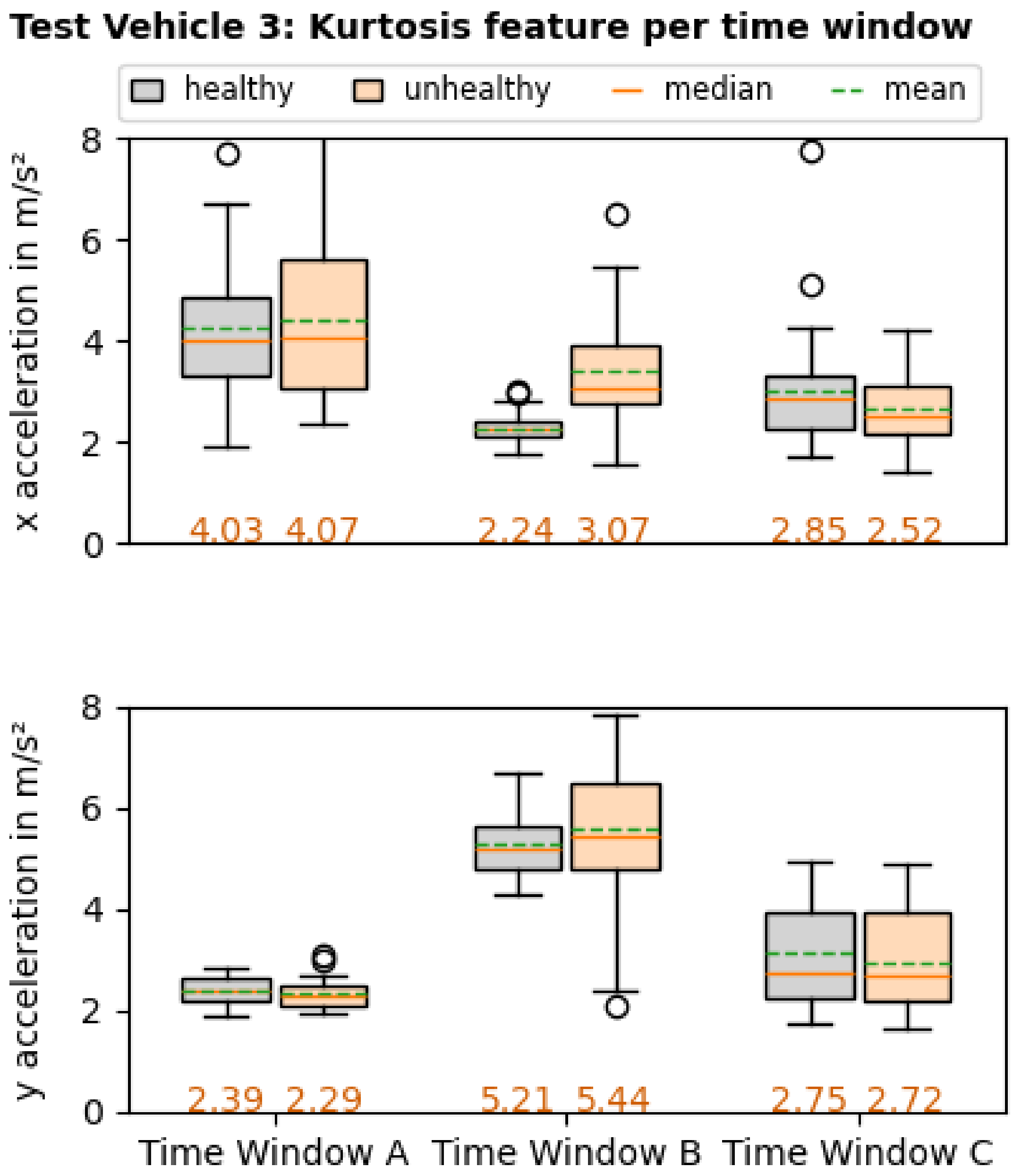

Figure 11: Box plot of Kurtosis features grouped over x and y accelerations, health state and time window of Test Vehicle 3.

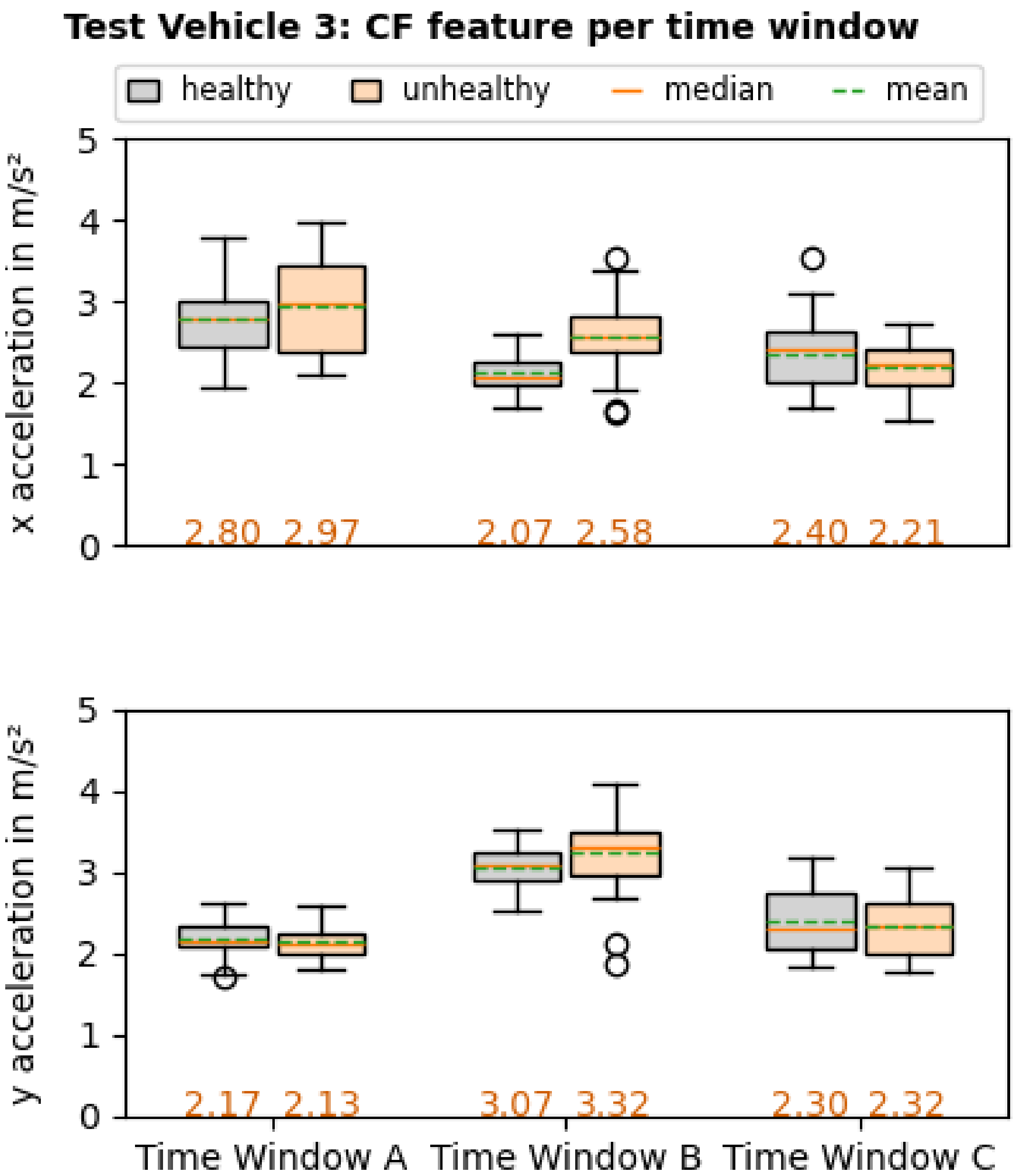

Figure 12: Box plot of CF features grouped over x and y accelerations, health state and time window of Test Vehicle 3.