Smartphone-Based Wheel Imbalance Detection

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SMARTPHONE-BASED WHEEL IMBALANCE DETECTION

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ABSTRACT

Onboard sensors in smartphones present new opportunities for vehicular sensing. In this paper, we explore a novel application of fault detection in wheels, tires and related suspension components in vehicles. We present a technique for in-situ wheel imbalance detection using accelerometer data obtained from a smartphone mounted on the dashboard of a vehicle having balanced and imbalanced wheel conditions. The lack of observable distinguishing features in a Fourier Transform (FT) of the accelerometer data necessitates the use of supervised machine learning techniques for imbalance detection. We demonstrate that a classification tree model built using Fourier feature data achieves 79% classification accuracy on test data. We further demonstrate that a Principal Component Analysis (PCA) transformation of the Fourier features helps uncover a unique observable excitation frequency for imbalance detection. We show that a classification tree model trained on randomized PCA features achieves greater than 90% accuracy on test data. Results demonstrate that the presence or absence of wheel imbalance can be accurately detected on at least two vehicles of different make and model. Sensitivity of the technique to different road and traffic conditions is examined. Future research directions are also discussed.

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1 Motivation

Rim and tire imbalance and unevenness of wheel geometry are common problems in vehicles, with effects ranging from minor annoyance to the driver due to diminished ride quality to severe impact on vehicle function and reduction in service life of high cost or safety-critical components. A bent wheel, or a wheel out of balance, imparts unintended vibration on suspension components and may manifest as a "shimmy" or "shake" on the steering wheel, rattle a vehicle and its contents, or cause loads to be applied on vehicle components in unanticipated ways. This varied loading can pose a challenge to gaining or maintaining traction due to complex dynamics. Additionally, wheel vibration can cause uneven tire tread wear and the presence of vibration due to imbalance is often an indicator correlated with the development of larger problem, such as a bent tie rod occurring from the same incident, causing the initial imbalanced condition. Large wheel deformations can even lead to slow leaks and air loss, which at best reduce fuel economy and vehicle performance, and at worst, lead to a blowout with potentially dire consequences.

It is for these reasons that monitoring wheel and tire balance is critical to the safe operation and proper long term maintenance strategy for any wheeled vehicle, particularly those which are lightweight and operate at high sustained speeds, such as many modern passenger vehicles. Unfortunately these imbalance issues are only detected and corrected for during vehicle maintenance and inspection checks, set at fixed, infrequent intervals. In-situ monitoring allows the collection of data about vehicle behavior in real-time and can mitigate driver annoyances, reduce the cost of ownership of a vehicle, and help to ensure safe and comfortable operation of a vehicle across a range of speeds and conditions. There have been several studies to enable real-time, in-situ monitoring by instrumenting wheels and suspension components with accelerometers and other sensors mounted to a vehicle [1] [2]. While these approaches work well, the process of instrumenting the vehicle with aftermarket external sensors is cumbersome and costly. An alternative of accessing data from manufacturer-proprietary sensors requires expensive and complicated hardware and software interfaces that limit the utility of a sensing algorithm to individual makes or models of vehicles.

In this work, we examine the possibility of using the onboard sensors on a smartphone as a substitute for these external or manufacturer-proprietary sensing devices so as to provide low cost and easily deployable wheel balance detection. To this end, we collect accelerometer data from the smartphone in both balanced and imbalanced wheel conditions. We induce an artificial imbalance by adding extra weights to the wheel, which mimics real world situation stemming from wheel damage or loss of balancing masses. Typically, are vibrations felt above 60mph [1], so we collected data at this speed on highways for balanced and imbalanced states. There is no unique distinguishing signature observed in an FFT of the accelerometer data. Therefore, we use a supervised learning approach by building a classification tree model using the FFT features, which yielded a classification accuracy of 79% on test data. We then make use of a PCA transform of the FFT data that helps uncover a single excitation frequency that can be used to uniquely distinguish between the balanced and imbalanced states. A classification tree trained with the PCA features demonstrates greater than 90% classification accuracy on test data.

Section 2 discusses the causes of imbalance in wheels and suspension systems. Section 3 discusses the related work in wheel imbalance detection and positions our work in that context. Section 4 discusses the experimental setup for our study, e.g how imbalance was artificially introduced in a vehicle as well as the mobile phone sensor data that was gathered to detect the imbalance and support our hypothesis. Section 5 presents data post processing and the development of machine learning algorithms that were used for imbalance detection. Section 6 discusses the sensitivity of the hypothesis to factors such as variable traffic flow, road conditions and vehicle make. Finally, Section 7 presents the conclusions of this study and directions for future work.

2 Sources of Imbalance

In use, moving vehicles suffer from non-cyclic or non-predictable vibration due to irregularities in the road surface. Additionally, imperfections in the manufacturing of tires and wheel rim components, or use-phase events, can create a vibration induced in a vehicle related to the rotation of wheels and tires. The net result of an unbalanced assembly or noncircularity is the same regardless of the source of the issue: an unbalanced mass distribution or a noncircularity will result in the creation of an internal source of vibration in a vehicle, for which the severity of the vibration depends upon the magnitude of the imperfection, the vehicle suspension, and the wheel rotational frequency.

To some extent, these imbalances can be offset by the use of balancing weights [3], but the efficacy of these weights need to be periodically reassessed over time and car use as deformations, wear, and related material loss continue to change the balanced state of the wheel. Due to the constant rotation of the wheels in motion, internal vibrations are a periodic phenomenon occurring at a determinable frequency related to the loaded tire diameter and vehicle velocity. Unbalanced wheels are the cause of several detrimental effects such as loss of ride comfort as well as wear and tear of suspension components [4] [5]. These vibrations apply unnecessary loading to wheel bearings, steering linkages, and fasteners in the vehicle not designed to withstand constant, cyclic loading. A severe imbalance can impact the traction of a tire and reduce cornering and braking abilities due to temporarily reduced grip.

There are many reasons a wheel might become out of balance. Common causes include a mechanical deformation of the metal wheel, or loss of weights due to impact. Drivers hit curbs while parking, warping or removing material and shifting the balance of the wheel and tire assembly, or a hub cap dislodges and shifts the center of mass of the wheel. An isolated impact can knock a balancing weight off of a wheel. Adhesive deteriorates over time for many weight backings, and clip-on weights are frequently secured improperly or the material properties of the clip degrade due to cyclic loading. Continued traversal of a stretch of road with poor surface roughness, corrosion, and many other factors can cause early, unanticipated failure and loss of balancing weights.

Tire wear and damage can also impact the balance of a rotating assembly. Steel belts inside a tire may become damaged in an impact, due to a manufacturing defect, or due to prolonged over or under inflation, causing a tire to go out of balance. Tires have non-uniform density, so wear and tread loss alone can cause a significant shift the balance of a wheel and tire assembly (poor alignment can exacerbate this situation). In the case of rapid acceleration and braking on a newly-seated or underinflated tire, the rubber and metal components can experience a relative slip causing a shift in the center of mass, while rubber bubbles that form due to damage of the inner layers of the rubber can cause the tire surface to become locally nonuniform.

In most cases, the risk and impact of wheel assembly imbalance is directly related to vehicle load and speed. Increasing vehicle load, or increasing speed even slightly, greatly amplify the potential for damage and resulting imbalances. As vehicle loads and speeds increase, the energy involved in an impact with a raised surface in the roadway increases and the likelihood of damage rises substantially [6]. The energy in an impact is related to the kinetic energy, $KE = \frac{1}{2}mv^2$. Thus, an increase in mass increases impact energy and the likelihood of damage, while even a small increase in velocity can make for a substantially more energetic collision. Similarly, the energy imparted by an imbalanced wheel rotating at high speed is higher than that of a wheel rotating at low speed, and the potential for damage and discomfort increases.

Less commonly, but still frequently occurring, there are other wear and tear factors, as well as temporary, environment-related conditions that can impact loading. Tires can pick up debris such as screws or rocks from the road, or even snow and ice buildup can temporarily shift balance to the point of inducing a noticeable vibration. A small mass rotating at a radius can generate a substantial loading at a radius with a high angular speed.

FIGURE 1. iPhone mounted in vertical orientation. The accelerometer directions are labeled.

3 Background

There are several well established practices to mitigate the effect of wheel imbalance. For example, *on-car balancing* techniques, which involve lifting a car and rotating each wheel to check for imbalance, make use of weights attached to the wheel rim to counteract the unbalanced mass of that particular wheel [7]. The benefits are debatable since the vibration dynamics of loaded, rolling tires on roadways can be significantly different from those of an unloaded tire lifted off the ground [8]. Road-force balancing offers an alternative approach, but it is difficult for drivers to know when a re-balance is required unless a problem has significantly manifested.

With the advent of MEMS accelerometers and the development of condition monitoring strategies there has been an increased interest in on-road monitoring of wheel imbalances [9]. For example, Oblizajek *et. al* propose a system that makes use of accelerometers and wheel rotation data to measure and mitigate the transference of vibrations from wheels to different components in a car [8]. There have been several other instances of wheel imbalance detection in instrumented vehicles [10]. A demonstrated in-car system for monitoring tire balance relies on accelerometers to identify radial and lateral acceleration of the tire and compare amplitudes to a known good baseline at characteristic frequencies, in effect examining differences in the amplitude of the Fourier component of radial acceleration [11] [12]. A variant on this setup uses an accelerometer on each wheel, to identify vibration and even calculate tire pressure, but cost and complexity of this system is significantly greater [13]. Another application of accelerometer examines the use of wavelet transforms for improved diagnostic accuracy while a Ford study relied on the use of already-installed ABS sensors to detect imbalances and and wheel hop, though access to this data is limited to particular makes and models of vehicles and requires low-level signal interfaces [2] [1].

These studies provide good results but require the instrumentation of the vehicle with custom hardware containing accelerometers, or data acquisition systems that average users do not have available. The use of commoditized hardware like a mobile phone greatly eases deployability and reduces cost of instrumentation. This study examines the feasibility of using the smartphone's accelerometer as a replacement.

4 Experimental Design

The ubiquity and low-cost of smart phones makes their use as tools in vehicle diagnostics appealing. Application development for smart phones is relatively simple, the devices are small, light, and easy to mount, and power options are abundant. In recent years, MEMS motion sensor resolution and sampling rates have greatly improved in mobile devices, making data capture increasingly useful [14]. Many mobile devices also include additional sensors which could provide additional information. As an example, most smartphones also have an on-board gyroscope which can provide vehicle turning information if necessary.

The mounting location of the phone was chosen to be in a rigid mount affixed to the windshield of the car in the vertical position (c.f Fig 1) as test data in the cupholder, door panel pocket, and on the arm rest underwent unpredictable rotation and faced additional vibration, picking up noise that would require significant filtering to eliminate. Keeping the phone in a fixed location and orientation prevented the need for tracking the motion of the phone itself, simplifying the analysis of accelerometer signal data and ensuring a higher signal to noise ratio for input data for the classifier.

An experiment was constructed using a 2015 Subaru Impreza with P195/65R15 tires and later repeated with a 2013 Nissan Versa with 15 inch steel wheels and high profile P185/65R15 tires [15] [16]. The high profile sidewall of the tire and small diameter of the wheel minimize the risk of pothole or curb damage due to its action as a compliant region, absorbing impact energy that would otherwise be transferred to the wheel. This helped to ensure a clean set of baseline data with minimal pre-existing balance defects. An iPhone 5S sampling at 100 Hz was mounted to the windshield, capturing 3-axis accelerometer data. By the Nyquist-Shannon criterion, this would allow us to detect features of up to 50 Hz without encountering aliasing issues. For the purposes of this study we focus on the y-axis component of acceleration, as this is the axis most impacted by wheel imbalance [17].

The vehicle was first driven at a controlled speed of 60 mph using the cruise control feature. Sampled data were available-captured for at least 10 minutes in aggregate, with accelerometer and gyroscope data captured to the smartphone mounted to the windshield. We refer to this set of data as the *baseline case* in our subsequent analysis. 60 mph was chosen as being a *significant* speed capable of exciting a perceptible imbalance, but not significantly over the *cutoff* frequency of 50 Hz (the Ford paper identifies this velocity as 58mph, for their vehicle configuration). [1] Next, four 1/4 oz adhesive-backed weights were applied to the inside edge of the front right and rear left and right wheels, for a total of 28g per wheel. The addition of these weights served to induce a moderate level of wheel imbalance, perceptible but not only when attention was drawn to it (in a similar study conducted by Ford, 60 *g* weights were referred to as *imperceptible* by two of three test drivers, indicating the subtlety of the imbalance). This ensured that any classification would be at or below the level of human sensitivity, and as such could be an early indicator capable of detecting a problem prior to the driver becoming aware of an issue. We refer to this data set as the *imbalanced case* in the subsequent analysis. We repeated the data collection for uncontrolled (driver throttle modulation) to analyze the impact of vehicle velocity constancy, throttle control, and traffic to gauge the efficacy of any devised algorithms in more realistic, real-world scenarios. In the following section, we present the analysis of the accelerometer data.

5 Data Analysis

The analysis of the accelerometer data proceeds in three phases. First, we apply signal processing techniques to reduce obvious sources of noise in the data. Next, we conduct a spectral analysis of the data. Finally, we discuss the development of machine learning techniques used to detect wheel imbalance conditions. The following sections discuss each phase:

5.1 Data pre-processing

We first mitigate the contaminating effects of low-frequency dynamics such as pothole striking events, road surface imperfections and infrastructure contributions such as expansion joint periodicity. This is achieved by passing the accelerometer data through a high-pass filter. The value of the cutoff frequency for this filter is obtained by considering both the low-frequency dynamics as well as typical wheel and tire sizes and common highway speeds. We assume that events such as pothole impacts and road imperfections are aperiodic one-off events, which have an impulse of energy diffused across the frequency spectrum. Expansion joints spaced at 5 m appear at a periodic 5.36 Hz for a vehicle speed of 60 mph, while acceleration and deceleration events under h control of the throttle tend to be modulated at low frequencies. In the case of our study, at 60 mph (26.8 m/s), and assuming a tire circumference of 1993.34 mm (for the P195/65R15 tire size of the Subaru Impreza) [1], we anticipate a tire rotational frequency of 13.4 Hz (13.6 for the Nissan Versa's smaller tire). We therefore set the cutoff frequency for the filter at 5 Hz, to minimize environmental measurement.

TABLE 1. Student t-statistics for peak frequencies observed in the imbalanced condition

Frequency (Hz)	t-stat	Result (α=0.05)
14	7.8810 (d.o.f 118)	Significant peak
28	6.9773 (d.o.f 118)	Significant peak

5.2 Spectral analysis

From Section 4, recall that we obtained 10 minutes of accelerometer data for both the baseline and imbalanced cases. We segment this data into 120 sub-sets each containing 5 s worth of data. We obtain a spectral representation of each sub-set using a Fast Fourier Transform (FFT). Fig 2 presents statistics from the spectral analysis of the 120 sub-sets for both the baseline and imbalanced case. We note significant energy contributions at the following frequencies:

> *Common peaks*: We note a peak in the Fourier Transform plots at about 10 Hz and another at 18-20 Hz. These occur in both the baseline and imbalanced cases. Section 5.3 discusses the sources of these energy components in more detail.
>
> *Imbalance specific peaks*: There also appears to be a visible peak at 14 and 28 Hz for the imbalanced case which are statistically significant under the Student's t-test (see Table 1).

It is also worth noting the variability between sub-sets of data as illustrated by the spread in the average data. Therefore, we explore the use of supervised machine learning techniques, and specifically a decision tree algorithm, to quantify the success of imbalance detection in the next section. Fig 3 presents a high level overview of the machine learning techniques. The reader is referred to Section 5.4 and Section 5.5 for details.

[1] `http://www.discounttire.com/dtcs/infoTireMath.do`

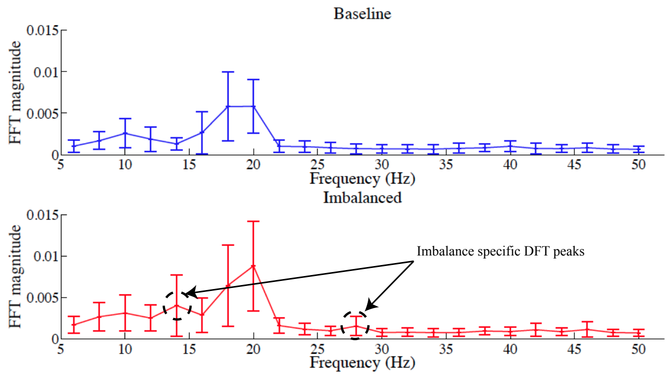

FIGURE 2. Spectral analysis statistics from the 120 sub-sets of data for both the baseline and imbalanced case. Each sub-set contains about 500 data points (for a sampling rate of 100 Hz). DFT magnitudes are computed in 2 Hz buckets from 6 - 50 Hz and the mean and standard errors are plotted across the 120 subsets of data.

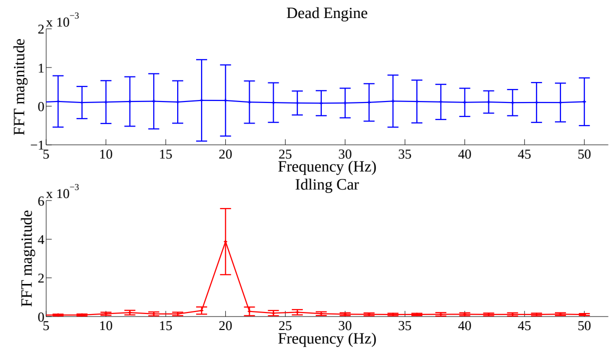

FIGURE 4. A plot showing a comparison of the Fourier Transform results for a vehicle with the engine off and the phone mounted, and idling with the engine on and phone mounted.

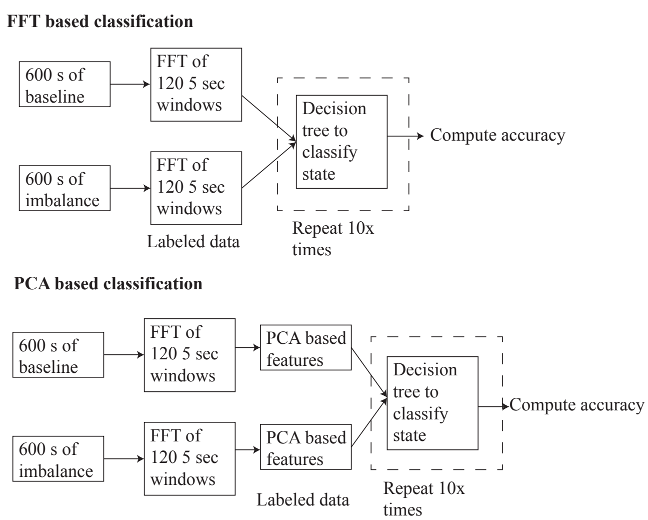

FIGURE 3. Supervised machine learning techniques that are implemented in this study

5.3 Common peak characterization

The frequency peaks observed at 10 and 18-20 Hz may be attributed to several factors — engine vibration dynamics, transmission rotating components or windshield and phone mount resonance. We investigate these excitation frequencies in more detail to make sure that they are not attributed to wheel motion or balance issues.

First, the car was allowed to idle and data was recorded with the vehicle engine on and the phone in the mount, and the data were recorded in the same vehicle and mount configuration with the engine off. The peak at 20Hz still appeared with the engine on, indicating that this excitation frequency is attributed to engine operations and its manifestation in windshield and phone mount vibrations. The comparison of engine on and engine off is shown in Fig 4. Second, we attempt to attribute the 10 Hz excitation frequency with the vehicle's mechanics. Few components in a vehicle rotate. The engine and wheels could be eliminated based on their difference the measured frequency. The transmission, however, rotates when the vehicle is in motion and contains several rotating elements operating at different speeds. An experiment was conducted to determine the relationship between transmission engagement and the 10 Hz signal. Data was collected for the vehicle with the engine on and in park, and with the engine on and in gear with the parking brake applied. In park, a pawl keeps the transmission from rotating. In drive, the rotating elements are free to move and a torque converter regulates engagement of the various rotating elements.

With a cold engine operating at fast idle to warm up, the Fourier Transform plot shows a 10 Hz peak when in gear but not when idling in park (c.f Fig 5). With a hot engine, the 10 Hz peak is not present, perhaps because engine speed is lower than the torque converter's stall speed (c.f Fig 6).

As a final validation, the experiment was repeated, comparing a warm engine with transmission in gear at idle and brake applied to a warm engine with transmission in gear at elevated RPM. The results clearly indicate a peak at the 10 Hz frequency in the case where throttle is applied, confirming that the peak is due to a transmission rotational component. This appears in (c.f Fig 7).

We therefore infer that the transmission's engagement appears to be closely coupled with the 10 Hz peak, and may explain

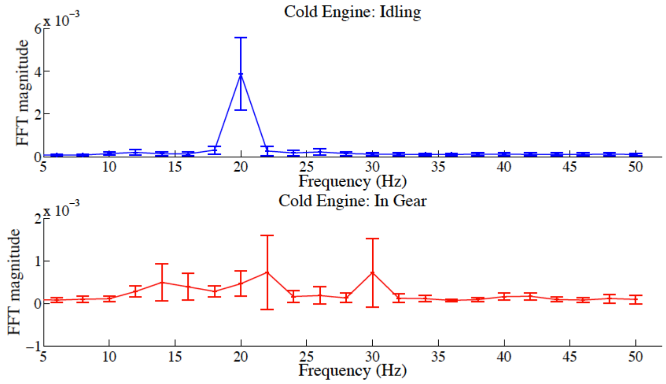

FIGURE 5. A plot showing a comparison of the Fourier Transform results for a vehicle with engine warming up from the cold state when in gear and when idling in park. The frequency shift from 10 Hz is due to the increased crankshaft speed to help warm up a cold engine

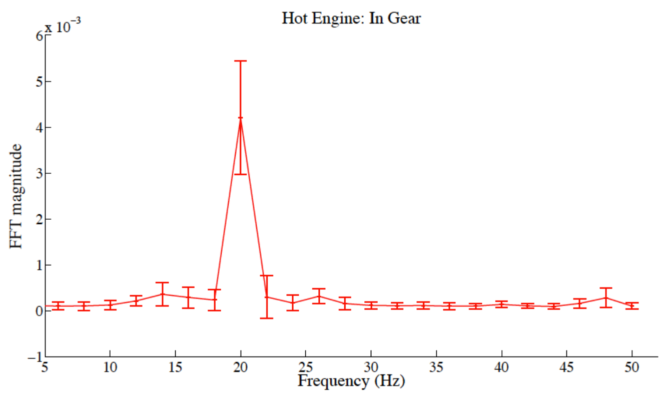

FIGURE 6. A plot showing the Fourier Transform results for a vehicle with a hot engine and when in gear

its presence in all of the motion studies. A detailed examination of the effect of operation of the individual component's of the vehicle's transmission is beyond the scope of this work.

5.4 Wheel balance state classification using Fourier Transform feature data

We utilize a decision tree algorithm to detect wheel imbalance from the spectral analysis of accelerometer data. Fig 8 and Fig 9 illustrate the process of feature selection, segmentation of the dataset into sub-sets for training and testing the algorithm and our metric for measuring classification accuracy. Following the process described in the algorithm, we compute a histogram of classification accuracy as illustrated in Fig 10. We observe that the accuracy is between 70-88% with a weighted average of 79.25%. Fig 11 illustrates a typical decision tree generated. The

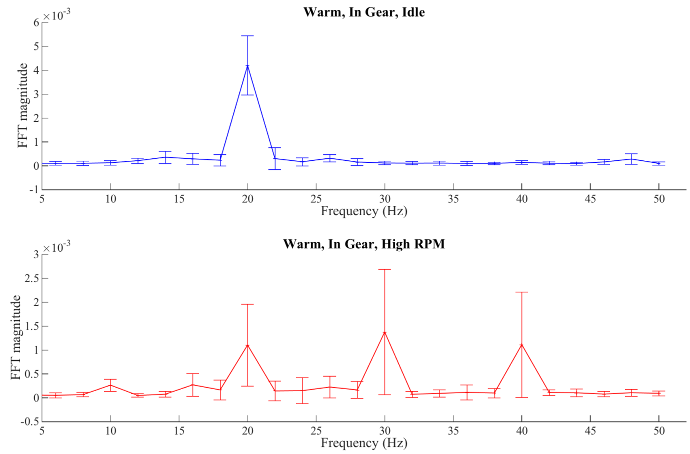

FIGURE 7. A plot comparing the Fourier results for a warm engine left in gear and with the brake applied for slow idle and elevated engine speed. In the elevated RPM case, the transmission's components engage and a 10 Hz peak appears.

TABLE 2. Student t-statistics for Fourier Transform feature frequencies used in decision tree training

Freq (Hz)	t-stat	Magnitude Diff. (α=0.05)
42	4.0475 (d.o.f 118)	Significant
10	2.2454 (d.o.f 118)	Significant
38	2.1805 (d.o.f 118)	Significant
6	5.9985 (d.o.f 118)	Significant
16	0.744 (d.o.f 118)	Not Significant
18	1.2384 (d.o.f 118)	Not Significant

algorithm uses Fourier Transform magnitudes of the following frequencies to make branching decisions for the tree in decreasing order of importance: 42, 10&38, 6&16&18Hz. The statistical significance of the differences in Fourier Transform magnitudes, between the baseline and imbalanced cases, at these frequencies is listed in Table 2. Referring to Fig 2, it seems surprising that the tree assigns most importance to the 42 Hz feature for classification while completely ignoring the statistically significant visible peaks at 14 and 28 Hz in the imbalanced case. The difference between the FFT magnitudes between the baseline and imbalanced case for the chosen frequencies of 16 and 18 Hz are not statistically significant either. Furthermore, the decision tree itself is quite complex consisting of at least 5 levels. To improve confidence in the tree's performance, we focus on improving the features being used for tree training and testing. In the subsequent section, we discuss a Principal Component Analy-

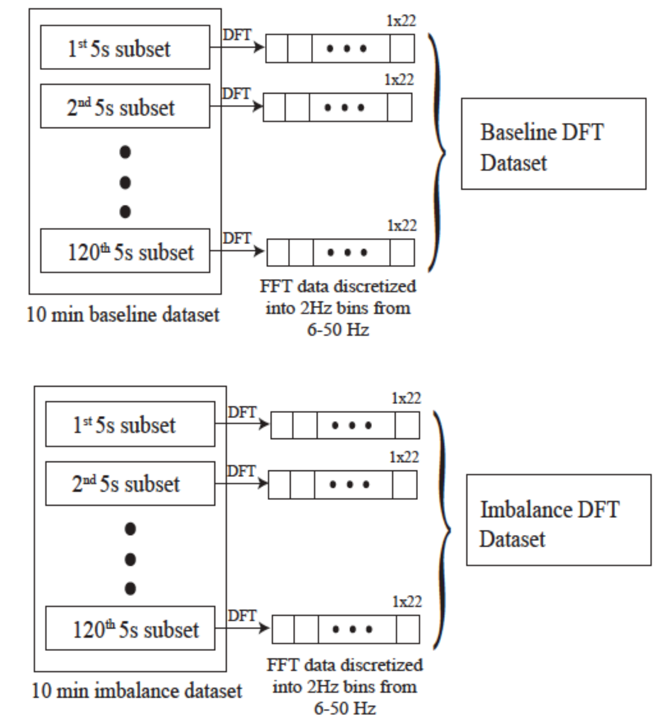

FIGURE 8. Generation of DFT transform from the baseline and imbalance datasets.

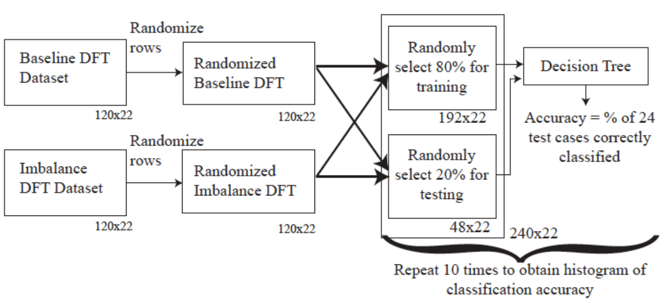

FIGURE 9. Using DFT features for decision tree training.

sis (PCA) transformation of the FFT data that seeks to generate a feature space having maximum separability between the baseline and imbalanced cases.

5.5 Wheel balance state classification using a PCA transform of FFT feature data

Fig 8 and Fig 12 illustrate the process of feature generation using the PCA transform, selection of training and test sets for

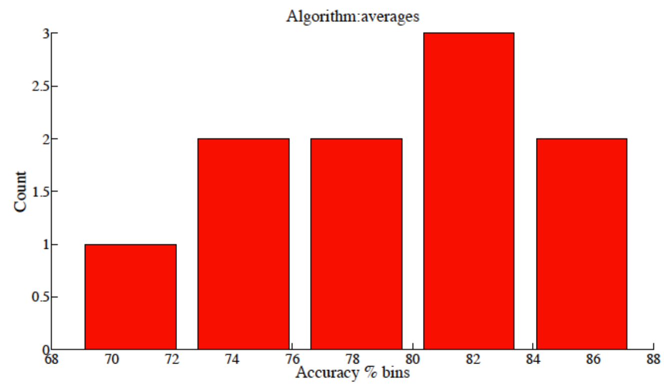

FIGURE 10. Histogram of classification accuracy across 10 runs of the decision tree algorithm.

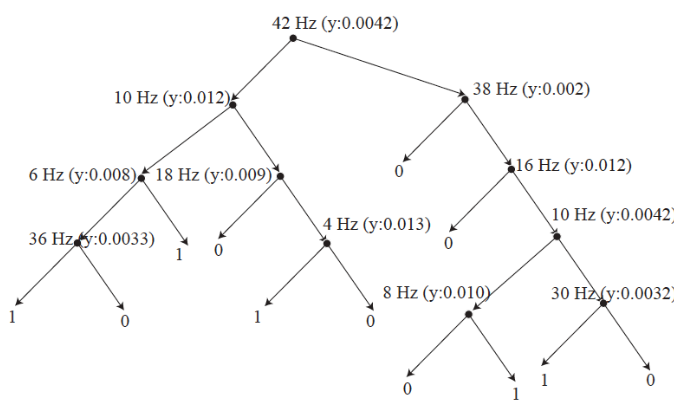

FIGURE 11. Decision tree generated using the FFT data as features. If the FFT magnitude at a node is < y, the left branch is chosen else the right branch is chosen

the decision tree algorithm. The 1x22 vector illustrated in Fig 12 represents the projection of FFT data along the most significant PCA component direction. Following the procedure outlined in the algorithm, a histogram of classification accuracy is computed as illustrated in Fig 13. There is a significant improvement in classification accuracy with a weighted average of 91.6%. Also, the decision tree, shown in Fig 14, the tree is only 1 level and uses the PCA transformed magnitude at 12 Hz to classify state. Referring to Fig 15, we notice a peak at 12 Hz for the imbalance case, and a corresponding trough in the baseline case, which is further confirmed by a statistically significant Student's t-test ($t_{stat} = 4.0791$ for 18 d.o.f. at $\alpha = 0.05$). We therefore conclude that the PCA transformation of the FFT data significantly boosts the ability of the decision tree to detect the presence of a wheel

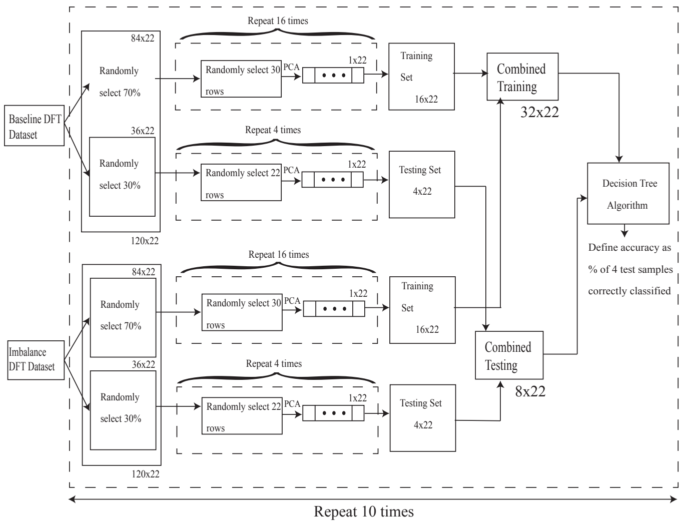

FIGURE 12. Using a PCA transformation of the FFT feature data for tree training and testing.

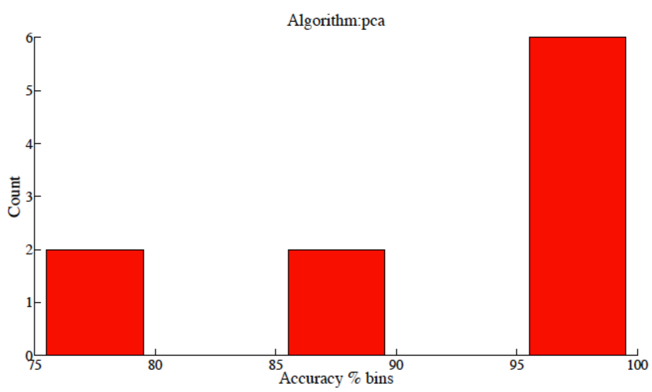

FIGURE 13. Histogram of classification accuracy across 10 runs of the decision tree algorithm using the PCA transformation.

imbalance.

6 Sensitivity Analysis

While we have demonstrated good detection of wheel imbalance using smartphone acceleration data, it is important to examine the universal applicability of this technique to vehicles of different makes, different road conditions and variation in vehicle speed due to variable traffic flow conditions. In this section, we examine the sensitivity of our algorithm to these variables.

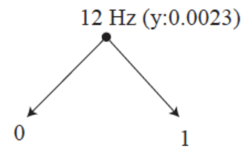

FIGURE 14. Decision tree generated using the PCA transformed FFT data. If the PCA transformed FFT magnitude at a node is $<$ y, the left branch is chosen else the right branch is chosen

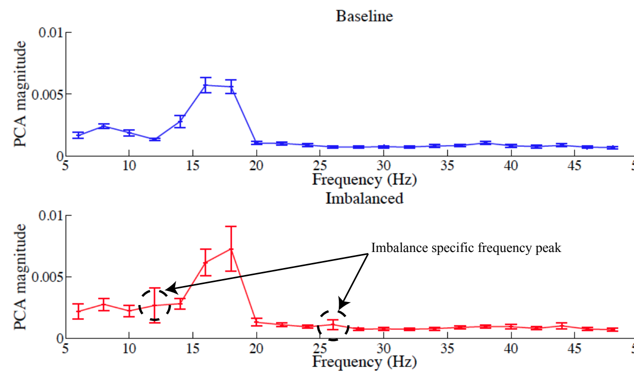

FIGURE 15. Spectral analysis statistics from the 120 sub-sets of data for both the baseline and imbalanced case using a PCA transformation of the FFT data. We choose the most significant PCA component in our analysis.

6.1 Effect of vehicle make and road conditions

The results presented in Section 5 were obtained by driving a 2015 Subaru Impreza Hatchback vehicle on a stretch of highway connecting Boston, MA and Albany, NY. We conduct another set of experiments using a Nissan Versa vehicle on a stretch of highway connecting Boston, MA and Kittery, ME. This vehicle was driven at a controlled speed of 60 mph as well. The only difference is that for this series of experiments we mounted 4 1/4 ounce weights on the front left and rear right tire to simulate imbalance conditions. Fig 16 illustrates the classification accuracy using a decision tree learning algorithm when using Fourier Transform features and PCA transformed Fourier features. We observe superior classification accuracy using the PCA transformed Fourier data in this case as well with a weighted average accuracy of 70% and 97.6% without and with using the PCA transformation respectively. These results indicate that smartphone accelerometer data can successfully be used to classify imbalance for at least 2 common passenger vehicles of comparable class, and at less than half the mass (28g vs. 60g) of prior art [1].

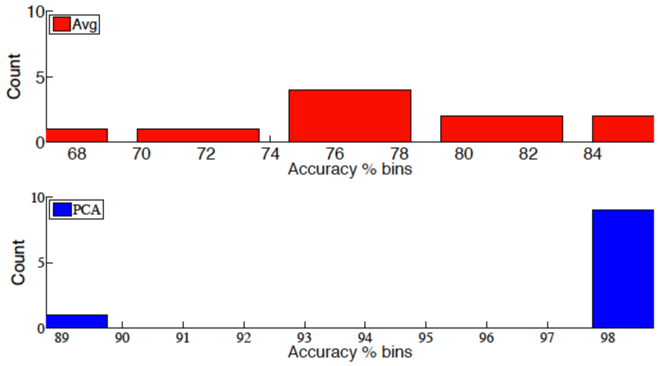

FIGURE 16. Histogram of classification accuracies using the FT features and PCA transformed FT features in decision tree training. The PCA transformed FT features yield better average accuracy.

6.2 Effect of traffic flow conditions

The experiments were conducted by driving the vehicle at a controlled speed of 60 mph. In general, traffic flow conditions may cause variations in speed brought about by lane changing, breaking and acceleration. We conducted another set of experiments, this time allowing vehicle speed variations of $\pm$ 8 mph. We consider the case where the decision tree is trained with PCA transformed FT features due its better classification accuracy. Fig 17 and Fig 18 illustrate the change in classification accuracy for the Subaru Impreza and Nissan Versa vehicle under variable vehicle speed conditions. Although variations in speed do reduce classification accuracy, the variation in weighted accuracy from 97.6% - 89.45% when using the Nissan Versa and 91.2% - 89.8% for the Subaru Impreza is within 10%. Therefore the trade-off between accuracy and need for controlled vehicle speed may in-fact be acceptable.

7 Conclusions and Future Work

We demonstrated that accelerometer data collected from a smartphone mounted on a vehicle's dashboard can successfully be used to detect wheel imbalance in a vehicle. A decision tree algorithm trained with features from an FFT transform of the accelerometer data yielded classification accuracies of 70-88%, with an average of about 79%. By using a PCA transformation of the FFT features, we were able to improve the average classification accuracy to 91%. We demonstrated that our technique works for at least 2 types of vehicles on different road conditions and is relatively robust to minor speed variations.

Future work will explore the implications of changing the feature and training set from randomized to sequential. It is our belief that due to the nonuniformity of the road surface, a sequential approach would diminish the accuracy of our the classification algorithm. A standardized testing route will allow for normalized data collection.

This model worked well, but relied on relatively heavy imbalances for detection. As next steps, we plan to examine the effect of reducing the weight added to the wheel rims and quantify the effect on algorithm performance, such that imbalances may be detected before the driver perceives anything is amiss. Also, this study focused on a simple case of identifying the presence of wheel imbalance. As a next step we seek to classify which wheel is out of balance, thus improving the utility of the study and providing a practical application.

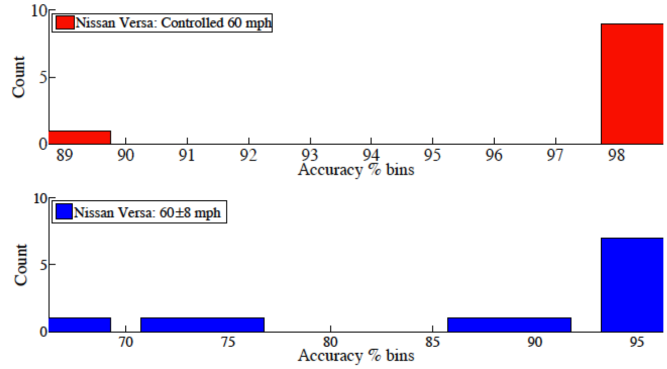

FIGURE 17. Histogram of classification accuracies for vehicles where vehicle speeds are controlled and where they are not allowed. Results from the algorithm where the decision tree is trained with PCA transformed FT features is presented. Results are shown for the Nissan Versa vehicle.

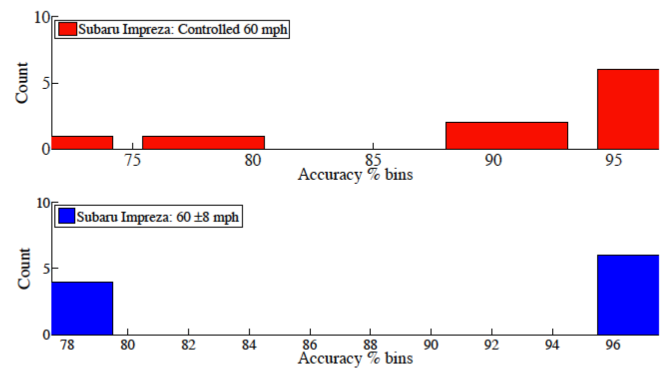

FIGURE 18. Histogram of classification accuracies for vehicles where vehicle speeds are controlled and where they are not allowed. Results from the algorithm where the decision tree is trained with PCA transformed FT features is presented. Results are shown for the Subaru Impreza vehicle.

In the future, additional data inputs may be used to enhance the model, or to apply the model to other problems in a vehicle. For example, OBD (On-Board Diagnostic) data may be used to identify trip segments at a constant velocity to mitigate the effects of traffic or turning on analysis, or the magnitude of acceleration may be used to identify braking events such that this model might be applied to identify warped or built up brake rotors.

Additional areas of model improvement will focus on more granular identification of particular wheels, as well as attempting to quantify the severity of imbalance such that maintenance may be performed prior to a vehicle sustaining lasting damage.

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