# Classifying Road Surface Conditions Using Vibration Signals

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***Abstract*—The paper aims to classify road surface types and conditions by characterizing the temporal and spectral features of vibration signals gathered from land roads. In the past, road surfaces have been studied for detecting road anomalies like bumps and potholes. This study extends the analysis to detect road anomalies such as patches and road gaps. In terms of temporal features such as magnitude peaks and variance, these anomalies have common features to road anomalies. Therefore, a classification method based on support vector classifier is proposed by taking into account both the temporal and spectral features of the road vibrations as well as factor such as vehicle speed. It is tested on a real data gathered by conducting a smart phone-based data collection between Thailand and Cambodia and is shown to be effective in differentiating road segments with and without anomalies. The method is applicable to undertaking appropriate road maintenance works.**

## I. INTRODUCTION

Roadways serve as the main infrastructure for public transportation, and the backbone for operations of vital industries such as logistics and manufacturing. The quality of these roadways, however, degrades through time and requires maintenance due to issues with respect to the safety of passengers and the protection of freight quality during transportation. Road surface types and conditions impact the comfort and safety of passengers. On the other hand, delivery delays and freight defects are aggravated by poor road surface condition. Therefore, identifying the existence of road anomalies is important for the purpose of conducting corrective actions such as road maintenance.

In the past, road surface conditions were profiled by utilizing specialized inclinometers to measure the longitudinal profile of roads. High-resolution accelerometers are later utilized in research. Recently smart phones that are equipped with low-cost accelerometers are practically used [1]-[9]. Similarly, this paper uses accelerometer from smart phones. It is motivated by the ubiquity of smart phones as well as the low computational resource requirement and the robustness of accelerometer-based road vibration analysis. In contrast, an image processing-based evaluation of road surface condition is computationally expensive, and is sensitive to varying environmental factors such as weather and ambient light.

The main topics of previous research works that utilized accelerometer data were to detect bumps and holes [1]-[3], to evaluate and visualize road condition on a computing server [4], to analyze acceleration differences from several vehicles types [5] and to characterize speed distribution of vehicle by detecting road anomalies including speed bumps [6]. To analyze vibration signals, research works employed threshold-based techniques in time domain. For instance, a study is conducted to compare various detection methods by analyzing the peak magnitude, peak-to-peak difference and standard deviation of acceleration signals [2]. These techniques are shown to be effective in detecting bumps and potholes by setting a pre-set threshold values based on the vibration magnitude of smooth road surfaces.

The effectiveness of time domain-based analysis, however, is limited by the presence of vibration signals that are *non-stationary*, or signals with frequency components that are varying in time. This limitation is addressed by utilizing frequency-based analysis such as Fast Fourier Transform (FFT). FFT, however, is inherently limited by its fixed window size requirement especially for non-stationary signals. On the other hand, wavelet analysis has reportedly solved this limitation. For instance, a wavelet analysis is applied for detecting vibration signals related to the material limits of an unmanned ground vehicle [12].

As aforementioned, previous studies had focused on detecting bumps and potholes. Fig. 1 shows the actual road anomalies gathered in this study. Whereas bumps are intentionally added to control vehicle speeds, cracking, potholes, and patches are manifestations of road deteriorations at different stages. Road cracking is a form of distress in asphalt or concrete pavement. If not prevented, the cracking leads to the formation of potholes, which are costlier to repair. Potholes are the results of poor road surface condition at later stages which are often repaired by filling in with asphalt. However, even with asphalt patches, road surfaces may further deteriorate. Due to varying weather condition, asphalt patches are weakened leading to uneven surface depressions over a large area. Detecting these anomalies are important since the cost of road reconstruction is estimated to be three times the cost of frequent road maintenance [13].

So far, vibrations of road anomalies such as road cracking, bridge gaps, and patches have not been analyzed for the purpose of road maintenance. These road anomalies have to be differentiated from other anomalies such as bumps and potholes since these requires different treatment in respect to road maintenance works. Therefore, a method that provides higher granularity for detecting road anomalies is necessary. This paper aims to classify road surface types and conditions

(a) No anomalies (b) Potholes (c) Patches (d) Gaps

Fig. 1 Road deteriorations and anomalies

by observing and characterizing the temporal and spectral features of vibration signals gathered from land roads.

The main contribution of this papers are as follows. (i) It extends the analysis to detect road anomalies such as gaps and patches aside from bumps and potholes using accelerometer-based road vibration signals. (ii) It utilizes road vibration data gathered in an actual logistics transport scenario as opposed to laboratory-simulated tests; thus, it takes into account the variability of other factors such as vehicle speed.

The rest of the paper is organized as follows. Section II provides the background concept and method for analyzing road surface condition. Section III describes the experiment conducted and result of the analysis. Finally, Section IV summarizes this paper and introduces future works.

## II. PROPOSED METHOD

Fig. 2 shows the main components of the proposed method. The goal is to find the road segments that have anomalies and determine the type of anomaly. At the minimum, road vibration signals and GPS location data are processed in detecting and classifying road anomaly; other information such as road surface type, vehicle speed can be utilized for potentially higher accuracy of classification.

### *A. Preprocessing*

In preprocessing, a time parameter $t$ is a reference point for creating a coherent manifold of road information that is associated to a specific road segment. This road information includes road vibration data $x_t$, a location where the vibration is sensed (e.g., latitude and longitude). The road segment with the above defined road information will then be analyzed for an existence of road anomaly and if needed, for the identification of a road anomaly.

### *B. Temporal Analysis*

Common methods for temporal analysis are employed. A peak-based method is implemented by measuring the maximum amplitude of $x_t$. It is suited for detecting potholes and bumps that cause large vibration amplitude. Aside from the peak-based method, the variance and range of vibration signals are calculated.

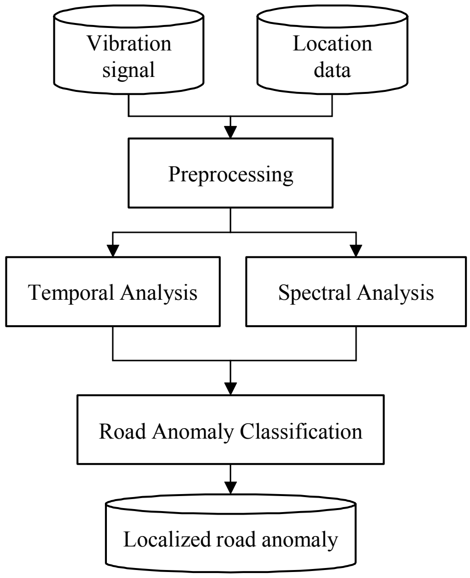


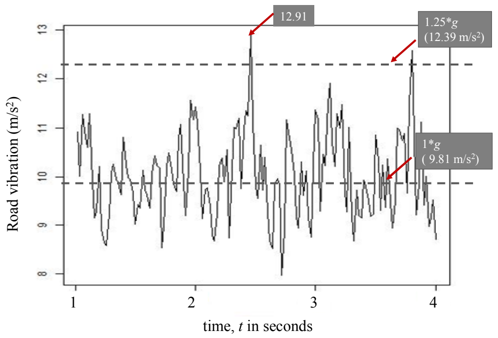

Fig. 2 Proposed methodology

For a stationary accelerometer, a reading of $1 \cdot g$, where $g$ is the acceleration due to gravity (9.81 m/s$^2$), is expected to be detected. If it is moving, for instance when it is placed on a moving vehicle, the reading tends to change. Fig. 3 is a plot of a vibration signal for a road segment with no anomaly. It shows 150 number of samples, which is equivalent to 3 seconds (150* 20ms sampling rate). The maximum amplitude detected is 12.91 m/s$^2$.

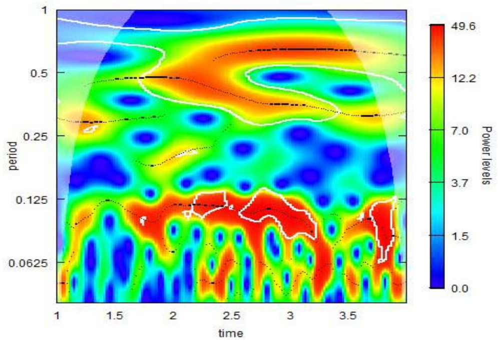
### *C. Spectral Analysis*

As aforementioned, the wavelet analysis is a type of spectral-based tool for analyzing data that has localized, nonstationary power at different frequencies. It is suited for the analysis of road vibration data since its frequency contents can change depending on the existence of a particular road anomaly.

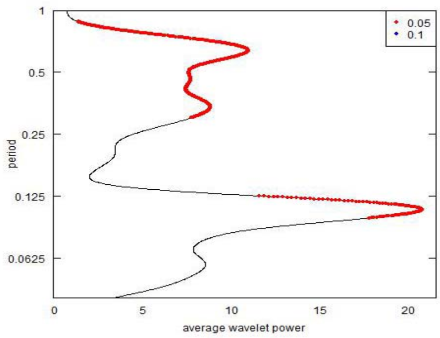
In this analysis, a wavelet function is needed with zero mean and that is localized in time and frequency spaces. For this reason, Morlet wavelet is commonly used. Subsequently, a wavelet transform is calculated. The WaveletComp library




(a) Vibration signal, $x_t$




(b) Frequency plot




(c) Average Power

Fig. 3 Sample Input and Output of Wavelet Analysis

for R Statistical Computing is utilized. See [14] for an introduction of the library.

In this study, a Morlet function with ω=6 is used so that the frequency is approximately equal to 1/period. Moreover, the period (frequency) ranges from 1[s] (1Hz) to 0.015625[s] (64Hz) considering that road vibration data is sampled every 20ms. Further, the periods are labeled by octave, as shown below:

*O1*: for period from 0.5[s] to 1[s] (1-2 Hz),
*O2*: for period from 0.25[s] to 0.5[s] (2- 4 Hz),
*O4*: for period from 0.125[s] to 0.25[s] (4-8 Hz),
*O8*: for period from 0.0625[s] to 0.125[s] (8-16 Hz), and
*O16*: for period from 0.03125[s] to 0.0625[s] (16-32 Hz).

An example result of the wavelet transformation utilizing the library in [14] is shown in Fig. 3. Based on the vibration signal in Fig. 3(a), the results of wavelet analysis are shown in Fig. 3(b) and Fig 3(c). In the frequency plot, the x-axis shows the time scale corresponding to the time length of $x_t$ and the y-axis describes the period. It can be seen in Figure 3(b) that *O8* showed high magnitude values compared to other octaves such as *O1*, *O2*, and *O4*. This can be seen also in Fig. 3(c) wherein a maximum average power of 20.78 is observed at the period 0.107331[s] which is within the range of *O8*.

Based on the result of the wavelet analysis, the maximum and average power per octave are used as spectral features of vibration signals. This hypothesizes that for a certain type of road anomaly, a corresponding octave or a group of octaves is excited or its power is magnified.

### *D. Road Anomaly Classification*

After extracting the temporal and spectral features of the vibration signal, these features are utilized for road anomaly classification. Initially, these features are tested to confirm its statistical significance. It is conducted to reduce the number of features, if possible. Afterwards, the road anomaly classification is performed. In this paper, support vector classifier is utilized due to its robustness to individual observations, and better classification of the training data. The classifier is based on a hyperplane that does not intend to separate exactly different classes or types [15].

The support vector classifier is compared to other methods such as linear discriminant analysis and k-nearest neighbor method. It is proven to be a better option in terms of accuracy rate; however, the details will not be explored in this paper for conciseness.

## III. Experiment and Results

This section first describes a data collection experiment to collect road information data including vibration signal. To establish the ground truth data for road anomaly classification, a video of the collected data is annotated to extract the location of road anomalies and its corresponding vibration signal. A preliminary result of the proposed classification method is provided in this section.

### *A. Data Collection*

An experiment was conducted to collect road vibration data including video, location and timestamps. A smart phone with installed Android application is utilized as the data collecting device to record vibration from accelerometers, GPS location and timestamp. The sampling frequency for the vibration is 50Hz while that of the GPS is 1 Hz.

The device is mounted under the driver's seat of a truck vehicle. It is oriented in a way that the accelerometer data measured is along the pull of gravity. With this orientation, the accelerometer reading along the z-axis coincides with the measurement of the road vibration along the vertical direction.

Another phone is mounted on the track's dashboard to collect video of road surfaces. The video is utilized to create ground truth data. During recording, it is timestamped so that it can be referenced with the vibration and location data.

The experiment was conducted in January 2016 between Bangkok Thailand and Poi pet, Cambodia. It lasted for 10 hours to collect the road vibration. Since the battery life of the device is limited, the video recording of road surface is only conducted for 90 minutes.

### *B. Data Preparation*

The collected video is annotated to determine the road segments with and without road anomaly, and the time period when a road anomaly is observed. For simplicity, the time period is uniformly set to 3[s]. It is also the reference in deriving the corresponding road vibration signal for analysis. In the annotation, a video segment is annotated as having patch, pothole, gap and no anomaly.

Table 1 shows the number of road anomalies observed from video annotation. Due to the small number of potholes observed (i.e. 7), the succeeding analysis will focus on classifying gaps, patches and no road anomaly. Moreover, there is no speed bump observed since the experiment covered highways only. The table also shows the number of road anomalies by vehicle speed. As can be shown in the table, the speed readings reached only up to 65 KPH due to the size and speed restriction of the truck trailer used in the experiment when driving in highways.

Moreover, the speed information from GPS data is used as the basis for vehicle speed, which is derived based on Doppler shift. Another way of estimating the speed is to utilize at least two GPS locations. An intermediate location based on two GPS data is derived when needed, to tag road vibration data with location information.

### *C. Comparison of Magnitude Peaks and Variances*

Fig. 4 shows a comparison of maximum amplitudes and variance of the data. In Fig 4(a), the road segments with no anomaly range from 11.2 to 14.7 [m/s$^2$]. These values are expected to be small magnitude peaks since the corresponding road segments are smooth. On the other hand, the road segments with patches have remarkably large amplitude peaks ranging from 12.0 to 19.6 [m/s$^2$] while that of the road segments with gaps range from 12 to 16 [m/s$^2$]. Moreover, Fig. 4(b) shows road segments with patches to have larger variances compared to that of with gaps and no anomaly.

The large amplitude peaks for patches is one important findings since asphalt patches are supposed to cover potholes or flatten uneven surfaces. However, the result showing large magnitude peaks means that instead of improving road surface condition, asphalt patches can even worsen road condition in the surveyed area.

The above result showed that the magnitude peaks and variances of vibration signals can be utilized for road anomaly classification.

TABLE I
GROUND TRUTH FROM VIDEO ANNOTATION

| Road Anomalies | Total | Vehicle Speed Range (KPH) | |
|---|---|---|---|
| | | 30-50 | 50-70 |
| Gaps | 47 | 10 | 37 |
| Patches | 62 | 22 | 40 |
| No anomaly | 56 | 7 | 49 |
| Total | 165 | 39 | 126 |

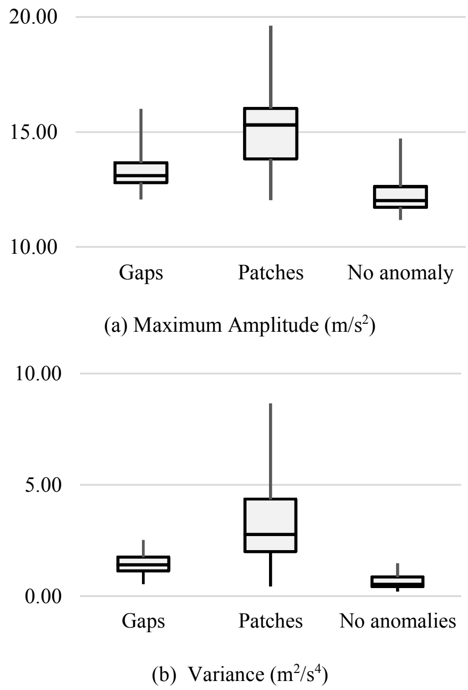



Fig. 4 Comparison of Maximum Amplitudes and Variances

### *D. Impact of Vehicle Speed in the Vibration Signals*

The magnitude peaks and the vehicle speed are subsequently evaluated. It is hypothesized that vibration magnitudes are magnified by vehicle speed. Fig. 5 shows that vibration signal on road segments with gaps and no anomaly are affected by vehicle speed if the speed ranges from 50 to 60 KPH. Moreover, no statistical significance is observed for vibration signals on road segments with patches, and for vehicle speed ranging from 30 to 50 KPH (i.e., the p-value is greater than 0.05). This evaluation shows that to some extent vehicle speed positively impacts the vibration signals.

### *E. Classification Result*

The support vector classifier is evaluated by utilizing the temporal features (magnitude, variance and speed) as well the spectral features (maximum and average power per octave utilizing *O1* to *O16*). It is compared to a support vector classifier utilizing only the temporal features.

Table 2 and Table 3 show the comparison of the actual and predicted values of the two classifiers. Based on this result, the accuracy rate of the proposed classifier is 86.15% while that of the compared classifier is 77%. These results show that the combination of temporal and spectral features can provide a more accurate road anomaly classification.

## IV. CONCLUSIONS

This paper analyzes the temporal and spectral features of road anomalies. The temporal features include maximum amplitude, variance and vehicle speed, while the spectral features are extracted by employing wavelet analysis to characterize signal power by octaves. A support vector classifier utilizing both the temporal and spectral features is shown to be more effective compared to that of using only the temporal features.

One important findings of this study is that asphalt patches have large vibration peaks compared to that of without anomaly and with gaps. It was observed in the video annotation that some patches have varying degrees of deteriorations. This observation will be explored as a future study.

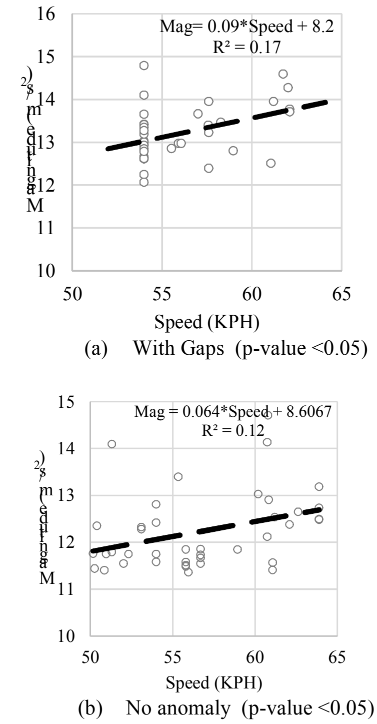



Fig. 5 Speed Impact on Road Segments with Gaps and No Anomaly

TABLE 2
CONFUSION MATRIX RESULT OF PROPOSED CLASSIFIER

| | Actual | | |
|---|---|---|---|
| Predicted | Gaps | Patches | No anomaly |
| Gaps | 34 | 4 | 2 |
| Patches | 6 | 57 | 3 |
| No anomaly | 7 | 1 | 51 |

TABLE 3
CONFUSION MATRIX RESULT OF COMPARED CLASSIFIER

| | Actual | | |
|---|---|---|---|
| Predicted | Gaps | Patches | No anomaly |
| Gaps | 30 | 11 | 5 |
| Patches | 11 | 51 | 5 |
| No anomaly | 6 | 0 | 46 |

Further analysis will also be conducted by testing the generality of the proposed classification method on other vehicle types and road anomalies, and by considering larger data size and high granularity of road anomaly information such as the size, length and depth of road anomalies for the purposed of improving the classification accuracy.

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