USE OF VEHICLE NOISE FOR ROADWAY DISTRESS DETECTION
AND ASSESSMENT

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ABSTRACT

This work evaluates the pavement surface condition and detects the pavement subsurface delamination through vehicle noise collected by microphones mounted underneath a moving vehicle. Such measurements will include tire-generated sound, which carries much information about the road condition, as well as noise generated by the environment and vehicle. A careful frequency analysis of the vehicle noise is carried out to localize the frequency range for surface characteristics and subsurface delamination respectively. The Principal Component Analysis (PCA) method is applied to differentiate important information about the road condition from noisy data contributions collected while the vehicle is moving. The analysis begins with acoustic pressure measurements made over constant and known road conditions. Fourier transforms are taken over various time windows and a PCA is performed over the resulting vectors, yielding a set of principal component vectors for the road condition. The condition of each road section is characterized by a set of principal component vectors. Pavement macrotexture Mean Texture Depth (MTD) is predicted from the principal component vector and then projected to the overall pavement condition index (PCI) as well as the pavement friction and uniformity evaluation. Pavement subsurface delamination is also detected from the principal component vector. The significant accomplishments of this study are as follows: (1) localize the frequency ranges of vehicle noise related to pavement surface and subsurface features respectively; (2) demonstrate the potential for PCA to reduce noise and illustrate the procedure to apply PCA in frequency domain for noise filtering; (3) find the relationship between MTD, sound pressure and driving speed; (4) optimize the microphone placement for data collection for the MTD prediction; (5) develop a calibration-free method for the MTD prediction with an error of 16%; (6) use the predicted Equivalent MTD found by the PCA Energy Method to explore pavement friction prediction, construction non-segregation evaluation, and the contribution to PCI prediction from the acoustic aspect; (7) differentiate the stiffness of the top layer pavement within 10 cm of surface from tire/road noise, and (8) detect the subsurface delamination from the shift of frequency in peak sound pressure level.
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1 Introduction

1.1 Overview

Pavement health monitoring is very important to our nation. The current road situation is in need of repair according to the ASCE card report (ASCE 2013). In order to solve the problem in a cost-effective way, updated data on conditions are required to make the right decision regarding maintenance strategy, and must be executed at the right time, the right place, and in the right way. “Right time” means the pavement should be repaired when it starts to degrade from which point on the cost of maintenance will dramatically increase. “Right place” means that the pavement locations requiring repairs is accurately located on a map, with 10 m resolution for example, which would greatly save the labor force to find the location within a large area of 230 m² as described in ASTM D6433 (ASTM 2011b), as well as the unnecessary digging for potential subsurface delamination. “Right method” indicates that the type of pavement distresses should be identified, such as potholes or cracking, then specific treatments for pavement would be determined to efficiently fix the problem. Moreover, this repair method should be fast and of high quality.

Current methods for pavement deterioration monitoring are classified into manual operation and automatic vehicle operation. The former, which is still widely used [ASTM D6433 (ASTM 2011b); Miller and Bellinger 2003; Pava 2011], requires highly skilled labor and the results will vary by operator. The latter (Huang and Xu 2006; Capuroco et al. 2006; Bandara and Gunaratne 2001; Timm and McQueen 2004) uses a laser and camera mounted on a test vehicle to collect the road data and post process the large data by checking and analyzing each picture taken by the camera. However, the laser-and-camera-based system usually needs one month to finish a 600 mile survey, while the manual needs three months (Wang et al. 2014). The road information could not be updated quickly and the “right time” might be missed.
Therefore, the need to use a multi-sensor enabled vehicle as an opportunity to monitor the pavement and analyze the collected data in real time is urgent. The “real time” in this study indicates that the data processing is faster than the data acquisition. More detailed definition of “real time” is described in Section 8.3.2.4 of Chapter 8. With this capability, it is possible to monitor and update road conditions at any time. Most importantly, the time to conduct the survey will be shortened from three months to one week for around 600 miles of roadway (Wang et al. 2014; Zhang et al. 2014a). In addition, the detailed information of pavement like roughness and surface texture is represented with the resolution of 6 m. Thus, right time, right location and right treatment are possible to achieve with this system.

Different road surface problems will cause different safety concerns. Too much bleeding on the road’s surface will reduce the friction between tire and pavement interface, causing vehicles to skid. Segregation is “a lack of homogeneity in the hot mix asphalt constituents of the in-place mat of such a magnitude that there is a reasonable expectation of accelerated pavement distresses” (Stoup-Gardiner and Brown 2000). Severe segregation will lead to pavement raveling, or even potholes. Besides, the invisible subsurface delamination or other kinds of deterioration may cause the sudden collapse of the top layer of the road. This is a potential danger for drivers on city roads, especially on interstate highways. Accordingly, both surface distresses and subsurface delamination need to be effectively monitored and transportation authorities must be alerted when the condition reaches critical levels. This system will improve driving safety and will decrease traffic hazards like crashes.

Hence, the VOTERS (Versatile Onboard Traffic Embedded Roaming Sensors) concept is proposed in order to develop a systemic approach to the problem of monitoring and maintaining our nation’s civil infrastructure of roads and bridge decks. The vision is to use vehicles of opportunity, which regularly travel on city roads and interstate highways, to collect and integrate sensor measurements and to perform onboard judgments about surface distresses and subsurface integrity of roadways and bridge decks. VOTERS would provide accurate, up-to-date condition information without setting up work zones or stopping traffic. By eliminating the need for dangerous and expensive work zones, VOTERS could provide data on all structures, regardless
of traffic volume. VOTERS will also improve safety for the driving public and for inspection personnel who would otherwise be exposed to traffic hazards.

In this study, the focus will be on the use of the sound generated by tire-road interaction for pavement condition assessment and distress detection. Several questions will be addressed: first, frequency content of vehicle noise related to road features; second, factors that influence road features; third, quantification of approaches for road feature measurement; fourth, the applications or physical meaning of road features; five, pavement subsurface delamination detection through vehicle noise.

1.2 Challenge

The challenge of this study is that no current technology is using acoustic measurements collected by microphone to directly assess pavement conditions. Some related literature discusses the use of tire-road noise for quiet pavement application (Sandberg and Ejsmont 2002), and also mentions that there exists some relationship between tire-road noise and pavement macrotexture – one road feature (Sandberg and Ejsmont 2002; Veres et al. 1975). The primary challenges are as follows:

- Noise removal from acoustic measurement
- Feature selection from acoustic measurement to correlate with pavement characteristics, i.e., which parameter of acoustic measurement to be used to correspond with pavement characteristics like macrotexture or road roughness
- Frequency band determination of tire/road interaction that related to road conditions
- Optimal sensor placement
- Speed effect, which is not considered in current state of art with laser-and-camera-based system
- Real time data analysis
- Subsurface delamination detection by microphone at traffic speed
1.3 Purpose of the Study

The purpose of this study can be broken down into five points:

1. To understand the frequency content of vehicle noise related to road features
2. To figure out the methodology for noise removal from collected vehicle noise so as to keep the pavement related signal for study
3. To monitor the pavement surface macrotexture MTD (Mean Texture Depth) and to recognize surface distresses, like potholes, raveling, or cracking, using a microphone
4. To evaluate pavement segregation level through the measurement of MTD to discover the severity of pavement deterioration
5. To investigate the possibility of subsurface delamination detection through a single microphone or microphone array

1.4 Hypothesis

In this study, the term signal refers to the sound generated by the tire-road interaction and noise refers to all other sounds measured by the microphone underneath the vehicle. This work contains four hypotheses: (1) The variations of the signal and noise with respect to frequency are different; (2) The pavement macrotexture is related to vehicle driving speed and the tire/road noise level; (3) The acoustic energy (integration of frequency spectrum of tire/road noise) below 1 kHz is positively proportional to the MTD of pavement; and (4) Subsurface signals may be hidden in the tire excited acoustic measurement. These assumptions will be explained and verified in the following discussion.

1.5 Significance of the Study

The significance of this study is summarized as follows:

- Driver safety is very important. Real time monitoring of road characteristics most closely related to safety is necessary decisions regarding maintenance and repair priorities.
• Real-time pavement condition monitoring through an under mounted microphone is cost effective and user friendly. It eliminates the need to find the location from a large area, or digging for potential subsurface delamination.
• Measurement can be conducted at traffic speed without traffic interruption. It not only eliminates the danger and expense from work zones, but also improves safety for inspection personnel who would otherwise be exposed to traffic hazards.

1.6 Conceptual Framework and Summary of Methodology

Generally, drivers and passengers can distinguish a difference in road condition as the vehicle travels from one type of surface to another (Sandberg and Ejsmont 2002; Veres et al. 1975; Ongel et al. 2008). To avoid variation due to the subjectivity of human ears, an acoustic sensor, namely a microphone, is used to “hear” and sense the road condition through the vehicle noise generated by tire. The microphone application idea allows testing at normal traffic speed, and makes continuous monitoring of road condition possible.

A Linear Regression analysis is performed to find the optimal frequency range of vehicle noise related to pavement macrotexture. After investigation of factors influencing pavement macrotexture MTD, noise filtering technology is needed for further data analysis. The variation of volume between tire tread pattern pitch and pavement macrotexture during tire/road interaction leads to different acoustic resonant frequencies, which causes the large variation of sound spectrum of tire/road noise versus frequency. Meanwhile, other acoustic sources like wind and surrounding traffic is relatively constant with frequency based on the data obtained. Hence, with the assumption that the variations of the signal and noise with respect to frequency are different, a Principal Component Analysis (PCA) is applied to the Fourier transform result of the acoustic measurement. The first Principal Component (PC) vector is extracted as the signal related to pavement macrotexture. Two approaches for MTD estimation are developed based on the first PC vector. The first approach, the PCA Method, directly uses the first PC vector representing the type of pavement to find a match from the database composed of 44 different types of pavements with known MTDs collected from National Center for Asphalt Technology.
The second approach is based on Taylor expansion theory and is developed by observing that the limitation of the 44 known pavements will confine the prediction to a certain MTD values. A mathematical model for MTD prediction is built based on two variables (driving speed and PCA treated acoustic energy) in the expression of Taylor expansion. After the model simplification, the equation for MTD prediction is determined, which extends the MTD prediction range from NCAT interstate highway (0.4 ~ 1.5 mm) to regular urban road (0.2 ~ 3 mm). With the predicted MTD, many applications are followed. First, pavement surface friction prediction; second, construction non-segregation evaluation; third, other pavement features recognition, such as pothole, cracking and patch through pattern recognition; finally, the MTD and the acoustic measurement are highly contributed (85%) to the VOTERS PCI prediction (Shamsabadi et al. 2014).

The novelty of the research could be summarized by two main aspects: (1) the use of a microphone to quantify road condition and recognize road features; and (2) the successful application of Principal Component Analysis to the frequency spectra of acoustic measurement for noise removal by utilizing the difference in variation of sound spectra from different acoustic sources. As to the first novelty, it is expanded to the following five parts.

1. Use of single microphone to quantify pavement macrotexture MTD in real time
2. Use of single microphone to quantify Pavement Condition Index (PCI)
3. Use of single microphone to predict pavement friction and evaluate the severity of pavement damage
4. Use of single microphone to identify other pavement features like pothole, cracking, raveling and bleeding
5. Use of single microphone or microphone array to explore the possibility of pavement subsurface delamination detection
1.7 Limitations

- The optimal frequency range related to pavement macrotexture may have a small shift as tire changed, but the tire effect is already studied and it turns out to be that its influence can be neglected.
- The final equation for MTD estimation is derived from 44 pavements driven through in NCAT for quantification purposes. However, in order to reduce the limitation, the limit condition with minimum and maximum MTD values for typical road are added.
- Study on subsurface delamination through microphone is not deep enough to be instructive, however, it shows the possibility that microphone might be able to detect road subsurface delamination through the studded tire.
- The use of a microphone is limited by weather conditions since it does not have a weather protection device. A better microphone with weather protection is needed for everyday use.

1.8 Definition of Terms

Pavement macrotexture – The deviations of a pavement surface from a true planar surface with the characteristic dimensions of wavelength from 0.5 mm up to 50 mm [ASTM E965 (ASTM 2004)].

MTD – Average macrotexture depth of pavement surface [ASTM E965 (ASTM 2004)].

PCA – Principal Component Analysis, a statistical approach for feature extraction from measurements (Wang et al. 2002). The fundamental purpose of PCA is to cut down the dimensionality of a data set containing a quantity of variables correlated to each other, so as to keep the maximum possible variation. To achieve this goal, an original data set is converted to a new set of uncorrelated variables, the Principal Component (PC) vectors, which are ordered in the descending variation (Jolliffe 2002).

PCI – Pavement Condition Index, is assigned to each street ranging from 0 to 100, where 0 is the worst possible condition and 100 is the best [ASTM D6433 (ASTM 2011b)].
IFI – International Friction Index, a measurement of pavement macrotexture and wet pavement friction, representing the friction coefficient provided by pavement especially in wet weather [ASTM E1960 (ASTM 2011a)].
2 Frequency Analysis of Vehicle Noise

Generally, drivers and passengers can distinguish the difference in road condition as the vehicle travels from one type of road surface to another (Sandberg and Ejsmont 2002; Veres et al. 1975; Ongel et al. 2008). Also, from the daily experience, people could also “hear” the road condition instead of “see”. When the vehicle drives over the smooth roads, the vehicle noise from tire/road interaction is very quiet; while vehicle drives over the damaged roads or rough roads, the vehicle noise is loud. Besides, Sandberg and Ejsmont (2002) concluded from a noise source distribution of a 74 dB vehicle study in driven-by test that noise generated by tire is the predominant one among all the noise from a moving vehicle, compared with other sources such as exhaust system, intake system, engine and remaining unidentifiable noise. A pilot study in Netherlands indicated that 90% of the equivalent sound energy in urban traffic is generated by tire/road noise (Sandberg and Ejsmont 2002). The most important noise source on the vehicle, during a driving-by test according to ISO 362 (ISO 2009), is the tires. Hence, tire/road noise is selected for pavement feature analysis. In order to make use of the tire/road noise for road feature detection, the first issue is to understand the frequency content of tire/road noise that is related to road features, i.e., the influence of road features on tire/road noise. In this chapter, the influence of road features on tire/road noise will be studied through literature and validated by the field test.

2.1 Influence of Pavement Features on Tire/Road Noise

Pavement features include two parts, surface and subsurface parameters. Pavement surface features contain texture (microtexture, macrotexture, megatexture and unevenness), tining, and friction. Pavement subsurface features include stiffness, porosity and thickness of top layer (Saurenman et al. 2005).
2.1.1 Texture

Pavement texture is “the deviations of a pavement surface from a true planar surface” (ISO 13473-1, 1997). The type of pavement texture is distinguished according to the ranges of texture wavelength (ISO 13473-1, 1997). Four types of pavement texture are classified as follows: microtexture, macrotexture, megatexture, and unevenness (Sandberg and Ejsmont 2002).

Microtexture in the order of single grains of sand, with wavelength less than 0.5 mm, can influence the friction and adhesion between the tire and the road surface (Saurenman et al. 2005). Note the equation \( f = \frac{v}{\lambda} \) (Sandberg and Ejsmont 2002), where \( v \) is vehicle driving speed (m/s), \( \lambda \) is texture wavelength (m), and \( f \) is the corresponding frequency (Hz). Assuming that the driving speed is 8.9 m/s (20 mph), and wavelength is <0.5 mm, the frequency is >17.8 kHz. Hence, the influence of microtexture on tire/road noise is in high frequency content, larger than 1 kHz (Sas 1999). Moreover, microtexture is highly related to pavement friction, especially at lower speed less than 64 kph (40 mph) (Hall et al. 2009). Larger microtexture depth will increase friction.

Macrotexture in the order of wavelength of tire tread patch, with wavelength of 0.5 mm to 50 mm, can also influence the friction between the tire and the road surface (Saurenman et al. 2005). Referring to the same equation, the frequency range is between 0.178 kHz to 17.8 kHz within the macrotexture wavelength at driving speed 8.9 m/s (20 mph). Sas (1999) and Sandberg (2003) indicate the effective frequency for macrotexture with a very strong influence on tire/road noise is below 1 kHz.

Megatexture in the order of wavelength of tire-pavement contact patch, with wavelength of 50 mm to 500 mm, exerts considerable influence on the noise generated, especially in the high frequency area larger than 1 kHz (Neithalath et al. 2005). It can be a defect in the pavement surface, resulting from the wear and fatigue of the surface material. Moreover, wavelength of 0.5 m to 50 m is termed as unevenness, or roughness, which is in the order of a stretch of pavement. Its influence on tire/road noise is not clear. Also, it is not in the scope of this dissertation.
2.1.2 Tining
Tining is one finishing technique for concrete pavement. Tining is achieved by dragging metal prongs on semi-hardened concrete pavement to create grooves longitudinally or transversely. The purpose of tining is to reduce hydroplaning in wet weather. However, sound level will increases significantly when the tining is transverse, while longitudinal tining has only a weak effect on sound levels.

2.1.3 Friction
Friction between tire and pavement will cause stick-slip noise. The mechanism of stick-slip noise is similar as the noise caused when running your palm over a smooth surface (Saurenman et al. 2005). Microtexture will tend to increase the stick-slip noise, so as the friction.

2.1.4 Stiffness
The stiffness here is referred to the effective hardness of the surface. Variations in stiffness are commonly attributed to variations in binder materials. For example, asphalt binder is relatively flexible compared to cement binder. To study the effects of stiffness to tire/road noise, Sandberg and Ejsmont (2002) conducted tests on pavement surface with and without rubber powder added to the binder and found no evident noise difference. Moreover, Saurenman et al. (2005) built the structural-acoustic model and theoretically prove that pavement stiffness has no influence on sound levels. However, both studies were performed on porous pavement, which is pavement with void ratio larger than 15 percent. One explanation is that the stiffness of pavements is much greater than that of a tire. Thus, as related to tire, all pavements act as rigid surfaces in terms of source mechanisms. Therefore, the acoustic benefits attribute to differences in stiffness, are more likely associated with porosity, which also varies along stiffness (Saurenman et al. 2005).

2.1.5 Porosity and thickness of top layer
Porosity is a measure of the void spaces in pavement top layer material. Porosity here is specially referred to the porous pavement. Porous pavement is a permeable pavement surface with a stone reservoir underneath. The reservoir temporarily stores surface runoff before infiltrating it into the subsoil. Runoff is thereby infiltrated directly into the soil and receives some water quality
treatment. Porous pavement often appears the same as traditional asphalt or concrete but is manufactured without “fine” materials, and instead incorporates void spaces that allow for infiltration. Apparently, porous pavement are more acoustically absorptive than non-porous pavement, so porous pavements tend to be quieter than non-porous pavements. Porosity parameters are composed of percent voids, the size of voids, the layer thickness, and the shape factor, among which the layer thickness will affects the peak frequency of tire/road noise. According to the research by Sandberg and Ejsmont (2002), the porosity and thickness of top layer has a strong influence on tire/road noise above the frequency of 1 kHz.

In summary, Fig. 2.1 presents the potential influence of tire/pavement parameters on tire/road noise (Sas 1999; Saurenman et al. 2005; Sandberg and Ejsmont 2002). Three observations should be noticed from Fig. 2.1: (1) pavement macrotexture is highly relevant to tire/road noise, comparing with megatexture and microtexture; (2) tire tread pattern pitch also has a very high level of influence on tire/road noise; (3) the relative frequency range for pavement macrotexture on tire/road noise is below 1 kHz. These observations bring pavement macrotexture to the tire/road noise study. Since macrotexture strongly influences tire/road noise, the use of vehicle noise for pavement condition assessment starts from pavement macrotexture measurement.

Another interesting phenomenon in Fig. 2.1 is that the tire/pavement parameters’ influence on tire/road noise has an intersection at 1 kHz. The author also found from the collected data that
there is a peak around 1 kHz in tire/road noise spectra. Sandberg (2003) named this peak around 1 kHz as “multi-coincidence peak”. He pointed out that it is a multi-functional region of frequency. Also, it is related to pavement macrotexture and vehicle tire tread pattern, both of which have many kinds of sound generation mechanisms coincidently over the frequency range from 700 to 1300 Hz (Sandberg 2003), which need be avoided during macrotexture estimation. Meanwhile, frequencies from 700 to 1300 Hz are termed “peak frequencies”.

2.2 Field Test Verification

A field test conducted in September 2010 at National Center of Asphalt Technology (NCAT) test track in Alabama verified the above discussions. The test track consists 46 sections of pavements, each 61 m in length. VOTERS test vehicle drove at 3 different speeds over the track, 32 kph (20 mph), 56 kph (35 mph), and 80 kph (50 mph), 3 rounds for each speed. Detailed test information will be introduced in Chapter 5. The following discussions will demonstrate how the pavement macrotexture influences tire/road noise from the experiment data, and how the top layer thickness affects peak frequency of tire/road noise.

2.2.1 Pavement Surface Features and Tire/Road Noise

In the NCAT test, the macrotexture depth (MTD) is known for all pavement sections of the test track. A Fourier transform was performed to the collected acoustic measurements with the microphone mounted underneath the vehicle behind the driver side rear tire. Four pavement sections with different MTDs are presented in Fig. 2.2. From Pavement A to Pavement D, the MTDs in order are 0.5 mm, 0.8 mm, 1.2 mm and 1.5 mm. It is apparently that the texture of pavement gets rougher as MTD increases. Referring to Fig. 2.3, with the same speed (32 kph), as the MTD of pavement increases from 0.5 mm to 1.5 mm, the sound pressure level (SPL) of tire/road noise goes up below 650 Hz, which is close to the peak frequencies (700 ~ 1300 Hz). The same trend is obtained by Sandberg’s research (Sandberg and Ejsmont 2002), which indicates the acoustic energy increases as MTD increases below the peak frequency at around 1 kHz. This strong correlation between MTD and tire/road noise below 1 kHz verifies the conclusion in Fig. 2.1 regarding the macrotexture part.
2.2.2 Pavement Subsurface Features and Tire/Road Noise

Pavement subsurface features include stiffness, porosity and thickness of the top layer. Figure 2.4 and Figure 2.5 respectively shows the influence of the top layer thickness and top layer stiffness on the tire/road noise based on NCAT data. Different from the above discussion, the difference in thickness does not have any shift in peak frequency. Figure 2.4 represents the frequency spectra of two pavements with different top layer thicknesses. Since other literature concluded that stiffness has no influence on the tire/road noise, the author selected pavements with different top layer stiffness to investigate their influence on the tire/road noise. In Fig. 2.5, the only difference of both pavements is the stiffness of the top layer: The stiffness of Pavement B is harder than that of Pavement A. However, a significant difference could be identified from
the sound pressure level at peak frequency, which is contrary to the above literature review. The reason for this contradiction might be that the tested pavements from NCAT are not porous pavement, so the theory discussed before is not adaptable to these regular pavements.

![Figure 2.4 Influence of Top Layer Thickness on Tire/Road Noise](image)

![Figure 2.5 Influence of Top Layer Stiffness on Tire/Road Noise](image)

Nevertheless, subsurface assessment through tire/road noise is a main objective for VOTERS. In the next chapters, technology of signal filtering is performed to explore the possibility of using tire/road noise for pavement subsurface condition assessment.
3 Factors Influencing Pavement Mean Texture Depth (MTD)

The macrotexture measurement is determined as a starting point for pavement condition assessment using vehicle noise after the discussion in Chapter 2. Hence, the first issue for macrotexture measurement is to explore the factors influencing pavement Mean Texture Depth (MTD). Generally, three factors effect MTD measurements through vehicle noise: tire/road noise level, driving speed, and acoustic sensor location. First, the pavement macrotexture is related to the vehicle driving speed and the tire/road noise level (Sandberg and Ejsmont 2002). Second, the acoustic energy (integration of frequency spectrum of tire/road noise) below 1 kHz is positively proportional to the MTD of pavement (Sandberg and Ejsmont 2002; Sandberg 2003; Saykin et al. 2013). Third, optimal sensor placement needs to be selected, i.e., which sensor should be used for MTD estimation. Meanwhile, the selection of an optimal sensor location will also be related to the previous two factors.

3.1 MTD and Tire/Road Noise Level

Theoretically, the first question that arises is whether the tire/road noise level should be included as an influence and, if so, which variable could represent it. Previous work by others has shown that the noise level of the tire/road interaction is related to MTD (Sandberg and Ejsmont 2002; Ongel et al. 2008; Lu et al. 2010; Veres et al. 1975). Moreover, the Energy Method for MTD estimation (Saykin et al. 2013) was developed based on this assumption. As introduced before, it concluded that the signal energy, defined as the integration of the frequency spectra of collected tire/road noise over a certain frequency range (40 to ~400 Hz), was linearly correlated with the macrotexture MTD (Saykin et al. 2013). Therefore, the energy was utilized to predict MTD of pavement through their linear relationship.

Figures 3.1 - 3.3 display the linear relationship between known MTD and the noise level (acoustic energy) at three speeds respectively, 32 kph, 56 kph, and 80 kph. The acoustic
measurement here was collected from the microphone set behind driver side rear tire. The MTDs of pavements were known in the test. Before the optimal frequency range related to MTD estimation is explored, the acoustic energy was computed within frequency range between DC to 1 kHz. As the following figures show, the noise level is linearly correlated to MTD with an average correlation coefficient of 0.87 (square root of 0.75).

Figure 3.1 Linear Relation between Acoustic Energy and MTD at 32 kph

Figure 3.2 Linear Relation between Acoustic Energy and MTD at 56 kph
Therefore, MTD and tire/road noise level have a high linear relationship. This can be understood from two aspects: (1) Frequency spectrum of tire/road noise could be directly used for MTD estimation; (2) Tire/road noise level (acoustic energy) could be considered as a variable for MTD estimation.

### 3.2 MTD and Driving Speed

Besides tire/road noise level, the speed effect should also be considered in the MTD prediction model. The reason for considering the speed effect comes from its influence on the acoustic energy. The acoustic energy is computed over a certain frequency range, while in this frequency range, the sound pressure level (SPL) will affect the result of this energy. Sandberg and Ejsmont (2002) already claimed that the SPL would increase as speed increases, i.e., the vehicle would create more noise with higher speed over the same road, resulting in higher energy computed from the frequency spectra. In addition, Sandberg (2003) pointed out that there is a “multi-coincidence peak” around 1 kHz below which the SPL will rise along with increased MTD. Thus, the speed will influence the acoustic energy since it will be computed below the “multi-coincidence peak” frequency, which will be discussed in the frequency band selection part of MTD estimation in Chapter 6. Figures 3.4 to Figure 3.6 represent the examples of speed effect.
for three pavements with three different MTDs. The sound pressure level increases with speed for the same pavement below about 1 kHz. Two solutions will be discussed in Chapters 5 and 6 to overcome the speed effect: (1) normalize the sound pressure level for different speeds; (2) consider speed as one variable for the MTD estimation.

Figure 3.4 Speed Effect for Pavement with MTD = 0.5 mm

Figure 3.5 Speed Effect for Pavement with MTD = 0.8 mm
3.3 Optimal Acoustic Sensor Placement

Considering the economic costs, one microphone is preferred for macrotexture measurements. A test for the optimal position of the acoustic sensor was conducted. Figure 3.7 is the configuration of the test vehicle. In Configuration A (Fig. 3.7 (a)), five microphone positions were tested, and the vertical distance from microphone to ground is 5.08 cm (2 in). These five directional microphones are produced by G.R.A.S, with the sensitivity from 44 ~ 52 mV/Pa. The principle for the selection of optimal sensor location is to compare the correlation of MTD and the acoustic energy as described in Section 3.1. The highest linear correlation between pavement MTD and acoustic energy will indicate the optimal location.

The test vehicle with Configuration A drove over the test track at three speeds, three rounds for each speed. The acoustic energy was computed within the frequency range from DC to 1 kHz. Table 3.1 represents the linear correlation coefficient between MTD and acoustic energy for each microphone at three speeds, 32 kph, 56 kph, and 80 kph. Microphones 4 and 5 perform best among all the microphones for any speed. It is reasonable since Microphones 4 and 5 are much more closer to the tire.
In order to find which microphone has the optimal position, test vehicle with Configuration B (Fig. 3.7 (b)) repeated the experiment again at three speeds. Also, it is noticed that the vertical distance from microphone to ground is increased to 38.1 cm (15 in). Table 3.2 indicates the performance of Microphones 4 and 5 at a higher vertical position. The linear correlation coefficient of Microphone 5 is consistently higher than that of Microphone 4 at any speed. Referring to Table 3.1, it is concluded that the distance from the microphone to ground influences Microphone 5 less than Microphone 4.

**Table 3.1 Linear Correlation Coefficient between Acoustic Energy and MTD for Configuration A**

<table>
<thead>
<tr>
<th>Speed (kph)</th>
<th>Microphone 1</th>
<th>Microphone 2</th>
<th>Microphone 3</th>
<th>Microphone 4</th>
<th>Microphone 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>0.29</td>
<td>0.54</td>
<td>0.62</td>
<td>0.79</td>
<td>0.82</td>
</tr>
<tr>
<td>56</td>
<td>0.38</td>
<td>0.68</td>
<td>0.66</td>
<td>0.73</td>
<td>0.75</td>
</tr>
<tr>
<td>80</td>
<td>0.31</td>
<td>0.50</td>
<td>0.72</td>
<td>0.80</td>
<td>0.79</td>
</tr>
</tbody>
</table>

**Table 3.2 Linear Correlation Coefficient between Acoustic Energy and MTD for Configuration B**

<table>
<thead>
<tr>
<th>Speed (kph)</th>
<th>Microphone 4</th>
<th>Microphone 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>0.62</td>
<td>0.78</td>
</tr>
<tr>
<td>56</td>
<td>0.67</td>
<td>0.81</td>
</tr>
<tr>
<td>80</td>
<td>0.59</td>
<td>0.77</td>
</tr>
</tbody>
</table>
In summary, the position of Microphone 5 is the optimal sensor placement with a consistently high linear correlation coefficient between MTD and the acoustic energy from the tire/road interaction. Additionally, the combination of multiple microphones would not improve the linear correlation coefficient (Saykin et al. 2013). Thus, the optimal acoustic sensor placement is selected to be behind the driver side rear tire, like Microphone 5 shown in Fig. 3.7.
4 Noise Removal by PCA Treatment

4.1 Motivation

Based on the experience of a previous study (Saykin 2012), as well as the same conclusion obtained in Chapter 3, acoustic data collected by Microphone 5 (Fig. 3.7) was chosen for the macrotexture investigation, since the acoustic signal spectra represented a good correlation with pavement macrotexture. Microphone 5 was directed to the interface of the rear tire with the ground, which is expected to be the source of most tire/pavement interaction, and somewhat shielded from wind and engine noise, compared to the other microphone locations tested earlier (Fig. 3.7). The measurements collected by microphone 5 include not only tire/road sound, but also undesired noise (Fig. 4.1). As stated before, the road macrotexture is related to the frequency dependence of the sound from tire/road interaction, while the noise such as wind and vehicle vibration is less frequency dependent than the signal from tire/road interaction, since wind and vehicle vibration are treated as steady – state noise under the test condition (wind condition outside is steady) (Cerrato 2009). Therefore, an assumption was made that frequency variations of noise may be different from those of signal. Consequently, a demand for noise elimination which can keep the most variation with frequency and remove the relatively constant information versus frequency is generated.

Figure 4.1 Acoustic Sources Collected by Directional Microphone
4.2 Application of Principal Component Analysis

Many approaches have been investigated to reduce noise. Compression-based induction, such as measures based on the Minimum Description Length (MDL) principle, is appropriate for handling noisy data in medical diagnosis (Gamberger et al. 1996). A hybrid algorithm is proposed to eliminate the varying background and noise simultaneously for multivariate calibration of near infrared (NIR) spectral signals. The method is based on the use of multi-resolution, which is one of the main advantages provided by wavelet transform. The signals are first split into different frequency components, which keep the same data points of the original signals. In conjunction with a modified uninformative variable elimination (mUVE) criterion, the method can be used to remove the low-frequency varying background and the high-frequency noise simultaneously (Chen et al. 2004). Quantile based noise estimation and spectral subtraction or Wiener filtering is employed to the elimination of additive noise from a speech signal (Stahl et al. 2000). Principal component analysis is applied for a noise reduction method for electromechanical systems diagnostic (Serviere and Fabry 2005), hyperspectral infrared data (Chen and Qian 2011), roving gas chromatography/mass spectrometry (CG/MS) measurements (Statheropoulos et al. 1999), and cleaning noisy ECGs (Romero 2011).

Regarding the acoustic application being considered in this study, data sets will be long and mixed with many unknown sources. Accordingly, a standard principal component analysis (PCA) is preferred because of its simple algorithm and straightforward manipulation to the data set, as well as its superior for isolation and removal of random noise.

In order to demonstrate that PCA is a much more efficient method, the author conducted an experiment to compare the noise elimination effect of both band-pass filter and PCA.
Figure 4.2 Time History of PCA (left) and Band-pass Filter (right) for Noise Removal
(Note: Plots from top to bottom are clean signal, random noise, clean signal + noise and filtered signal.)

In this case, a portion of music was chosen and embedded in MATLAB as a clean signal, and a random noise with the amplitude as 100% of the clean signal was added. PCA and band-pass method was used to eliminate noise from the artificial signal including clean signal and noise. The results are shown in Figures 4.2 and 4.3.

Figure 4.2 indicates that after PCA, the filtered signal retained the most significant information of the clean signal in the time domain, while the band-pass filter could not reconstruct the signal similar to the clean one.

As to Fig. 4.3 in frequency domain, the PCA did a good job in capturing the dominant information; while the band-pass method only picked two frequency bands of 200 - 690Hz and
890 - 1350Hz from the “clean + noise signal” and abandon the signal beyond those two bands, which actually changes the signal.

In conclusion, PCA tries to keep the characteristic of the original signal information over the whole frequency band, while the band-pass filter only keeps the information at certain frequency bands which may change the signal.

The attractive property of PCA at mostly keeping the original signal encourages the author to utilize this method for noise elimination of acoustic measurement in this road condition study.

Figure 4.3 Comparison of the PCA (left) and Band-pass Filter (right) for Noise Removal

4.3 PCA Theory

Principal component analysis (PCA) is a well-known statistical approach for feature extraction from measurements (Wang et al. 2002). Pearson (1901) and Hotelling (1933) first described this technique (Jolliffe 2002). The fundamental purpose of PCA is to cut down the dimensionality of a data set containing a quantity of variables correlated to each other, so as to keep the maximum possible variation. To achieve this goal, an original data set is converted to a new set of uncorrelated variables, the principal component vectors, which are ordered in the descending variation (Jolliffe 2002).
PCA forms new variables using a linear combination of the original variables. The basic equation is given below (Abdi 2010):

\[ A_{m\times n} = Q_{m\times m} \times B_{m\times n} \]  

(4.1)

where,

- \( A \) = Matrix containing the principal component vectors (PCs);
- \( B \) = Original variable matrix;
- \( Q \) = Weighting coefficients matrix to build the linear relationship between \( A \) and \( B \);
- \( m \) = number of variables in original matrix; and
- \( n \) = number of experiments/observations.

The new variables in matrix \( A \) are principal component vectors (PCs). The first row of \( A \) is first principal component vector, which holds the maximum variance of the data, and the second principal component vector holds the maximum of the remaining variance. Generally, only a handful of PCs are needed to account for the maximum of the variance of the original data set, and for this reason, PCA is generally known as a data reduction technique (Statheropoulos et al. 1999).

In order to find such a matrix \( Q \) to best represent the original variables \( B \) into \( A \), there are the following assumptions (Shlens 2005).

I. Linearity

Linearity makes the problem as a linear transformation. The mapping from \( B \) to \( A \) is linear.

II. Large variance possesses interesting information.

This assumption also covers the belief that the data has a high signal-to-noise ratio (SNR). Hence, principal components with larger associated variances represent interesting features, while those with lower variances represent noise.

III. Orthogonality
The weighting coefficients matrix is orthogonal (rows of Q is not correlated to each other), i.e., \( Q^\top = Q^T \). This assumption offers an intuitive simplification that makes PCA soluble with linear algebra decomposition techniques.

With these assumptions, we begin to derive the algorithm of PCA. Because the weighting coefficients are orthogonal, \( Q^\top = Q^T \), according to the matrix properties, we could refer that \( A^{-1} = A^T \). Thus, the covariance matrix of \( A \), \( C_A \), could be expressed as following:

\[
C_A = \frac{1}{(n-1)} \times A \times A^T = \frac{1}{(n-1)} \times (QB) \times (B^T \times Q^T) = \frac{1}{(n-1)} \times Q \times (B \times B^T) \times Q^T
\]  

(4.2)

As we know from the matrix theory, \( C_A \) needs to be diagonalized to satisfy the above assumptions.

Now, the problem becomes how to find a matrix \( Q \) that could make \( C_A \) diagonal. While looking at the covariance matrix of the original variable matrix \( B \), \( C_B = BB^\top \), it is clear that \( C_B \) is symmetric according to the property of covariance matrix.

Consider the eigendecomposition of matrix \( C_B = EDE^\top \), where, \( E \) is eigenvector matrix of \( C_B \), \( D \) is a diagonal matrix with the corresponding eigenvalues (i.e., variances) in the diagonal direction. Let \( Q = E^\top \), we obtain \( C_A \) as shown below.

\[
C_A = \frac{1}{n-1} \times Q \times (Q^\top D) \times (Q^\top) = \frac{1}{n-1} \times (QQ^\top) \times D \times (QQ^\top) = \frac{1}{n-1} \times D
\]  

(4.3)
It is evident that the choice of $Q$ diagonalizes $C_A$. Thus, the transformation matrix $Q$ is obtained. Consequently, the results of PCA is summarized in matrices $Q$ and $C_A$. The matrix $Q$ is defined as follows: If $C_B$ is the covariance matrix of the original data matrix $B$, i.e., $C_B = BB^T$, matrix $Q$ is the transpose of the eigenvector matrix of $C_B$. The $i$th diagonal value of $C_A$ is the variance of $B$ along the $i$th row of $Q$.

In practice, computing PCA of a data set $B$ includes three steps. (1) normalize the original data matrix $B$: subtracting off the mean of each measurement type (each variable) and then dividing the standard deviation of each measurement type; (2) obtain weighting coefficients $Q$: computing the eigenvectors of $BB^T$, and then reordering those eigenvectors corresponding to the descending order of the eigenvalues of $BB^T$; (3) obtain the principal components (PCs) according to Eq. 4.1.

After matrix $A$ is obtained by Eq. 4.1, the number ($L$) of the first few components to be selected for research is often determined by the following equation (Jolliffe 2002):

$$\frac{\sum_{i=1}^{L} \sigma_i^2}{\sum_{i=1}^{M} \sigma_i^2} \geq 0.8$$

(4.4)

where,

$L$ = number of most principal component vectors;  
$M$ = number of variables in original data matrix; and  
$\sigma_i^2$ = variance associated with the $i$th principal component vector.

Equation 4.4 is chosen based on the assumption that data with high variance possesses high signal – to – noise ratio (SNR). SNR could be expressed as the variance ratio of signal to noise (Shlens 2005), so a high SNR indicates high quality data with less noise. Hence, if a 2D variable dataset along certain direction with highest variance, the variance of the signal along this direction is highest. Meanwhile, the variance of the noise along this direction is lowest based on PCA theory. Consequently, the signal possesses the highest SNR. In the following study, the first principal component vector is usually considered to carry most information from tire/road interaction.
5 MTD Estimation by PCA Method

5.1 Motivation

Pavement texture is “the deviation of a pavement surface from a true planar surface” (ISO 13473-1, 1997). It determines factors such as tire/road friction, tire/road noise, rolling resistance and ride quality (Rasmussen et al. 2011). Therefore engineering methods for measuring surface texture are valuable. The type of pavement texture is classified according to the range of texture wavelength (ISO 13473-1, 1997). Four types of pavement texture are classified: microtexture, macrotexture, megatexture, and unevenness (Sandberg 2003). Among these four types of pavement texture, macrotexture is the pavement texture with spatial wavelengths from 0.5 mm to 50 mm (ISO 13473-1, 1997). Macrotecture depth is related to tire/road friction in wet weather, noise characteristics, and assessment of the suitability of paving materials or pavement finishing techniques (ISO 13473-1, 1997; Rasmussen et al. 2011; Sandberg 2003; Gunaratne et al. 2000). It is an important index for pavement condition rating. Thus, the focus of this paper is on seeking an accurate, easy, safe approach to test and monitor the pavement macrotexture depth.

The current state of the art for macrotexture depth measurement is investigated. One traditional method for macrotexture depth measurement is introduced by ASTM E965 – 96 (ASTM E965, 2004) and named the “sand patch method”, or “volumetric patch method” (ASTM E965, 2004). This method characterizes surface macrotexture by the quantity MTD (ASTM E965, 2004) as described in Chapter 3. It is easy to apply and the result is three-dimensional. However, this method may give different results by different operators (China 2012), and it may only be applied to pavement when traffic is closed. An alternative method commonly used now is the laser-based profilometer method, which is considered to be more advanced, safer, and economical. Several types of equipment or systems were developed based on laser application. The standard ASTM E2157 – 09 proposed this method by using a Circular Track Meter (CT Meter) (ASTM E2157, 2009b) to measure and evaluate pavement macrotexture profiles for
laboratory investigations and actual paved surfaces in the field (ASTM E2157, 2009b; ASTM E1845, 2009a). A robotic-based texture measurement system (Robo Tex) with higher accuracy was developed in 2005 (Rasmussen et al. 2011; Cackler et al. 2006). However, the CT Meter and Robo Tex systems require disruption of traffic flow. Another laser-based profilometer system, the road surface analyzer (ROSAN) system, was developed by Sixbey’s research team for FHWA in 1997 (Koklanaris 1998). ROSAN can perform at speeds up to 120 kph (Peña et al. 1997), so the traffic control problem is eliminated. Nevertheless, because the system includes many accessories, such as the beam and bumper hitch, the cost issue may hinder its widespread use.

Five issues motivate the acoustic approach described in this paper. The first issue is that human error may be avoided by mounting a microphone underneath a vehicle near one of the rear tires, which only records the sound pressure. The second consideration is to reduce or eliminate traffic disruption. The microphone application idea allows testing at normal traffic speeds. Third, the microphone application makes continuous monitoring of macrotexture possible. The fourth concern is regarding cost-effectiveness. Elimination of vehicle vibration increases the cost of the laser-based profilometer system for other accessories, but it does not restrict the use of a microphone measurement when appropriate signal processing techniques are used. The last, as well as the most important issue is that drivers and passengers can often distinguish a difference in the vehicle noise generated by tire as the vehicle travels from one type of road surface to another. One may conclude that pavement macrotexture has a large effect on tire/pavement noise, and controlled studies have confirmed this (Sandberg 2003; Ongel et al. 2008; Lu et al. 2010). Being aware of the feasibility of characterizing pavements of different macrotexture by their tire noise spectra (Veres et al. 1975), the author initially attempted to use the acoustic measurement as a measure of pavement macrotexture (Saykin 2012). The present work seeks to improve the accuracy of this approach.

While the vehicle is moving, dynamic interactions between the tire and the road surface produce sounds whose frequency dependence is related to the road macrotexture (Veres et al. 1975; Saykin 2012; Zhang et al. 2012; Hegmon 1979). However, there are other sources of sound present, such as those caused by wind and vehicle vibration. In the discussion that follows, the
The term “signal” refers to the sound generated by the tire-road interaction and the term “noise” refers to all other sound measured by the microphone underneath the vehicle. This work investigates the possibility that the variations of the signal and noise with respect to frequency are different. In such situations, a Principal Component Analysis (PCA) (Jolliffe 2002) may be used to approximately extract the signal from measurements that include the signal and noise. The signal may then be compared to signals from roads with known macrotexture depth such that the road macrotexture depth may be estimated. Additionally, with an expectation of defect identification such as potholes and severe cracking in pavement structure by acoustic measurements, subsurface information hidden in the extracted signal is also explored.

In summary, the goal of this study is to create a new pavement macrotexture depth prediction model that only uses measurements from an acoustic sensor installed beneath a moving vehicle; also, to seek the possibility for subsurface information from the acoustic measurements. To reach this goal, the following objectives were pursued: 1) Investigate the relationship between tire/pavement sound and pavement surface macrotexture; 2) Develop a method to eliminate noise not related to pavement surface condition collected by the acoustic sensor; 3) Estimate macrotexture depth using filtered data from first principal component vector and compare to other methods; and 4) Explore for subsurface information inside the extracted signal being used for macrotexture estimation.

5.2 Method Description

5.2.1 Configuration of NCAT Test

The microphone configuration mounted underneath the test vehicle is shown in Fig. 5.1. The type and sensitivity of these microphones were described before in Chapter 3. The sampling frequency of this test is 40 kHz. Since the type of tire will influence the frequency spectra of acoustic signal, especially in the typical “tire-band” range 500 ~ 1300 Hz (Cerrato 2009), the same tire was used throughout the experiment to exclude the possibility of tire effect.
In September 2010 the test was conducted at the National Center for Asphalt Technology (NCAT) test track in Lee County, Alabama. A detailed illustration of the track is shown in Fig. 5.2. The track is 2.7 km (1.7 miles) long, consisting of 46 sections of pavement, each 61 m (200 ft) in length. The vehicle collected over 50 GB of acoustic data as it drove around the track for different testing configurations. Among the 46 pavement types, 45 are considered in this paper as listed in Table 5.1. The vehicle drove at 3 different speeds over the track, 32 kph (20 mph), 56 kph (35 mph), and 80 kph (50 mph), 3 rounds for each speed. For each round there are 45 measurements corresponding to the 45 pavement sections listed in Table 5.1.
Table 5.1 Pavement Properties at NCAT

<table>
<thead>
<tr>
<th>Type</th>
<th>Design</th>
<th>MTD (mm)</th>
<th>Type</th>
<th>Design</th>
<th>MTD (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>SMA</td>
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<td>S3</td>
<td>OGFC</td>
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<tr>
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<tr>
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<td>Superpave</td>
<td>1</td>
<td>S7</td>
<td>Superpave</td>
<td>0.5</td>
</tr>
<tr>
<td>E5</td>
<td>Superpave</td>
<td>0.7</td>
<td>S8</td>
<td>PFC</td>
<td>1.4</td>
</tr>
<tr>
<td>E6</td>
<td>Superpave</td>
<td>0.7</td>
<td>S9</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>E7</td>
<td>Superpave</td>
<td>0.9</td>
<td>S10</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>E8</td>
<td>Superpave</td>
<td>0.8</td>
<td>S11</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>E9</td>
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<td>0.5</td>
<td>S12</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>E10</td>
<td>Superpave</td>
<td>0.5</td>
<td>S13</td>
<td>Superpave</td>
<td>0.9</td>
</tr>
<tr>
<td>W1</td>
<td>SMA</td>
<td>1.2</td>
<td>N1</td>
<td>PFC</td>
<td>1.3</td>
</tr>
<tr>
<td>W2</td>
<td>SMA</td>
<td>0.9</td>
<td>N2</td>
<td>PFC</td>
<td>1.2</td>
</tr>
<tr>
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<td>Superpave</td>
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<td>N3</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>W4</td>
<td>Superpave</td>
<td>0.5</td>
<td>N4</td>
<td>Superpave</td>
<td>0.7</td>
</tr>
<tr>
<td>W5</td>
<td>Superpave</td>
<td>0.6</td>
<td>N5</td>
<td>Superpave</td>
<td>0.5</td>
</tr>
<tr>
<td>W6</td>
<td>Superpave</td>
<td>0.5</td>
<td>N6</td>
<td>Superpave</td>
<td>0.5</td>
</tr>
<tr>
<td>W7</td>
<td>SMA</td>
<td>1.4</td>
<td>N7</td>
<td>Superpave</td>
<td>0.6</td>
</tr>
<tr>
<td>W8</td>
<td>Novachip</td>
<td>0.8</td>
<td>N8</td>
<td>SMA</td>
<td>0.7</td>
</tr>
<tr>
<td>W9</td>
<td>Superpave</td>
<td>0.4</td>
<td>N9</td>
<td>SMA</td>
<td>0.8</td>
</tr>
<tr>
<td>W10</td>
<td>Superpave</td>
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<td>N10</td>
<td>Superpave</td>
<td>0.5</td>
</tr>
<tr>
<td>S1</td>
<td>SMA</td>
<td>0.9</td>
<td>N11</td>
<td>Superpave</td>
<td>0.5</td>
</tr>
<tr>
<td>S2</td>
<td>Superpave</td>
<td>0.5</td>
<td>N12</td>
<td>SMA</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>N13</td>
<td>OGFC</td>
<td>1.2</td>
</tr>
</tbody>
</table>

(Note: SMA = Stone Matrix Asphalt; OGFC = Open Graded Friction Course; PFC = Porous Friction Course.)

5.2.2 Data Preprocessing for PCA
Based on the experience of a previous study (Saykin 2012), acoustic data collected by microphone M5 was chosen for the macrotexture investigation, since the acoustic signal spectra from M5 represented good correlation with pavement macrotexture. Microphone M5 was directed to the interface of rear tire and ground, which is expected to be the source of most
tire/pavement sound, and shielded from wind and engine noise, compared to the other microphone locations shown in Fig. 5.1. The measurement collected by microphone M5 includes not only tire/road sound, but also the undesired noise. As stated before, the road macrotexture is related to the frequency dependence of the sound from tire/road interaction, while the noise such as wind and vehicle vibration is less frequency dependent than the signal from tire/road interaction, since wind and vehicle vibration are treated as steady – state noise under the test condition (wind condition outside is steady) (Cerrato 2009). Therefore, an assumption was made that the noise may vary differently from signal with frequency. Consequently, a demand for noise elimination by PCA is motivated.

PCA was performed to the acoustic data collected for each pavement section. Taking one pavement section for example, the data preprocessing procedure is as follows. The first step is windowing the measurements in time domain. The measurements for each section were windowed with data length of $2^{13}$ as one window. The second step is performing discrete-time short time Fourier Transform. Frequency spectra for 45 pavement sections are displayed in Fig. 5.3. The color bar represents the sound pressure level. White color means intense sound pressure, while black color means weak sound pressure. Figure 5.3 indicates that the frequency spectrum for each pavement section is highest in the frequency range of 0–2 kHz. Meanwhile, the macrotexture wavelength is 0.5 mm to 50 mm (ISO 13473 – 1, 1997). With the equation $f = \frac{V}{\lambda}$
\( \lambda \), where \( V \) is the driving speed (m/s), \( \lambda \) is the texture wavelength (m), and \( f \) is frequency (Hz), the frequency range reflecting macrotexture will shift with different driving speeds. By computation, the frequency range is \( 20V \sim 2000V \) Hz, in which \( V \) is the driving speed as mentioned above. With the three different driving speeds in the test from low to high, the frequency range is \( 179 \sim 17900 \) Hz, \( 313 \sim 31300 \) Hz, \( 447 \sim 44700 \) Hz, separately. The upper frequency band is selected as 2 kHz since the amplitude of sound pressure level is weak after 2 kHz. In order to contain complete pavement surface information, also for the convenience of program input, the lower frequency band is selected as 0 kHz. Observing the lower frequency band for macrotexture of \( 20V \) Hz with different speeds, it is concluded that the signal is mainly related to the macrotexture in the frequency range of \( 0 \sim 2 \) kHz. Consequently, the focus on the frequency spectrum will be under 2 kHz. The original data matrix is formulated with \( m \) rows according to \( m \) time windows, \( n \) columns according to \( n \) frequency values under 2 kHz. The matrix element is the sound pressure level. The third step is data normalization. For each window, it is subtracted off the mean value and then divided by the standard deviation of the row vector. Accordingly, the normalized original data matrix \( B \) is expressed as below:

\[
\begin{bmatrix}
P_1@f_1 & \cdots & P_1@f_n \\
\vdots & \ddots & \vdots \\
P_m@f_1 & \cdots & P_m@f_n
\end{bmatrix}_{m \times n} \rightarrow \text{time window l}
\]

The element \( P_i@f_j \) is the sound pressure level in the \( i \)th time window under frequency \( f_j \) with the unit of dB. In addition, from the view of principal component analysis, the time window is treated as the variables and the different frequencies are viewed as different observations in this study. The normalized matrix \( B \) would be used to perform PCA. The fourth step is PCA treatment. Compute the eigenvectors of \( BB^T \). The matrix \( Q \) is obtained after reordering those eigenvectors in descending order of the associated eigenvalues of \( BB^T \). The principal component vectors in terms of \( A \) through Eq. 4.2 are thus found. In this study, the author chose the first principal component vector (first row in matrix \( A \)) for research because the associated variance of the first principal component vector usually accounted for over 90% of the summation of
variances, i.e., the first PC represented overall curve shape for those \( m \) window vectors along \( n \) frequencies in matrix \( B \).

### 5.2.3 Post PCA Analysis

As the first principal component vector was selected for analysis, following phase angle formula was applied to compare two vectors:

\[
\cos \alpha = \frac{a \cdot b}{|a||b|}
\]  

(5.1)

where,

\( a \) = first principal component vector of tested pavement;

\( b \) = first principal component vector of known pavement; and

\( \alpha \) = phase angle between \( a \) and \( b \).

Large values of \( \alpha \) indicate large differences between two vectors \( a \) and \( b \), while small values of \( \alpha \) indicate small differences between \( a \) and \( b \). In this study, the mean texture depth (MTD) is used to quantify the pavement surface condition. The method computes the phase angle between the first PC vector of the tested pavement section and several known pavement sections with known MTD values. The MTD value of the tested pavement is estimated as that of the known pavement with the smallest phase angle. One requirement for this approach is that the MTD values of those known pavement sections need to have a broad range to cover most road conditions, i.e., different pavement surface conditions are needed to be analyzed as a database for the MTD estimation.

### 5.3 Macrotecture Depth Estimation through PCA

#### 5.3.1 First Principal Component Extraction

##### 5.3.1.1 Frequency Domain

Surface conditions of pavements W6 and S4 from NCAT are shown in Fig. 5.4. Pavement W6 with small MTD of 0.5 mm is much finer while pavement S4 is coarse with large MTD of 1.5 mm. The principal component vectors of the acoustic measurement for pavement W6 are shown
in Fig. 5.5, with driving speed at 56 kph (35 mph). Figure 5.5a is the original frequency spectrum with normalized Sound Pressure Level (SPL), where, different lines measured sound pressure level divided by different time windows. Figure 5.5b shows all the principal component vectors. The dotted curve in Fig. 5.5b is the first principal component vector, which is extracted in Fig. 5.5c. It is assumed as the most representative vector for characterizing pavement W6. The other solid curves in Fig. 5.5b are assumed to be noise. Additional experiments were conducted at driving speeds of 32 kph (20 mph) and 80 kph (50 mph). The first principal component vector has the same trend and magnitude as shown in Fig. 5.5c. Figure 5.5 indicates that the first principal component vector is able to represent the most variation of the original data set in this study. Thus, further research will focus on the first principal component vector.

Figure 5.4 Surface Condition of Pavement W6 and Pavement S4

(Note: square side length of both pictures is 5 cm.)

Figure 5.5 Principal Component Vectors of Acoustic Measurement at 56 kph
The comparison of spectra before and after PCA treatment for pavements W6 and S4 are illustrated in Fig. 5.6. Figure 5.6a shows the original sound pressure level versus frequency, while Fig. 5.6b shows the first principal component vector. It is difficult to clarify the difference between pavement S4 (solid curve) and W6 (dot curve) as those two curves overlap each other in the left plot. However, after PCA treatment, the first principal component vector of pavement S4 (solid curve) is clearly distinguished from that of pavement W6 (dotted curve) as shown in Fig. 5.6b. Referring to Fig. 5.4, it is concluded that PCA effectively differentiate two pavements by the first principal component vector, which supports for the assumption that first principal component vector could characterize road condition.
5.3.1.2 Time Domain

With the interest in time domain signal after PCA treatment, the author reconstructed the signal from the first principal component vector. Figure 5.7 represents the comparison of sound pressure varying with time before and after PCA treatment. The amplitude of sound pressure after PCA treatment is around $1/3$–$1/2$ of that before PCA. By hearing the audio of the sound shown in Fig. 5.7, most background noise is reduced in the reconstructed one, which means that to some extent noise is eliminated by the PCA.

5.3.1.3 Speed Effect

It is demonstrated that first principal component vector has kept most pavement surface information for quality assessment. Its ability to characterize different road condition is also proven. However, one question came into consideration: will the first principal component vectors of the same pavement collected by different speeds be similar? In other words, will speed limit the performance of first principal component vector? To answer this question, an experiment with varying speeds (32 kph, 56 kph, and 80 kph) on the same part of pavement W6 was conducted. Figure 5.8 demonstrates the speed effect on first principal component vector and original data of pavement W6. Figure 5.8ab shows the first principal component vectors for different speeds and they are very similar to each other, while in Fig. 5.8cd the sound pressure level of the same pavement obviously increases with speed. Thus, the speed effect could be ignored when the original data is treated with a PCA, which not only shows that the first principal component vector carries most road surface information, but also offers one possibility for real time data processing regardless of speed. However, the normal driving speed of above 40 kph (25 mph) is recommended to provide the most consistent results.
5.3.2 MTD Estimation

Since the first principal component vector is a representative vector for one type of pavement, it is applied to estimate MTD of pavement. Using the approach described in Section 5.2.3 “Post PCA Analysis”, five different pavements were chosen as known pavements, and a different pavement from NCAT was used as the tested pavement. In this blind test, the MTD of the tested pavement was first assumed unknown, estimated by the present method, and then checked against the known value. Using Eq. 5.1, the phase angle between tested pavement and known pavements were calculated separately. After comparison of the phase angle, one of those five known pavements was chosen as the most similar one to the tested pavement because of the smallest phase angle between these two pavements’ first principal component vectors. Hence, the road surface conditions of both pavements are supposed to be alike. Since mean texture depth (MTD) is an index for pavement surface characteristics (ISO 13473-1, 1997), it is reasonable to estimate MTD of the tested pavement equal to that of the selected pavement. After verifying that
the true MTD of tested pavement is the same or closest as estimated, it is shown that the first principal component vector can be used for MTD estimation.

The author performed three experiments at speeds of 32 kph, 56 kph and 80 kph. The known pavements were N5, E1, N12, N2 and S4, while the tested pavements were W8, N6 and E4. All of these pavements were from NCAT as Table 5.1 indicates. Table 5.2 listed the tested and known pavements in each experiment as shown in Fig. 5.9, as well as their MTD values. The known pavement with the same MTD as the tested pavement in the experiment was marked in bold in Table 5.2. For example, taking the result in Fig. 5.9a, on the left side, among the five known pavements, pavement E1 (circled in Fig. 5.9a) with a MTD of 0.8 mm was selected as the one most similar to the tested pavement W8 with a minimum phase angle between their associated first principal component vectors. Hence, MTD of pavement W8 was estimated as the same as that of pavement E1, 0.8 mm. After checking against the true MTD of pavement W8, the estimation matches the real condition. On the right side of Figure 5.9a, three curves were compared. They are first principal component vectors for W8, E1 and S4 respectively. The dotted curve is for pavement W8 and the light solid curve for pavement E1, they are very similar to each other, while the heavy solid curve for pavement S4 differs from both. Turning back to the left side of Fig. 5.9a, pavement S4 and pavement W8 have the maximum phase angle among the known pavements, which may explain why the first principal component of pavement S4 seems
much different from W8 as well as E1. The same situation occurred in Fig. 5.9b and Fig. 5.9c. By observing many results, in addition to Fig. 5.9, a phase angle below 20° indicates similar pavements with same or close macrotexture depths, and a phase angle above 40° indicates a big difference between two pavements. These three experiments come to the same conclusion—the MTD could be estimated effectively by PCA method.

It is clear that the tested pavement used in the estimation has the same MTD as one of the known pavements in the above example, which might make the accurate estimation easier. In order to validate the feasibility of the method, another example is used to demonstrate how the MTD is determined if the MTD of the tested pavement is within the range of the MTDs of known
pavements but not the same. Table 5.3 shows the MTD estimation for the tested pavement N5. As observed, the real MTD of N5 is 0.5 mm from Table 5.1, which is within the range of the MTDs of known pavements but not the same. The estimated MTD of the tested pavement N5 is determined as 0.4 mm, same as that of W9, since the phase angle between the first principal component vectors of N5 and W9 is the smallest among the ten known pavements. The result for this case has an error though, it is close to the real MTD. It also indicates that sufficient and complete calibration data is important for an accurate MTD estimation.

Table 5.3 Another Example of MTD Estimation

<table>
<thead>
<tr>
<th>Known Pavement</th>
<th>W9</th>
<th>W5</th>
<th>E5</th>
<th>N9</th>
<th>S1</th>
<th>E4</th>
<th>W1</th>
<th>N1</th>
<th>S8</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Known MTD (mm)</td>
<td>0.4</td>
<td>0.6</td>
<td>0.7</td>
<td>0.8</td>
<td>0.9</td>
<td>1</td>
<td>1.2</td>
<td>1.3</td>
<td>1.4</td>
<td>1.5</td>
</tr>
<tr>
<td>Phase Angle (°)</td>
<td>26.6</td>
<td>33.9</td>
<td>35.9</td>
<td>36.1</td>
<td>36.2</td>
<td>40.5</td>
<td>42.5</td>
<td>47.0</td>
<td>61.7</td>
<td>69.1</td>
</tr>
</tbody>
</table>

(Note: Phase Angle means the phase angle between the first principal component vectors of tested pavement and known pavement; the phase angle is calculated between the tested pavement N5 and the known pavement listed in Table 5.3.)

Based on both examples, it is concluded that PCA could be applied as an efficient method for pavement identification. Moreover, the first principal component vector of a pavement does carry pavement surface feature. The successful MTD estimation from NCAT data adds confidence to this point. However, the accuracy of the result will be limited by the availability of the calibration data (known pavements).

In order to investigate the success of PCA treatment to the measured data, as well as to check the effects of noise elimination by PCA, the same approach for MTD estimation was also applied to the original data set. The original data was also normalized, but not treated by PCA. The experiment had the same known pavements and tested pavements listed in Table 5.2. Figure 5.10 shows the results of two speeds, 32 kph and 80 kph.
Comparison of the first principal component vector and normalized original data set for MTD estimation yields a conclusion that principal component analysis is very useful for the road feature extraction and noise elimination. By referring to the frequency spectra in Fig. 5.9 and Fig. 5.10, it is clearly demonstrated that PCA amplifies the variation of the data which makes the data set much “thinner” and “cleaner”. It is concluded that the first principal component vector of pavement contains the road feature and eliminates the noise that physically varies less with
frequency than signal. Hence, first principal component vector may be used to identify pavement characteristics, such as MTD estimation.

5.4 Accuracy Analysis

In consideration of assessing the proposed method, an accuracy analysis was conducted. Additionally, the accuracy of proposed method was compared with the energy method (Saykin 2012), which also utilized the acoustic measurement from microphone M5 as shown in Fig. 5.1. As to the energy method, for each pavement section, the “energy level” is calculated from the integration in the frequency spectra of the acoustic measurement within a certain frequency range. The lower frequency was fixed to 40 Hz, while the upper frequency varied dependent on the speed of the test vehicle and pavement macrotexture wavelength. MTD was determined by a linear equation with two variables of vehicle speed and “energy level”. The parameters of that equation were computed by linear regression approach.

The accuracy analysis of both methods was carried out as the following description. First, choose 10 sections of pavement from NCAT data as tested pavements, the remaining 35 sections of pavement are treated as known pavements. Secondly, use PCA method or energy method described in Saykin (2012) to estimate MTD values of these 10 tested pavements. The third step is to compare the estimated MTD with real MTD of tested pavements, and compute the accuracy of the estimation using the following equations:

\[
\text{Error} = \frac{|\text{estimated MTD} - \text{real MTD}|}{\text{real MTD}} \times 100\% \\
\text{Accuracy} = 100\% - \text{Error}
\]

\[
\text{If Error} \geq 100\%, \text{Accuracy} = 0\%
\]

At last, compute the probability of the accuracy falling into the range of 0~50%, 50~60%, 60~70%, 70~80%, and 80~100% accordingly.
The accuracy analysis results and comparison of both methods are shown in Fig. 5.11. Taking Fig. 5.11a for example, with PCA method, 90% of the tested pavements have accuracies in the range 80~100%, and 10% of the tested pavements have accuracies in the range 70~80%. However, while looking at the energy method, only 50% of the tested pavements have accuracies in the range 80~100%. Accuracy of the PCA method exceeds that of the energy method. Referring to Fig. 5.11b and Fig. 5.11c, PCA method still performs better than the energy method, especially for the accuracy range of 80~100%. Hence, it is concluded that the proposed PCA method has high accuracy at any speed.

Figure 5.11 Accuracy Analysis of PCA Method and Energy Method at (a) 32 kph; (b) 56 kph; (c) 80 kph
5.5 Conclusions and Limitations

This investigation uses tire excited acoustic signal measured by a moving vehicle equipped with a directional microphone. The objective is to eliminate the noise and extract the tire/pavement sound which is related to the pavement surface texture characteristics. A statistical analysis approach is employed. The chosen approach is the Principal Component Analysis (PCA) and the acoustic measurements were transformed to the frequency domain. Experiments were performed by applying PCA treatment on data collected by a test vehicle moving around an engineered test track with known surface and subsurface properties. Conclusions are outlined below for a set of experiments that considered 45 pavement types.

1. After PCA treatment, the first principal component vector is extracted to best represent pavement surface features. Meanwhile, noise that varies less with frequency is eliminated through PCA.

2. No matter what speed the vehicle is running at, the first principal component could always be extracted with the same trend and same order of magnitude, which makes PCA independent of moving speed.

3. Macrotexture depth, i.e., MTD, is successfully estimated through matching the first principal component vector of tested pavement to that of a set of known pavements. Original data sets without PCA treatment could not identify the difference between two pavements correctly because of noise, which demonstrates that PCA is useful for noise elimination. The probability to estimate MTD value of pavement with the accuracy over 80% is around 90%, and the average accuracy is 90%, which is much higher than the energy method.

4. Limitation of the proposed method is that, though it can identify the change of road surface condition, calibration data is needed currently for a specific MTD estimation. In addition, the accuracy of the estimation is partially dependent on the sufficiency of calibration data.
6 MTD Estimation by PCA-Energy Method

6.1 Motivation

Pavement texture is “the deviation of a pavement surface from a true planar surface” within a specific wavelength range [ISO 13473-1 (ISO 1997)]. Macrotexture of pavement is one type of pavement texture in the same order of size as coarse aggregate or tire tread elements, with spatial wavelengths from 0.5 mm to 50 mm [ISO 13473-1 (ISO 1997); Gendy et al. 2007]. Referring to the physical meaning of macrotexture, macrotexture depth is related to tire/road friction in wet weather [ISO 13473-1 (ISO 1997)], and the severity of segregation, which will lead to raveling, a type of pavement distress (Stroup-Gardiner and Brown 2000; Jones et al. 2012). Hence, the main applications of surface macrotexture in engineering are: (1) to measure the frictional properties of the pavement surface (skid resistance) (Henry 2000); (2) to evaluate construction segregation or non-uniformity (Stroup-Gardiner and Brown 2000; Flintsch et al. 2003). The first application is directly related to crash rate especially on rainy days, and the second application is related to pavement condition rating. Therefore, an accurate, easy, safe, and cost-effective approach to test and monitor the pavement macrotexture depth is needed.

Current methods for macrotexture measurement could be divided into two main classes: manual measurements and automatic measurements. Manual measurements include the sand patch method [ASTM E965 (ASTM 2004)], the outflow meter, and the circular texture meter (Flintsch et al. 2003); automatic measurement is the vehicle – mounted laser profilometer [ASTM E1845 (ASTM 2009a)]. The manual measurement could only be taken when traffic is closed; while the automatic measurement has cost issues that may hinder its widespread use. Based on the limitation of the mentioned methods, the author developed approaches to estimate macrotexture based on the acoustic measurement of tire/road noise. In the discussion that follows, the term “tire/road noise” refers to all the sound measured by the microphone underneath the vehicle, including the “tire-generated sound” by tire-road interaction and the “noise” caused by wind and
vehicle vibration. Previous research on tire/road noise indicates that dynamic interactions between the tire and the road surface produce sounds whose frequency dependence is related to the road macrotexture while the vehicle is moving (Veres et al. 1975; Hegmon et al. 1979; Sandberg and Ejsmont 2002), therefore the idea to utilize tire/road noise for macrotexture measurement has potential. The acoustic measurement is collected from one microphone mounted behind the driver side rear tire, directed at the tire/road interface. Two approaches are developed. The first approach, referred to here as the Energy Method, uses an integration of the frequency spectra of the collected acoustic measurement over a certain frequency band (40 to ~400 Hz) to linearly correlate with the macrotexture Mean Texture Depth (MTD) (Saykin et al. 2013). However, the Energy Method includes noise from wind and vehicle vibration that is unrelated to MTD. In order to increase the accuracy of the Energy Method, the author developed the second approach referred to here as the PCA Method. A broader frequency band (DC to 2 kHz) is selected and a Principal Component Analysis (PCA) is applied for noise and speed effect reduction (Zhang et al. 2012; Zhang et al. 2014b). The MTD is estimated by matching the principal component vector set derived from the tested pavement with one of the vector sets of known road conditions at an average accuracy of 90% (Zhang et al. 2012; Zhang et al. 2014b). However, the Energy Method may produce some negative MTD values in regular driving test because of speed effect, which reduces the accuracy and applicability of the method. Also, the PCA Method requires a database of the first principal component vectors with known pavement MTD values to match with the test pavement, which will limit the prediction to the MTD values in the database. The accuracy of MTD prediction depends on the diversity of pavement types with different MTDs in the database. In reality, it is difficult to build a database including as much as possible types of pavement surface within a broad MTD range. The current database in use by the author is from an engineered track with 44 pavements of different MTD values, which already presents drawbacks caused by the limited database when testing on regular urban roads.

Hence, an improved approach for MTD estimation is needed, which should include three improvements: (1) elimination of noise not related to road macrotexture; (2) reduced speed effect or appropriate consideration of speed effect; (3) not strictly limited by the diversity of known road database. Before the improved approach is proposed, two assumptions are made based on the previous study about the relation between tire/road noise and pavement macrotexture. First,
the pavement macrotexture is related to vehicle driving speed and the tire/road noise level
(Sandberg and Ejsmont 2002); secondly, the acoustic energy (integration of frequency spectrum
of tire/road noise) below 1 kHz is positively proportional to the MTD of pavement (Sandberg
and Ejsmont 2002; Sandberg 2003; Saykin et al. 2013). Hence, based on the advantage of those
two developed methods described above, one approach to combine both methods is explored and
this is the PCA Energy Method. A study of frequency band selection for MTD estimation was
conducted first. Then data from the test over an engineered track was used to build a model as a
function of PCA energy (integration of the first principal component over the selected frequency
band) and vehicle driving velocity to predict the MTD of pavement. After the model parameters
were determined, an error analysis was conducted over the same data. A comparison of accuracy
was made over the proposed method and the previous two ones. After confirming that the
accuracy of the proposed approach is acceptable, a feasibility study was conducted to validate
the approach on regular urban road. Finally, conclusions were made based on the accuracy
analysis and the field test results.

6.2 Data Collection

Figure 6.1 shows the sensor arrangement on the test vehicle for data collection. The microphone
is mounted behind the driver side rear tire and directed to the tire/road interface to collect the
tire/road noise, which will be utilized in this paper. The data acquisition system is located inside
the test vehicle. The directional microphone is produced by G.R.A.S, with the sensitivity of 44
mV/Pa. The same tire was used throughout the experiment to exclude the possibility of a tire
effect.

Two experiments were carried out in this study. The first experiment was conducted in
September 2010 on an engineered track at the National Center for Asphalt Technology (NCAT)
in Lee County, Alabama. A detailed illustration of the track is shown in Fig. 5.2. The track is 2.7
km long, consisting of 46 sections of pavement, each 61 m in length. The vehicle collected over
50 GB of acoustic data as it drove around the track for different testing configurations. The sampling frequency of this test is 40 kHz. Among the 46 pavement types, 44 are considered in this paper as listed in Table 5.1. The vehicle drove at 3 different speeds over the track, 32 kph (20 mph), 56 kph (35 mph), and 80 kph (50 mph), 3 rounds for each speed. For each round there are 44 measurements corresponding to the 44 pavement sections listed in Table 5.1. The collected data would be analyzed to explore the potential for MTD prediction and to build the prediction model.

The second test was conducted with the same vehicle (Fig. 6.1) in August 2012. The vehicle was driven over 20 two-lane two-way streets in the northeast section of Brockton, Massachusetts. Three loops of the route were driven in the clockwise direction and three loops were drive in the counter clockwise direction (to include the opposite lane). The sampling frequency of this test is 50 kHz. Brockton, Massachusetts was selected because the City of Brockton and CDM Smith (a consulting, engineering, construction and operation firm headquarters in Cambridge, MA) agreed to share an existing pavement condition survey from 2006. For this survey, performed by CDM Smith, a Pavement Condition Index (PCI) value was assigned to each street ranging from 0 to
100, where 0 is the worst possible condition and 100 is the best. Results of the survey for seven streets considered in this paper are shown in Table 6.1. The PCI values in Table 6.1 are the forward projected values to 2012 using Micro PAVER’s (KMS & Associates, Inc. 2007) built-in deterioration model. This survey information provides a valuable tool for validating algorithms for pavement MTD prediction using the test vehicle (Fig. 6.1), because a high MTD value of pavement predicted from the tire/road noise will result in a low PCI value indicating poor pavement condition (Metro Nashville 2006). Therefore, the collected data would then be used to test the feasibility of the MTD prediction model developed from the data collected in NCAT.

Table 6.1 Pavement Condition Index (PCI) at Brockton, Massachusetts

<table>
<thead>
<tr>
<th>Road Name</th>
<th>Randolph St</th>
<th>Brookville Ave</th>
<th>Lynn St</th>
<th>Field St</th>
<th>Lisa Rd</th>
<th>N Montello St</th>
<th>Hovendon Ave</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI (No Dim.)</td>
<td>0</td>
<td>6</td>
<td>13</td>
<td>41</td>
<td>64</td>
<td>84</td>
<td>91</td>
</tr>
</tbody>
</table>

6.3 Method Description

The general idea of this study is to combine the Energy Method and the PCA Method together in order to include the advantages of both methods in one method. A central question addressed in the present study is the choice of model used to predict MTD, and in particular the choice of measured variables to include. Based on the first assumption given in the introduction section, pavement macrotexture is related to the tire/road noise level and the driving speed of vehicle. Hence both tire/road noise level and driving speed need to be included in this model. The reason for this assumption will be described below.

The first question that arises is whether or not the tire/road noise level should be included and, if so, what measured quantity should represent it. Previous work by others has shown that the noise level of the tire/road interaction is related to MTD (Sandberg and Ejsmont 2002; Ongel et al. 2008; Lu et al. 2010; Veres et al. 1975). Moreover, the previous Energy Method was developed based on this assumption (Saykin et al. 2013). As introduced before, it concluded that the signal energy, defined as the integration of the frequency spectra of collected tire/road noise over a certain frequency range (40 to $\sim$400 Hz), was linearly correlated with the macrotexture MTD.
Thereupon, the energy was utilized to predict MTD of pavement through their linear relationship. In this study, the energy idea is also utilized to build the model for MTD prediction. In order to obtain better estimates of energy with the purpose to get a more linear relationship with MTD, a principal component analysis (PCA) is incorporated. Principal component analysis (PCA) is a well-known statistical approach for feature extraction from measurements (Wang et al. 2002). Pearson (1901) and Hotelling (1933) firstly described this technique (Jolliffe 2002). The fundamental purpose of PCA is to reduce the dimensionality of a data set containing a quantity of variables correlated to each other, so as to keep the maximum possible variation. To achieve this goal, an original data set is converted to a new set of uncorrelated variables, the principal component vectors, which are ordered in the descending variation (Jolliffe 2002). PCA was applied to the tire/road noise by the author in previous study. Zhang et al. (2014b) assumed that the variations in frequency of the noise are small compared to the variations in frequency of the tire-generated sound related to the road features, which allows the PCA approach to separate noise from tire-generated sound that carry information about the road condition, including macrotexture. Moreover, because of the normalization of original data, the speed effect on the amplitude of sound pressure level is largely reduced (Zhang et al. 2012; Zhang et al. 2014b). It was shown by Zhang et al. (2014b) that the first principal component vector carries pavement macrotexture information with a high Signal-to-Noise Ratio (SNR), which is why the present study uses the first PC vector for energy computation instead of the original data. The energy computed from that first PC vector is named PCA energy. Hence, PCA energy will be one variable for consideration representing tire/road noise level in the MTD prediction model. A flow chart is listed in Fig. 6.2 to show the procedure for PCA energy computation. The data collected for analysis was loaded into MATLAB with $2^{13}$ data points for each window. After windowing, a Fast Fourier Transform (FFT) was performed for each window.
Hence, the original data matrix was assembled with the FFT results of each window as columns. Referring to Zhang et al. (2014b), the data matrix between DC to 2000 Hz was used for PCA treatment. After that, the first PC vector was extracted. Detailed information of data normalization and PCA treatment may be found in the paper by Zhang et al. (2014b). Finally, the PCA energy is computed from the integration of the first PC vector over an optimally selected frequency band that will be investigated in the next section. One issue needs to be pointed out is the unit conversion during the procedure. The data used is sound pressure with the unit of Pascal; after FFT, the Pascal is converted to the sound pressure level (SPL) decibel. Accordingly, data normalization would make the first PC vector have negative and positive values at decibel. In order to obtain positive energy as an integration of the first PC vector, the decibel of the first PC vector is converted back to Pascal to make all the scales of the vector be positive.

Besides PCA energy, the speed effect should also be considered in the MTD prediction model. The reason for speed effect consideration comes from its influence on PCA energy. The PCA energy is computed over a certain frequency range, while in this frequency range, the SPL will influence the result of the PCA energy. Sandberg and Ejsmont (2002) already claimed that the SPL would increase as speed increases, i.e., the vehicle would create more noise with higher speed over the same road, resulting in higher energy computed from the frequency spectra. In addition, Sandberg (2003) pointed out that there is a “multi-coincidence peak” around 1 kHz below that the SPL will rise along with MTD. Through the equation \( f = \frac{v}{\lambda} \) (Sandberg and Ejsmont 2002), where “\( f \)” is frequency (Hz), “\( v \)” is the driving speed (m/s), and “\( \lambda \)” is the texture wavelength (m), the “multi-coincidence peak” will shift with different driving speeds, which also needs to be considered. It is demonstrated by Zhang et al. (2014b) that the influence
from speed to SPL could be eliminated by PCA through normalization, however, it generally refers to a broad frequency band (DC to 2 kHz). The peak frequency could not be influenced after PCA treatment as shown in Fig. 6.3. Figure 6.3 (a) is the frequency spectra for one road at different speeds before PCA treatment. A clear trend is observed that the SPL increases as speed increases. Meanwhile, the speed effect in Fig. 6.3 (b) is eliminated in the first PC vector through normalization over DC to 2 kHz. Yet, the trade-off of this normalization is that the SPL of the first PC vector decreases as speed increases below the “multi-coincidence peak”, and increases as speed increases above the “multi-coincidence peak”, which is noticed in Fig. 6.3(b). Thus, the speed will influence the PCA energy since it will be computed below the “multi-coincidence peak” frequency, which will be discussed in the frequency band selection part. A solution for this issue is to consider the speed effect in the MTD prediction model.

Therefore two variables will be included in this model: PCA energy ($e$) and driving speed ($v$). With these two variables, a MTD prediction model based on a Taylor series expansion will be developed. The model parameter will be determined using NCAT test data. The next section will discuss how to determine the frequency band for PCA energy computation first, and then explain the model creation and model parameter calculations.
6.4 Optimal Frequency Band Determination

Because macrotexture depth is going to be predicted from PCA energy, the frequency band of the tire/road noise related to pavement macrotexture needs to be investigated. Chapter 2 already conducted the frequency analysis of vehicle noise. Referring to Fig. 2.5, it is noticed that pavement macrotexture and the tire tread pattern pitch influence on the similar frequency range of tire/road noise from Fig. 2.5. The reason is that the wavelength of tire tread pattern texture is 20 to 40 mm, which is within the macrotexture wavelength (0.5 to 50 mm). Hence, tire effect could not be excluded in the investigation on macrotexture, however, it could be ignored by using the same type of tire throughout this study. Moreover, the frequency of 700 ~ 1300 Hz should be avoided in the MTD estimation due to the “multi-coincidence peak” mentioned in Chapter 2. Consequently, the frequency range related to pavement macrotexture that is good for MTD estimation is below 700 Hz until current discussion.

As the relevant frequency of pavement macrotexture is narrowed to below 700 Hz, a specific frequency band for PCA energy computation is needed. The strategy for the frequency band determination is based on the second assumption made in the introduction that the acoustic energy below 1 kHz is positively proportional to the MTD of pavement, which is also demonstrated in the “Method Description” section. This assumption is created based on Sandberg’s research (Sandberg and Ejsmont 2002), which indicates the acoustic energy increases as MTD increases below the 1 kHz peak area. Moreover, the data analysis of NCAT test also shows the same trend (Fig. 6.4). In Fig. 6.4, with the same speed (32 kph), as the MTD of pavement increases from 0.5 mm to 1.5 mm, the sound pressure level (SPL) of the tire/road noise goes up below 650 Hz, which is close to the “multi-coincidence peak” area.
Accordingly, the frequency band that stably provides high linear correlation between the PCA energy and MTD of pavement is the optimal one. In order to find the optimal frequency band, the linear correlation between PCA energy and MTD was studied for different speeds from NCAT data. The results are shown in Fig. 6.5 with three driving speeds: 32 kph, 56 kph and 80 kph. The frequency band is composed from the lower frequency limit to the upper frequency limit. The former varies from DC to 200 Hz as shown in the Y axis of Fig. 6.5, and the latter varies from 400 Hz to 1000 Hz as displayed in the X axis of Fig. 6.5. The linear correlation coefficient between the PCA energy computed from different frequency band is printed as contour in Fig. 6.5, where dark color represents high linear correlation and light color means low linear correlation. If taking linear correlation coefficient of 0.7 as a threshold, all the upper frequency limit with correlation coefficient over 0.7 are listed in Table 6.2, i.e., all the upper frequency limits included in the black area of Fig. 6.5 are represented in Table 6.2. The experiment number from 1 to 9 represents 9 runs over NCAT test track. Experiments No. 1 to No. 3 are three runs at 32 kph, experiments No. 4 to No. 6 are three runs at 56 kph, and experiments No. 7 to No. 9 are three runs at 80 kph. In order to make the upper frequency limit have stable high correlation coefficient (> 0.7) over all the 9 runs, a intersection is obtained from Table 6.2, 700 ~ 800 Hz. Because the frequency of 700 ~ 1300 Hz needs to be avoided for the “multi-coincidence peak” issue, the upper frequency limit is determined as 700 Hz. Coincidently, the effective macrotexture wavelength is above 12.7 mm (Saurenman et al. 2005), the corresponding effective frequency is below 704 Hz at 32 kph through the equation $f = \frac{v}{\lambda}$ as introduced in method description. Since this frequency will increase with speed, from the view of taking the
same frequency band for consistent computations with different speeds, 700 Hz is an optimal choice for the upper frequency limit. Then, the lower frequency limit is determined in the same way with a fixed upper frequency limit at 700 Hz as shown in Table 6.3. The intersection of lower frequency limit obtained from Table 6.3 is 140 Hz. Therefore the optimal frequency band for PCA energy computation is determined, from 140 Hz to 700 Hz. Meanwhile, as explained before, the tire effect could not be excluded in this frequency range. However, since the same tire is used throughout the experiment in NCAT as well as in the city of Brockton, the tire effect will not influence the result in this study.

![Figure 6.5 Correlation Analysis between PCA Energy from Different Frequency Bands and MTD](image)

[Note: vehicle driving speed: (a) 32 kph (20 mph); (b) 56 kph (35 mph); (c) 80 kph (50 mph)]

### Table 6.2 Upper Frequency Limit with Linear Correlation Coefficient over Threshold (0.7)

<table>
<thead>
<tr>
<th>Experiment No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper Frequency Limit (Hz)</td>
<td>400 ~ 840</td>
<td>400 ~ 860</td>
<td>520 ~ 820</td>
<td>400 ~ 1000</td>
<td>400 ~ 980</td>
<td>400 ~ 880</td>
<td>700 ~ 800</td>
<td>400 ~ 980</td>
<td>400 ~ 1000</td>
</tr>
</tbody>
</table>

### Table 6.3 Lower Frequency Limit with Linear Correlation Coefficient over Threshold (0.7)

<table>
<thead>
<tr>
<th>Experiment No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Frequency Limit (Hz)</td>
<td>140 ~ 160</td>
<td>20 ~ 200</td>
<td>40 ~ 200</td>
<td>20 ~ 200</td>
<td>20 ~ 200</td>
<td>40 ~ 200</td>
<td>140, 180 ~ 200</td>
<td>100 ~ 200</td>
<td>40 ~ 200</td>
</tr>
</tbody>
</table>

(Note: the upper frequency limit is fixed at 700 Hz)
6.5 Equivalent MTD (MTD) Estimation

6.5.1 Modeling for MTD Estimation

6.5.1.1 Analytical Basis for Model

As described in method description, two variables will be considered for MTD prediction: PCA energy \((e)\) and driving speed of vehicle \((v)\). Also, the frequency range used for computing PCA energy has been figured out. The next question is that how to build a mathematical model to obtain the MTD of pavement. The concept of a Taylor series expansion (Greenberg 1998) motivates the idea to use a two-dimensional (2D) Taylor series to build the model for MTD prediction. Any function, as long as analytic at a certain point, could be expressed as Taylor expansion (Greenberg 1998). The accuracy of the function will be improved with the order of the variables. The general Taylor expansion (Dienes 1957) for 2D function \(f(x, y)\) at \((x_0, y_0)\) is listed in Eq. (6.1).

\[
\frac{f(x, y)}{(x_0, y_0)} = \sum_{n=0}^{\infty} \left\{ \frac{1}{n!} \sum_{k=0}^{n} \binom{n}{k} \frac{\partial^n f(x, y)}{\partial x^{n-k} \partial y^k} \right\} (x - x_0)^{n-k} (y - y_0)^k \quad (6.1)
\]

Where,

- \(n\) = order considered in Taylor expansion,
- \(k\) = integer from \(0\) to \(n\),

\[
\binom{n}{k} = \frac{n!}{k!(n-k)!} .
\]

Considering the case for MTD prediction, the input variables \(x\) and \(y\) in Eq. 6.1 are PCA energy \((e)\) and driving speed \((v)\) respectively, and the output \(f(x, y)\) is the predicted MTD. Given that the order above 3 will be neglected in this model, Eq. 6.1 could be converted to Eq. 6.2, which is more readable.

\[
f(e_n, v_n)|_{e_{n0}, v_{n0}} = c_0 + c_1 e_n + c_2 v_n + c_3 e_n^2 + c_4 v_n^2 + c_5 e_n v_n + c_6 e_n^3 + c_7 v_n^3 + c_8 e_n^2 v + c_9 e_n v_n^2 + O[(e_n - e_{n0})^4 + (v_n - v_{n0})^4] \quad (6.2)
\]

Where,
\( e_n = \) normalized PCA energy (no dimension), see Eq. 6.3,
\( v_n = \) normalized driving speed (no dimension), see Eq. 6.4,
\( c_i = \) derivative of the corresponding terms of Taylor expansion (constant),
\( e_{n0}, v_{n0} = \) center of Taylor expansion of \( f(e_n, v_n) \),
\( f(e_n, v_n) = \) predicted MTD (mm),
\( O[(e_n - e_{n0})^4 + (v_n - v_{n0})^4] = \) terms to be neglected.

The normalized PCA energy \( (e_n) \) and normalized driving speed \( (v_n) \) are calculated in Eq. 6.3 and Eq. 6.4 separately.

\[
e_n = \frac{e - e_{\text{min}}}{e_{\text{max}} - e_{\text{min}}} \quad (6.3)
\]

Where,
\( e = \) PCA energy computed from tire/road noise of the tested road (Hz-Pa),
\( e_{\text{min}} = \) minimum PCA energy, i.e., sound collected from stationary vehicle with engine on (Hz-Pa),
\( e_{\text{max}} = \) maximum PCA energy of the analysis data in NCAT test (Hz-Pa),
\( e_n = \) normalized PCA energy \( (0 \leq e_n \leq 1, \text{no dimension}) \).

\[
v_n = \frac{v - v_{\text{min}}}{v_{\text{max}} - v_{\text{min}}} \quad (6.4)
\]

Where,
\( v = \) driving speed over the tested road (m/s),
\( v_{\text{min}} = \) minimum driving speed in NCAT test (8.94 m/s),
\( v_{\text{max}} = \) maximum driving speed in NCAT test (22.35 m/s),
\( v_n = \) normalized driving speed \( (0 \leq v_n \leq 1, \text{no dimension}) \).

The minimum and maximum values in Eq. 6.3 and Eq. 6.4 are both collected from NCAT test.
6.5.1.2 Model Parameter Computation

As the general form of the model is listed in Eq. 6.2, the model parameter $c_i$ needs to be determined. In order to estimate a reasonable MTD value from this model, limiting conditions are required. Roe et al. (1991) claimed that a typical macrotexture depth is from 0.2 mm to 3 mm. Hence the limits should define the minimum MTD as well as the maximum one in the model. They are listed in Eqs. (5) and (6).

\begin{align*}
  f(e_n, v_n) &= 0.2 \text{ when } e_n = v_n = 0 \quad (6.5) \\
  f(e_n, v_n) &= 3 \text{ when } e_n = v_n = 1 \quad (6.6)
\end{align*}

By substituting Eq. 6.5 and Eq. 6.6 into Eq. 6.2 respectively, Eq. 6.7 and Eq. 6.8 are obtained.

\begin{align*}
  c_0 &= 0.2 \quad (6.7) \\
  \sum_{i=1}^{9} c_t + c_0 &= 3 \quad (6.8)
\end{align*}

Accordingly, a Least-squares (LS) analysis is performed over the NCAT test data. The following linear equation is derived from Eq. 6.2.

$$AX = B$$  \hspace{1cm} (6.9)

Where,

$$A = \begin{bmatrix}
  e_{n1} & v_{n1} & e_{n1}^2 & v_{n1}^2 & e_{n1}v_{n1} & e_{n1}^3 & v_{n1}^3 & e_{n1}^2v_{n1} & e_{n1}v_{n1}^2 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
  e_{ni} & v_{ni} & e_{ni}^2 & v_{ni}^2 & e_{ni}v_{ni} & e_{ni}^3 & v_{ni}^3 & e_{ni}^2v_{ni} & e_{ni}v_{ni}^2 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
  e_{nm} & v_{nm} & e_{nm}^2 & v_{nm}^2 & e_{nm}v_{nm} & e_{nm}^3 & v_{nm}^3 & e_{nm}^2v_{nm} & e_{nm}v_{nm}^2
\end{bmatrix},$$

$$X = \begin{bmatrix}
  c_1 & c_2 & c_3 & c_4 & c_5 & c_6 & c_7 & c_8 & c_9
\end{bmatrix}^T,$$

$$B = \begin{bmatrix}
  f_1 & \cdots & f_i & \cdots & f_m & 3
\end{bmatrix}^T - 0.2,$$

$i$ = the $i$th pavement section used for analysis, varying from 1 to $m$, 
$f_i$ = actual MTD value of the $i$th pavement section.

Using the LS analysis, the model parameter vector $X$ could be computed by Eq. 6.10.
The boundary conditions defined in Eqs. (7) and (8) are embedded in matrices $A$ and $B$, which make sure that the MTD predicted from this model will be in the typical range from 0.2 mm to 3 mm.

6.5.1.3 Model Simplification

As the model is set and the model parameters are computed through the LS method, the final model will be in the similar form as in Eq. 6.2. The next decision is the number of terms retained in the series. Furthermore, which items should be kept in the model with the purpose of simplifying the model within an acceptable accuracy. This problem is solved in two steps. The first step is to decide to which order should be contained in the model; the second step is to choose the items to be kept in the model. Both steps would be performed based on the accuracy analysis. The normalized mean square error (NMSE) will be computed for each case and treated as an index to make the decision. Eq. 6.11 shows the calculation for NMSE.

$$NMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (f_i - f_{ei})^2}$$

(6.11)

Where,

$f_i$ = the actual MTD for the $i$th pavement,

$f_{ei}$ = the estimated MTD for the $i$th pavement.

The $f_{ei}$ are computed according to Eq. 6.2 after the model parameter vector is obtained. Taking the order to three as an example, the order above three will be ignored. As shown in Eq. 6.11, the NMSE is the overall error of the estimated MTD from the actual MTD of the tested pavement. The smaller the NMSE, the better the prediction model.
For the first step to determine the highest retained order, the first order, the second order and the third order were all tried to evaluate their influence on the accuracy of the model. The reason for only the first three orders being considered is that higher order will result in more parameters to be determined in Eq. 6.10, which in turn will lower the applicability for other data than NCAT since more parameters to be determined means more uncertainty. The accuracy analysis with different orders being contained in the model is shown in Table 6.4.

<table>
<thead>
<tr>
<th>Order to consider</th>
<th>1</th>
<th>1 &amp; 2</th>
<th>1 &amp; 2 &amp; 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMSE</td>
<td>0.177</td>
<td>0.1493</td>
<td>0.1487</td>
</tr>
</tbody>
</table>

Table 6.4 shows that the NMSE by considering the first two orders reduced largely from that by considering the first order, meanwhile, it is slightly higher than that by including the first three orders. Therefore the first question for the model simplification is answered: the prediction model will consider to the second order, i.e., the first two orders will be retained in the model (see Eq. 6.12).

\[
f(e_n, v_n) = 0.2 + c_1 e_n + c_2 v_n + c_3 e_n^2 + c_4 v_n^2 + c_5 e_n v_n + O[(e_n - e_{n0})^3 + (v_n - v_{n0})^3]
\]

(6.12)

Next, the second question needs to be answered is: which items would be kept in the model. Referring to Eq. 6.12, there are five items excluding the constant. From the view of simplification, perhaps some items do not have too much influence on the output \( f(e_n, v_n) \), then they could be excluded in the model. A sensitivity analysis was performed to evaluate the influence of each item in Eq. 6.12 on the accuracy of the model. The sensitivity analysis is done as follows: first, moving one item in Eq. 6.12, keeping others at where they are, then forming the matrix \( \mathbf{A} \) from the remaining items of Eq. 6.12, which is in a similar shape as the matrix \( \mathbf{A} \) in Eq. 6.9, finally, computing the parameter vector and the NMSE with one item missing from Eq. 6.12; after that, returning the item to Eq. 6.12, then repeating for each of the other items in the same way. The NMSE from each missing item is represented in Table 6.5. The “none” column is the
NMSE with all the items in Eq. 6.12, which is 0.1493, i.e., the accuracy of the predicted MTD is 85.07%. With single item excluded, the NMSE was calculated. The relative change of the NMSE with one item excluded to that of the “none” is computed in Table 6.5 as well. For example, if the normalized PCA energy \(e_n\) is excluded, the NMSE will increase to 0.2646, which is 77.23% higher than the NMSE computed directly from Eq. 6.12. The item with large relative change is important to the model. A threshold 5% is set for the relative change of NMSE. Consequently,

\[
\text{Table 6.5 Sensitivity Analysis to the Items in the 2nd Order Model}
\]

<table>
<thead>
<tr>
<th>Excluded Item</th>
<th>none</th>
<th>(e_n)</th>
<th>(v_n)</th>
<th>(e_n v_n)</th>
<th>(e_n^2)</th>
<th>(v_n^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMSE</td>
<td>0.1493</td>
<td>0.2646</td>
<td>0.1709</td>
<td>0.1592</td>
<td>0.1567</td>
<td>0.1534</td>
</tr>
<tr>
<td>NMSE Relative Change to “none”</td>
<td>--</td>
<td>77.23%</td>
<td>14.47%</td>
<td>6.63%</td>
<td>4.96%</td>
<td>2.75%</td>
</tr>
</tbody>
</table>

the items \(e_n^2\) and \(v_n^2\) are eligible to be ignored, while the product of \(e_n\) and \(v_n\) \((e_n v_n)\) is kept as the 2nd order item. Also, this sensitivity analysis reveals that the first order of PCA energy is very important for the prediction model, so as the first order of driving speed, though not as much as the former. Thus, the answer to the second question of which items should be kept in the model is clear: the normalized PCA energy \((e_n)\), the normalized driving speed \((v_n)\), and the product of these two variables \((e_n v_n)\). Eq. 6.13 is the final model.

\[
f(e_n, v_n) \approx 0.2 + c_1 e_n + c_2 v_n + c_3 e_n v_n
\]

(6.13)

Moreover, the matrix \(A\) and parameter vector \(X\) in Eq. 6.9 is reduced to matrix \(A_S\) and \(X_S\) (the subscript “s” represents simplified), which are

\[
A_S = \begin{bmatrix}
e_{n1} & v_{n1} & e_{n1} v_{n1} \\
\vdots & \vdots & \vdots \\
e_{ni} & v_{ni} & e_{ni} v_{ni} \\
\vdots & \vdots & \vdots \\
e_{nm} & v_{nm} & e_{nm} v_{nm}
\end{bmatrix}, \text{ and } X_S = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix}^T.
\]

By using the NCAT test data to construct the matrices \(A_S\) and \(B\), the parameter vector \(X_S\) was computed from Eq. 6.10, resulting in \(c_1 = 1.55\), \(c_2 = 0.44\), and \(c_3 = 0.76\). The NMSE computed
from Eq. 6.11 is 0.1639, i.e., the accuracy of this model over NCAT data is 83.61% of the actual MTD, which is an acceptable value. By substituting $c_1$, $c_2$, and $c_3$ to Eq. 6.13, Eq. 6.14 is obtained.

\[ f(e_n, v_n) \approx 0.2 + 1.55e_n + 0.44v_n + 0.76e_nv_n \]  \hspace{1cm} (6.14)

In summary, the model for MTD prediction is given in Eq. 6.14, with an acceptable accuracy of 83.61% as compared to NCAT data. Then, the feasibility of the model will be tested from two aspects. One is a comparison of accuracy of the model with the previous two approaches (Energy method and PCA method), the other is its application to an urban road test.

### 6.6 Feasibility of The MTD Prediction Model

The next concern is the feasibility of this model. Feasibility here includes two parts: (1) advantage of the proposed approach over the previous two approaches developed by the author for MTD estimation, as well as the advantage of PCA treatment before computing the acoustic energy; (2) reasonable prediction of MTD in field test. The first part for accuracy comparison will be done to the NCAT test data. Besides the proposed method and the developed two methods, another energy based method is added, which is very similar to the procedure of the proposed method but without PCA treatment to the data. If the accuracy level of the proposed approach is as much as or higher than the other three approaches, more confidence will be gained for the application to an urban road. Then the second part for field test ability will be performed over the Brockton test data. Even though the MTD of the road in Brockton is unknown, the condition could be checked from the camera at the back of vehicle (Fig. 6.1) as well as the PCI value from CDM Smith as introduced in the data collection part.

#### 6.6.1 Accuracy Analysis

The advantage of the present method is investigated through the accuracy comparison of MTD estimation with Energy Method. The Energy Method here has the exactly same procedure as PCA Energy Method but PCA treatment. The accuracy is computed from all the runs and speeds
at NCAT test. Figure 6.6 is an example for MTD prediction by both methods at 56 kph. Figure 6.6 shows PCA Energy Method (dash line with “+”) has a high accuracy (83.6%) compared to Energy Method (dash line with “O”), which proves that PCA treatment contributes a lot to high accuracy. Therefore, PCA Energy Method is improved by PCA treatment, which motivates its use for the urban road test.

![Figure 6.6 MTD Prediction at 56 kph by Two Methods](image)

6.6.2 Field Test Performance

The advantages of the PCA Energy Method are found through the comparison with other two methods. However, the data used for the comparison were collected on an engineered NCAT track. A field test is needed to validate the feasibility of the model for a “real” road. Therefore, the test data collected from Brockton Massachusetts is analyzed to evaluate its performance on an urban road.

![Figure 6.7 Predicted MTD along Field Street](image)
A detailed investigation was conducted for a randomly selected road – Field St. Figure 6.7 is the MTD predictions along the distance of the road. For this case, acoustic data collected along a certain distance 7.8 m is used to estimate one MTD value as displayed in Fig. 6.7. As explained before, high MTD corresponds to a poor road condition, and vice versa. Four points A, B, C and D in Fig. 6.7 are selected to check against the pavement surface pictures taken by the camera in Fig. 6.1.

The predicted values of MTD of A, B, C and D are 0.77 mm, 0.82 mm, 0.92 mm, and 1.02 mm in ascending order. Accordingly, the pavement surface macrotexture of the corresponding pictures (Fig. 6.8) is supposed to vary from fine to coarse in order. The pictures shown in Fig. 6.8 coincide with their predicted MTDs. The surface macrotexture does change from fine to coarse with the predicted MTD increases from A to D as indicated in Fig. 6.7. Also, Fig. 6.8 illustrates how PCI value will decrease as MTD increases by checking that the area and severity of cracking in Fig. 6.8 intensifies as MTD increases. Therefore, the predicted MTD values match the true pavement macrotexture from observation of the corresponding pictures.
Moreover, Fig. 6.9 shows the MTD predictions over two years on the same streets in the city of Brockton. Good repeatability is displayed. Additionally, most predicted MTDs in the year 2013 are higher than those in the year 2012, which matches the situation that road condition gets worse from the year 2012 to the year 2013.

Based on the single road MTD variation analysis and the comparison of the MTD prediction over two years, it is concluded that the proposed PCA Energy Method is a promising tool for MTD prediction. Besides, the MTD value could indicate the road condition.

6.7 Conclusions and Limitation

An overall study to produce the PCA Energy Method for MTD prediction based on the previous methods, Energy Method and PCA Method, is conducted. Firstly, the most relevant frequency band, 140 ~ 700 Hz, is chosen to linearly correlate MTD of pavement with PCA energy from tire/road noise. Then, a model based on Taylor expansion theory for MTD prediction is determined as a function of two variables, PCA energy and driving speed. Three terms in this model are contained, normalized PCA energy, driving speed, and the product of both. Additionally, in order to make sure the predicted MTD is within a typical MTD range from 0.2 to 3 mm, two limits are defined. The accuracy of this model is 83.61% for NCAT test data, which is 10% higher than the Energy Method. The comparison indicates that PCA treatment is necessary in noise elimination so that to improve the linear correlation between PCA energy and MTD of pavement; on the other hand, the energy idea incorporated in thePCA Energy Method extends the prediction value of MTD from the NCAT data set (0.4 to 1.5 mm) to a typical MTD range from 0.2 to 3 mm, which broaden the use of the proposed approach. Moreover, the speed effect is also considered in this model. Therefore it is concluded that the PCA Energy Method takes advantages from both methods to reach a reasonable and reliable prediction. In the urban road test at Brockton Massachusetts, the MTD was predicted every 7.8 meters, and correctly reflected the pavement surface macrotexture condition, which enhances the feasibility of the proposed approach. Generally, the PCA Energy Method is a valid, efficient, and cost effective way to predict MTD for engineering application.
However, since the parameter of the prediction model is determined based on NCAT test data, limitations may exist in the minimum and maximum driving speed and PCA energy used for the normalization of variables applied to the model. Hence the predicted MTD may be more accurate at the driving speed within 32 kph to 80 kph, and at a certain range of PCA energy. For speeds out of that range, or the PCA energy higher than the maximum one at NCAT test, the predicted MTD is still reliable because the function shown in Eq. 6.14 is obtained from all the NCAT test data (3 speeds, 3 rounds for each speed, 44 pavements included in each run), it must be able to project to other speeds out of the range 32 kph to 80 kph, though the prediction might be less accurate. Another problem involves the predicted value of MTD. If one of those two variables is not within the defined minimum and maximum range, the predicted MTD might be less than 0.2 mm or larger than 3 mm. The pavement condition for this kind of situation needs to be defined after a thorough investigation on the relationship between MTD and pavement surface condition, i.e., raveling or bleeding. Another possible solution to avoid this out-of-range output is to redefine the minimum and maximum limit of those two variables during the model parameter determination.
7 Tire Effect

7.1 Motivation

The influence of tire type on the MTD estimation is an important issue. Figure 2.1 in Chapter 2 indicated that both tire tread pattern pitch and pavement macrotexture have strong influences on tire/road noise between the frequency range of 0.5 to 1 kHz, which is overlapped with the frequency content used for MTD calculation. Hence, the effect of tire tread pattern pitch on tire/road noise needs to be considered. To exclude the tire effect, the same type of tire is used through all the tests for MTD estimation. However, tire effect is worth exploring to complete the MTD prediction study.

![All Season Tire (left) and Studded Tire (right)](image)

Figure 7.1 All Season Tire (left) and Studded Tire (right)

7.2 Experiment

A test was conducted at Burlington Campus of Northeastern University in June 2014 with VOTERS test vehicle (Fig. 6.1). Two types of tires were used in this test as shown in Fig. 7.1, all season tire without studs and studded tire. All season tire is popular in some parts of USA which combine properties of summer and winter tires and may be used during the whole year. Studded
tire is usually tires with a lot of studs mounted on tire tread, widely used in a number of countries such as Sweden, Finland, Norway, Russia, parts of Japan, large areas in Europe, Canada and some states in the USA. For each type of tire, the test vehicle drove at four speeds: 24 kph (15 mph), 32 kph (20 mph), 48 kph (30 mph), and 64 kph (40 mph). Each speed has three runs, 60 m (200 ft) for one run. The test vehicle drove through the same path for each run, which means the MTD should be the same provided that no tire effect exists.

7.3 Results and Discussions

The tire regularly used is the all season tire without studs as shown in the left hand side of Fig. 7.1. The model for MTD estimation is also developed from the all season tire. Figure 7.2 through Figure 7.5 illustrate the frequency content comparison between all season tire and studded tire. The original sound pressure level of Fourier transform result is shown on the left side of each figure, and the first Principal Component (PC) is shown on the right side. The PCA Energy for MTD prediction is computed from the first PC in the frequency range from 140 Hz to 700 Hz.
Figure 7.3 Frequency Content of All Season Tire and Studded Tire at 32 kph

Figure 7.4 Frequency Content of All Season Tire and Studded Tire at 48 kph

Figure 7.5 Frequency Content of All Season Tire and Studded Tire at 64 kph
Table 7.1 MTD Prediction from Different Tires at Different Speeds

<table>
<thead>
<tr>
<th>Speed (kph)</th>
<th>24</th>
<th>32</th>
<th>48</th>
<th>64</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTD from All Season Tire (mm)</td>
<td>0.81</td>
<td>0.6</td>
<td>0.54</td>
<td>0.55</td>
</tr>
<tr>
<td>MTD from Studded Tire (mm)</td>
<td>0.53</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
</tr>
</tbody>
</table>

The studded tire creates an increase in Sound Pressure Level (SPL) of 3~10 dB than all season tire referring to all the figures. However, except at 24 kph (Fig. 7.2), the difference of the first PC between all season tire and studded tire is very small at other speeds. Table 7.1 lists the MTD estimated from the two types of tire at four speeds respectively. Likely, no tire effect exists above 32 kph (20 mph). However, care should be taken for speed below 32 kph.

The above experiment and its result demonstrate that there is no tire effect during the MTD estimation above 32 kph. Some theoretical explanation also could be found. First, Sandberg and Ejsmont (2002) concluded that studded tire will cause the increase of sound pressure level, around 3~10 dB, depending on speed and the type of stud. Referring to the right side of Fig. 7.2 through Fig. 7.5, the difference in amplitude along frequency is minimized by the normalization in PCA treatment. Secondly, according to the studded tire generation mechanisms, the sound emission increase due to studs is due to the impact of stud central pin on the road surface and the associated scratching of the pin on the pavement when tangential movements occur. The noise emission is concentrated at high frequencies above 6 kHz, which will not influence the low frequencies below 700 Hz. In addition, the difference below 32 kph probably comes from that the parameters of the MTD prediction model is derived between speed 32 kph to 80 kph, which might lead to some error below 32 kph.
8 Application of MTD

The estimation model of equivalent MTD is constructed and the effect from tire tread pattern is proved to be unimportant to the MTD prediction. The next step is to find how to apply the estimated MTD for pavement condition assessment. As mentioned in Chapter 6, macrotexture is related to tire/road friction in wet weather [ISO 13473-1 (ISO 1997)], and the severity of segregation, which will lead to raveling, a type of pavement distress (Stroup-Gardiner and Brown 2000; Jones et al. 2012). Therefore, the first application to discuss is the frictional properties of the pavement surface, which is directly related to crash rate on rainy days; the second application is to investigate the relationship between MTD and pavement condition index (PCI); the third application is to evaluate the severity of pavement deterioration, which is relative to construction segregation, also leading to pavement condition rating.

8.1 Pavement Friction Prediction

Sandberg and Ejsmont (2002) discussed the relation between pavement texture and friction. It is concluded that both macrotexture and microtexture determine pavement friction (Hall 2007; Li et al. 2003). Microtexture is dominant for friction at low speed, while macrotexture is dominant for friction at high speed. Macrotexture accounts for over 90% of friction above 90 kph (56 mph). The friction is usually measured on wet surfaces since the friction is generally a problem only on wet surfaces. Also, dry friction measurements create a big deal of wear on test tires. Field test of noise-friction relations also represented different results because of two different road surface characteristics’ influence.

It appears that with macrotexture depth and microtexture depth, the friction could be predicted. However, microtexture can be measured with present techniques only with very special methods, which have rarely been applied for tire/road noise studies (Sandberg and Ejsmont 2002). Researchers have only measured microtexture directly by observing tire/road friction, most often using the British Pendulum Method or Dynamic Friction Tester (ASTM 2009c) for measuring friction. ASTM E1960 (ASTM 2011a) provides a method for calculating International Friction
Index (IFI) of pavement surface, which also need both macrotexture depth and microtexture information tested from Dynamic Friction Tester to obtain the pavement friction.

However, Li et al. (2010a) found that surface friction is related to macrotexture linearly with a coefficient of 0.97 when pavement is wet, as shown in Fig. 8.1 (modified from Li et al. 2010a).

![Figure 8.1 Variation of Wet Pavement Coefficient of Friction (COF) with MTD](image)

In Fig. 8.1, the y axis is the wet pavement coefficient of friction (COF). ASTM E-274 provides a field test method by using a locked wheel device to measure the friction coefficient. The x axis is the macrotexture MTD. Figure 8.1 represents the potential to predict wet pavement friction through MTD. The predicted friction could be used as a reference for pavement quality assessment since it is related to the accident rate on road as shown in Table 8.1 (Wallman and Astrom 2001). The average coefficient of friction requirement by DOTs of different states in the United States is 0.3. Meanwhile, the critical macrotexture depth is 0.4 mm, below which the accident rate on rainy days increases noticeably.

<table>
<thead>
<tr>
<th>MTD (mm)</th>
<th>Wet Pavement COF (No Dim.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>0.25</td>
<td>0.2</td>
</tr>
<tr>
<td>0.5</td>
<td>0.3</td>
</tr>
<tr>
<td>0.75</td>
<td>0.4</td>
</tr>
<tr>
<td>1.0</td>
<td>0.5</td>
</tr>
<tr>
<td>1.25</td>
<td>0.6</td>
</tr>
<tr>
<td>1.5</td>
<td>0.7</td>
</tr>
<tr>
<td>1.75</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Table 8.1 Accident Rates at Different Friction Intervals
Friction interval | Accident rate
--- | ---
< 0.15 | 0.80
0.15 - 0.24 | 0.55
0.25 - 0.34 | 0.25
0.35 - 0.44 | 0.20

(Note: Accident rate = personal injuries per million vehicle kilometers)

Moreover, Li et al. (2010b) concluded the linear relation between Friction Number (FN) and MTD at 64 kph (40 mph) and 80 kph (50 mph). The relations are listed as follows:

\[
\begin{align*}
\text{FN} &= 44.1 - 7.53\text{MTD}, \text{ for 64 kph} \quad (8.1) \\
\text{FN} &= 41.8 - 7.21\text{MTD}, \text{ for 80 kph} \quad (8.2)
\end{align*}
\]

Where,
FN = friction number, which is a production of COF and 100, no dimension;
MTD = mean macrotexture depth, mm.

The two equations above motivate the use of MTD only to predict pavement friction. However, they could not be the solution for friction prediction because no further literature could prove the repeatability and accuracy. Also, it is not consistent with the standard method described in ASTM E1960 (ASTM 2011a). One possible improvement of the method introduced by Li et al. (2010b) is to use smooth tires instead of patterned tires, since the tire/road noise-friction relation is rather clear for the smooth tire but less clear for the patterned tire (Sandberg and Ejsmont 2002).

In summary, it is not sufficient to use macrotexture estimated from tire/road noise only for friction prediction at current state, because the microtexture could not be measured directly from tire/road noise. Other tools like Dynamic Friction Tester is encouraged to be used in the test and quantities of experiments are required. Hence a library may be established to refer to the friction measurement FS in ASTM E1960 (ASTM 2011a) at certain tire/road noise level. Then it is probable to lead to the real-time pavement friction measurement from MTD and parameter from tire/road noise level.
8.2 Contribution to Pavement Condition Index (PCI) Prediction

8.2.1 Motivation

Pavement Condition Index (PCI), originated in 1976 by the U.S. Army Construction Engineering Research Laboratory (CERL) for the United States Air Force, is a numerical rating for road surface quality between 0 and 100 to every stretch of road based on visual inspection of subsection of roads and extending these results to urban road sections between intersections (ASTM 2011b). PCI measures the type and severity of pavement surface distresses, as well as the smoothness and ride comfort of the road (ASTM 2011b). It is an important scale for pavement maintenance. First, different ranges of PCI values will determine different maintenance alternatives as well as the road repair needs and priorities; second, it could be used to rate the deterioration of the road network over time; third, as a feedback on pavement performance, PCI could validate or improve the current pavement design and maintenance procedures (ASTM 2011b; Shahin et al. 1981). Therefore, an accurate, sensitive and timely PCI value is important for effective pavement maintenance.

The current state of the art for Pavement Condition Index measurement is investigated. The most widely used pavement management system (PMS) is Micro PAVER, which was developed by U. S. Army Corps of Engineers in the late 1970’s (Sharaf et al. 1987). Micro PAVER introduced the PCI methodology, which became an ASTM standard in 1999 (MicroPaver 1987). With the input of the collected pavement data, the Micro PAVER will produce a PCI as a scale for pavement quality assessment. The vital component to a quality PMS is quality data collection. The traditional manual survey method for data collection is described in the ASTM D6433 – 11 standard (ASTM 2011b). The results should be repeatable, but only well trained and experienced inspectors make it less subjective. In some cases traffic blocking is required when inspectors have to walk on the pavement to perform the survey. Automated pavement condition surveys are developed in recent two decades to overcome the limitation of the manual inspection. It consists of driving along the road at or near highway speeds while collecting data using different sensors attached to the vehicle. A lot of technology on camera and image processing was developed for cracking identification in the automated data collection system (Wang 2000). However, the PMS would require recalibration for the automatically collected data since most PMS have been
developed around manual data, which hindered better acceptance of the automated data collection technology (Timm and McQueen 2004).

Generally, the current methods for PCI calculation has several shortcomings, which are subjectivity, cost, and it is time consuming (Mustaffar et al. 2008). Even with the automated data collection technology, the PCI could not be obtained immediately while driving over the roads since the PMS performs post-processing. Since PCI keeps varying along time without routine maintenance (Shahin et al. 1981), and currently surveys are usually taken 3 or 5 years apart. This may mislead decision makers as they might miss the opportunity to consider road repair alternatives, which are potentially more cost effective. Therefore the overall objective of this study is to find a way to get PCI timely and monitor the PCI much more frequent, even at the order of months. Based on Sandberg’s research on the tire/road noise (Sandberg and Ejsmont 2002), as well as the author’s preliminary work on pavement macrotexture estimation (Zhang et al. 2012), it is concluded that the tire/road noise data collected with a microphone behind the driver side rear tire could be used for pavement condition assessment. Figure 8.3 also hints that the MTD might be used for pavement condition assessment since larger MTD corresponds to worse pavement condition. Therefore, the tire/road noise is utilized for comparison with PCI calculations.

A study on the relationship between PCI and MTD predicted from tire/road noise is conducted. Roads at the city of Brockton are classified to the same type of mixture design method, whose MTD fall in the range from 0.6 to 1.2 mm. Since they have the same mixture type, the MTD is directly used. PCI values along with the predicted MTD of seven streets in the city of Brockton are listed in Table 8.4 as examples.

<table>
<thead>
<tr>
<th>Road Name</th>
<th>Randolph St</th>
<th>Brookville Ave</th>
<th>Lynn St</th>
<th>Field St</th>
<th>Lisa Rd</th>
<th>N Montello St</th>
<th>Hovendon Ave</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI (No Dim.)</td>
<td>0</td>
<td>6</td>
<td>13</td>
<td>41</td>
<td>64</td>
<td>84</td>
<td>91</td>
</tr>
<tr>
<td>Predicted MTD (mm)</td>
<td>1.03</td>
<td>0.98</td>
<td>0.95</td>
<td>0.83</td>
<td>0.75</td>
<td>0.63</td>
<td>0.57</td>
</tr>
</tbody>
</table>
Table 8.2 represents the predicted MTD of the roads in Brockton Massachusetts with corresponding PCI values. The results shown in Table 8.2 are plotted in Fig. 8.2. The predicted MTD increases as the PCI decreases in Fig. 8.2, i.e., the predicted MTD increases as the road condition gets worse, which matches the expectation explained by Metro Nashville (2006). Figure 8.3 is more convincing with MTD and pavement condition appearance at randomly selected location on the map. One explanation is that MTD could be an index for the severity of raveling (one type of pavement surface distresses), which is related to the PCI value (Stroup and Brown 2000; Flintsch 2003). The high linear correlation between MTD and PCI encourages the author to utilize the tire/road noise for PCI prediction. After several tries of acoustic parameters from tire/road noise, the standard deviation of the average amplitude of the Short Time Fourier Transform was extracted to estimate PCI.

Figure 8.2 Variation with Predicted MTD of Different Roads

Figure 8.3 Real Map of Pavement Condition Rating along with Predicted MTD
8.2.2 PCI Calculation from Acoustic Measurements

As described in Chapter 6, a field test was conducted in the City of Brockton in August 2012. CDM Smith (a consulting, engineering, construction and operation firm headquartered in Cambridge, MA) shared an existing pavement condition survey from 2006 with VOTERS. For this survey, performed by CDM Smith, a PCI value was assigned to each street ranging from 0 to 100, where 0 is the worst possible condition and 100 is the best. This survey information provides a valuable tool for developing and validating algorithms for pavement condition assessment using the test vehicle setup in Fig. 6.1. Results of the survey for the 17 streets to be considered in this paper are shown in Table 8.3. The PCI values in Table 8.3 are the forward projected values to 2012 using Micro PAVER’s built in deterioration model.

<table>
<thead>
<tr>
<th>Street Name</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Quincy St</td>
<td>90</td>
</tr>
<tr>
<td>Hovendon Ave</td>
<td>90</td>
</tr>
<tr>
<td>Jordan St</td>
<td>80</td>
</tr>
<tr>
<td>Intervale St</td>
<td>75</td>
</tr>
<tr>
<td>Sawtell Ave</td>
<td>75</td>
</tr>
<tr>
<td>North Montello St</td>
<td>75</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Street Name</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lisa Drive</td>
<td>64</td>
</tr>
<tr>
<td>Ridge St</td>
<td>55</td>
</tr>
<tr>
<td>Field St</td>
<td>41</td>
</tr>
<tr>
<td>Christopher Rd</td>
<td>31</td>
</tr>
<tr>
<td>Lynn Rd</td>
<td>15</td>
</tr>
<tr>
<td>Boundary St</td>
<td>14</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Street Name</th>
<th>PCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gary Rd</td>
<td>12</td>
</tr>
<tr>
<td>Boyle Rd</td>
<td>10</td>
</tr>
<tr>
<td>Brookville Ave</td>
<td>7</td>
</tr>
<tr>
<td>Randolph St</td>
<td>0</td>
</tr>
<tr>
<td>Tina Ave</td>
<td>0</td>
</tr>
</tbody>
</table>

8.2.2.1 Data Processing

A flow chart of the data processing is shown in Fig. 8.4. The data collected for one street is loaded into MATLAB for processing. According to the information collected by GPS and the camera systems (Fig. 6.1), the acoustic measurements were divided into many processing units, each with a distance of 1.3 m, which is the longitudinal distance covered in each photo from the camera. Then windowing was done for each processing unit, with $2^{10}$ as data length for each window. After windowing, a Short Time Fourier Transform (STFT) was performed for each window. The average amplitude of the Fourier Transform was obtained over all the windows. A standard deviation (STD) of the average amplitude of the STFT was computed within the frequency range from DC to 2 kHz. The frequency band selection is based on the author’s
preliminary experience for macrotexture measurement using acoustic data (Zhang et al. 2012; Zhang et al. 2014b), which indicates that the frequency content in DC ~ 2 kHz could represent pavement condition effectively. Thus, each processing unit (1.3 m) will output one STD. For example, if the street is 260 m long, 200 STDs will be obtained for the whole street. A PCI of this street will be computed from the mean value of the 200 STDs. Figure 8.5 represents an example of data outputs for one road. Each circle is the STD of the amplitude of a STFT for 1.3 m data. The average STD value (bold black line) is computed from around 180 STDs and will be used to predict the PCI for this road.

Figure 8.4 Flow Chart of Data Processing

Figure 8.5 An Example of Data Outputs for One Road
8.2.2.2 Correlation between Acoustic Measurements and PCI

Through the observation during test, it is concluded that change of road condition will excite the vehicle resonance varying with frequency, leading to the pressure varying with frequency. The larger variation with frequency (STD), the worse the road conditions are. Therefore, the STD of the amplitude of the STFT is explored for the PCI prediction.

8.2.2.3 Linear Regression Analysis for PCI Prediction

A linear regression analysis is performed to obtain the equation for PCI prediction from the STD of the amplitude of STFT. Eleven streets (Table 8.4) were selected as the database for the analysis. The measured PCI and the average STD for each street are listed in Table 8.5. Since three loops were surveyed for each street, the average STD is the mean value over the three loops. The general trend of the average STD decreases as the road condition getting better (PCI increases). In addition, the data in Table 8.5 was used for the linear regression analysis.

Table 8.4 Road Information for Linear Regression Analysis

<table>
<thead>
<tr>
<th>Street Name</th>
<th>Randolph St</th>
<th>Tina Ave</th>
<th>Boyle Rd</th>
<th>Gary Rd</th>
<th>Lynn Rd</th>
<th>Field St</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>12</td>
<td>15</td>
<td>41</td>
</tr>
<tr>
<td>Average STD (dB)</td>
<td>7.7047</td>
<td>7.9432</td>
<td>7.8780</td>
<td>7.8954</td>
<td>7.0390</td>
<td>7.1052</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Street Name</th>
<th>Lisa Drive</th>
<th>Intervale St</th>
<th>North Montello St</th>
<th>Jordan St</th>
<th>Hovendon Ave</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI</td>
<td>64</td>
<td>75</td>
<td>75</td>
<td>80</td>
<td>90</td>
</tr>
<tr>
<td>Average STD (dB)</td>
<td>6.9269</td>
<td>6.1179</td>
<td>5.9480</td>
<td>7.5960</td>
<td>6.2543</td>
</tr>
</tbody>
</table>
Figure 8.6 (left) shows the average STD as x axis and the measured PCI as y axis. Eleven points were plotted in Fig. 8.6 (left). The linear regression equation is obtained by the linear regression analysis with the linear correlation coefficient equal to -0.77.

\[ PCI = -36.4612 \times STD + 301.8967 \]  

(8.1)

After obtaining the linear regression equation, six other streets from Table 8.3 those which haven’t been used for the linear regression analysis were introduced for the PCI prediction, with the purpose to check the accuracy of Eq. 8.1. The PCI prediction results are shown in Fig. 8.6 (right). The numbers 1 to 6 in the x axis represent the six streets as indicated in Table 8.5. These streets were not used in the linear regression analysis. Except the results for Brookville Ave. and Boundary St., the PCI prediction for the four other streets has an average relative error of 11.22%, which is acceptable. Moreover, Eq. 8.1 is speed independent since the regression analysis is based on varied speed.

The large relative error over 80% for the other two streets may come from the complete measurements with this proposed approach compared with the sample unit measurements by the conventional approach introduced in ASTM standard (ASTM 2011b). In the proposed approach, the PCI of one street is measured every 1.3 meters (Fig. 8.5), and the final PCI is a mean value over the continuous inspection of the street. The overall condition taken every 1.3 m may be different from the sample unit inspection result, but the predicted PCI for each 1.3 m is reliable through the observation of the corresponding picture (Fig. 8.7).
Table 8.5 PCI Prediction Results

<table>
<thead>
<tr>
<th>Street Name</th>
<th>Brookville Ave (1)</th>
<th>Christopher Rd (2)</th>
<th>North Quincy St (3)</th>
<th>Ridge St (4)</th>
<th>Boundary St (5)</th>
<th>Sawtell Ave (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average STD (dB)</td>
<td>7.9041</td>
<td>7.3823</td>
<td>6.1578</td>
<td>7.0175</td>
<td>8.2081</td>
<td>6.4076</td>
</tr>
<tr>
<td>Estimated PCI (a)</td>
<td>13.7</td>
<td>32.7</td>
<td>77.4</td>
<td>46</td>
<td>2.6</td>
<td>68.2</td>
</tr>
<tr>
<td>Measured PCI (b)</td>
<td>7</td>
<td>31</td>
<td>90</td>
<td>55</td>
<td>14</td>
<td>75</td>
</tr>
<tr>
<td>Error</td>
<td>95.75</td>
<td>5.58</td>
<td>14.03</td>
<td>16.3</td>
<td>81.3</td>
<td>8.98</td>
</tr>
</tbody>
</table>

Figure 8.7 Pavement Condition with Their Corresponding Prediction PCI Values for Brookville Avenue
(Note: each picture is 1.9 m in length and 1.3 m in width)

8.2.2.4 Advantage of the Proposed Method

The proposed method above could be utilized for PCI prediction as a guide of maintenance alternatives in real time. The processing time in MATLAB 2011a for one second of data is 31.133 milliseconds on a computer system with the information listed in Table 8.7. Since the definition for “real – time” in digital signal processing is that the data processing time should be less than the time of the incoming data, plus the “real-time” response time is understood to be in the order of milliseconds and sometimes microseconds, the data processing indicated in Fig. 8.4 could be considered as real time capable. In addition, as long as the database includes a broad range of PCI values, the obtained linear regression equation could be used for PCI prediction on
any roads. Except that the type of the tire of the vehicle needs to be the same to exclude the tire effect as mentioned in experimental description, no calibration is need for this proposed approach. Hence the approach is calibration free with the condition that the type of the tire needs to be identical throughout the survey.

8.2.3 Summary

The STD of the amplitude of STFT of acoustic measurements for road quality inspections has a linear correlation coefficient of -0.77 with PCI in this study, which assures that the linear regression equation obtained from this investigation is acceptable for PCI prediction. Furthermore, the processing time for one second of data is 31.133 milliseconds, which allows for real-time on-board processing. Moreover, no calibration is need as long as the type of tire for the test vehicle is kept the same. Hence, the proposed approach is able to perform continuous network-wide health monitoring of roadways in real time and provide frequently updated condition information without stopping traffic.

Table 8.6 Computer System Information

<table>
<thead>
<tr>
<th>Windows Edition</th>
<th>Windows 7 enterprise</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Rating</td>
<td>3.6 windows experience index</td>
</tr>
<tr>
<td>Processor</td>
<td>Intel (R) Core (TM)2 Duo CPU E8400 @ 3.00 GHz</td>
</tr>
<tr>
<td>Installed Memory (RAM)</td>
<td>4.0 GB (3.21 GB usable)</td>
</tr>
<tr>
<td>System Type</td>
<td>32 - bit Operating System</td>
</tr>
</tbody>
</table>

Shamsabadi et al. (2014) developed the VOTERS PCI using three parameters collected by the test vehicle in Fig. 6.1: predicted MTD from microphone, STD of the average amplitude of STFT as discussed above (StdFFT), and the STD of dynamic tire pressure (StdDTPS) recorded by dynamic tire pressure sensor inside the rear tire. As to the two parameters from tire/road noise, the contribution of MTD varies from 40% to 87%, and the contribution of StdFFT varies 28% to 80.6%.
8.3 Pavement Deterioration Evaluation

8.3.1 Pavement Segregation

Segregation is a lack of homogeneity in the hot mix asphalt constituents of the in-place mat of such a magnitude that there is a reasonable expectation of accelerated pavement distresses (Stroup and Brown 2000). The constituents here mean asphalt binder, aggregates, and air voids. In other words, segregation indicates the aggregate of the pavement starts to lose good bonding and depart from each other. Severe segregation will lead to potholes.

Recommended approaches for segregation evaluation are infrared thermography, ROSANv laser surface texture measurements (Meegoda et al. 2002). Stroup and Brown (2000) introduced a term of Texture Ratio (TR), which is a ratio of predicted MTD over the MTD with no segregation. With this ratio, one can evaluate the segregation level according to the threshold defined by Stroup and Brown (2000) in Table 8.7. The “high level segregation” usually indicates severe raveling condition, sometimes even pothole; the “no segregation” shows good pavement condition; the “fine level segregation” commonly corresponds to pavement bleeding since the pavement macrotexture is too small comparing to the normal value (Johnson 2000). It is noticed that how to determine the MTD with no segregation is the key to this problem. The way to determine the MTD with no segregation needs the information of aggregate properties such as smallest sieve size with 100% passing, the percent passing the 4.75 mm sieve, coefficient of curvature and coefficient of uniformity (Stroup and Brown 2000).

<table>
<thead>
<tr>
<th>Segregation Level</th>
<th>Fine</th>
<th>No Segregation</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>TR (No Dim.)</td>
<td>&lt; 0.75</td>
<td>0.75 ~ 1.15</td>
<td>1.15 ~ 1.56</td>
<td>1.56 ~ 2.09</td>
<td>&gt; 2.09</td>
</tr>
</tbody>
</table>

8.3.2 Severity of Pavement Deterioration

Motivating by the knowledge of pavement segregation and its way to determine the segregation level, a method to evaluate the severity of pavement deterioration is derived. Figure 8.8 shows the MTD range for pavements with different mixture types. For example, for open grade friction course (OGFC) pavement, the MTD is ranged from 2.2 to 3 mm, and for stone matrix asphalt
(SMA) pavement, the MTD varies from 1.0 to 1.6 mm. Therefore, it is concluded that high MTD does not indicate bad pavement condition, and low MTD does not mean good pavement condition. A more reasonable scale need be developed to indicate pavement condition in real time. Referring to segregation level identification, the concept of texture ratio can be incorporated to represent the severity of pavement deterioration. Equation 8.2 is developed to calculate the texture ratio (TR) for pavement condition indication.

\[
TR = \frac{MTD}{MTD_{good}} \tag{8.2}
\]

Where,

\( MTD = \) predicted MTD from tire/road noise by PCA Energy Method (mm);

\( MTD_{good} = \) mean MTD of the range for a certain mixture type of pavement with good condition (mm);

\( TR = \) Texture Ratio (no dim.).

The key in Eq. 8.2 to get the TR is to define the \( MTD_{good} \), which represents the mean MTD of the range for a certain mixture type of pavement with good condition. Moreover, \( MTD_{good} \) is the denominator, so the function of this \( MTD_{good} \) is to classify the mixture type of pavement. Then dividing the predicted MTD by \( MTD_{good} \), the texture ratio is obtained. Since different surface treatment and mix type will lead to different MTD scale level (Table 8.8), a statistical method to identify different type of mixture is necessary.

![MTD Range for Pavements with Different Mixture Types](image)

**(Figure 8.8 MTD Range for Pavements with Different Mixture Types)**

(Note: OGFC is short for Open Grade Friction Course; SMA is short for Stone Matrix Asphalt)
Table 8.8 MTD Range for Different Surface Mixture Types with Good Pavement Condition

<table>
<thead>
<tr>
<th>MTD (mm)</th>
<th>0.4 ~ 0.6</th>
<th>0.6 ~ 1.2</th>
<th>1.5 ~ 3.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixture Type</td>
<td>Asphalt Concrete (fine)</td>
<td>Asphalt Concrete (coarse)</td>
<td>Open Grade Friction Course</td>
</tr>
</tbody>
</table>

The flow chart to determine the MTD_good is indicated in Fig. 8.9. For a road section about 200 m, if over 60% of the predicted MTD falls in the range listed in Table 8.8, this road section is identified as the corresponding type of surface mixture and the MTD_good is determined to be the minimum value of the range shown in Table 8.8. For instance, for MTD predictions in 200 m distance, if over 60% of predicted MTDs are in the range of 0.6 to 1.2 mm, the mixture type of this section is classified as course asphalt concrete, and the MTD_good is 0.6 mm. The number of 60% is obtained by testing over 960 km of urban road. Moreover, up to the year 2000, course asphalt concrete with the mixture method of superpave has accounted for 62 percent of the total hot-mix asphalt (HMA) across the United States (WesTrack 2001). Thus if the predicted MTDs within 200 m does not fall in any of the three ranges, it will be defaulted as coarse asphalt concrete. Also, because the pavements in the City of Brockton were all classified as coarse asphalt concrete, the PCI calculation in Section 8.2 can be derived directly from the predicted MTD.

![Flow Chart](image-url)
With the flow chart in Fig. 8.9, an approach to rate the pavement deterioration level based on the predicted MTD through microphone is investigated and an example is shown in Fig. 8.10. In this example, the $MTD_{good}$ is 0.6 mm since the pavement is identified as course asphalt concrete pavement. Hence, the range of MTD with good pavement condition varies from 0.6 mm to 1.2 mm. The minimum value (0.6 mm) is selected to be the $MTD_{good}$. Accordingly, the MTD is converted to the texture ratio (TR) at each second corresponding to about 7 m distance. From the corresponding pictures of Pavement A to Pavement G (Fig. 8.10), the pavement condition gets worse as the TR increases. Moreover, the Pavement F and G start to appear some patches besides cracks, which also indicates that this texture ratio has potential to identify the distress type combining with a certain PCI.

This approach converts MTD from a local scale (MTD) to a global scale (TR), eliminating the influence on MTD scale from different mixture types of pavement. It is a significant improvement for pavement condition assessment. With the Texture Ratio (TR), the difference caused by different pavement mixture design would be phased out, and the pavement condition assessment would become more objective.
8.4 Conclusions

The predicted MTD could be used as one parameter for pavement friction prediction. Moreover, the MTD and STD of tire/road noise contribute to accurate VOTERS PCI prediction. In addition, the acoustic based MTD prediction could also be applied to evaluate the severity of pavement deterioration. An interesting discovery is that the texture ratio (TR) can be used as a global scale for MTD to rate pavement conditions. The new scale of TR eliminates the influence from different mixture design types of pavement surface. The next focus will be the pavement distress type identification with the help of predicted MTD under a certain PCI value. Thus the detailed pavement treatment could be determined according to specific pavement distresses.
Chapter 2 already stated that pavement stiffness has no influence on sound levels from the structural-acoustic model by Saurenman et al. (2005). However, from the analysis of experimental data from NCAT, different phenomena appear to indicate the possibility that subsurface information can be detected from tire/road noise.

In Chapter 5 and Chapter 6, it was proven that the principal component analysis performs well on the pavement surface texture characterization through MTD estimation. It was also shown that noise could be eliminated to some extent using the first principal component vector so that the road feature was amplified. One remaining question was if the first principal component vector could represent the road surface condition, would it also contain any hint of the road subsurface structure? Further exploration of the first principal component vector was made to investigate if any subsurface information was hidden in it.

Figure 9.1 First Principal Component Vectors of Pavement Sections N5, N6 and N10
Three curves displayed in Fig. 9.1 are the first principal component vectors of pavement N5, N6 and N10. As indicated in Fig. 9.1, pavement N5 (light solid curve) has very similar road condition with pavement N6 (dot curve), but pavement N10 (heavy solid curve) is different from both N5 and N6, especially in the frequency range of 700~1000 Hz. What creates this difference? Firstly, the visible surface conditions of N5, N6 and N10 were compared in Fig. 9.2. They are very similar to each other. Plus, referring to Table 5.1, these three pavements have the same MTD value of 0.5mm.

Thus, it is not the visible surface conditions such as macrotexture, air void or roughness that creates differences in the first principal component vectors. Accordingly, other invisible road properties such as layer thickness and modulus, as well as the subsurface structure were
investigated. Figure 9.3 lists the pavement profiles of N5, N6 and N10 from the NCAT reference. Material and thickness of each layer is clearly indicated. As indicated in Table 9.1, different patterns shown in Fig. 9.3 represent different material properties such as elastic modulus and

Table 9.1 Pattern Illustration for Pavement Profile

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Design Method</th>
<th>Material</th>
<th>Elastic Modulus (MPa)</th>
<th>Poisson's Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>superpave</td>
<td>PG67-22 (N10) or PG76-22</td>
<td>13,790-27,580</td>
<td>0.35</td>
</tr>
<tr>
<td>B</td>
<td>theopave</td>
<td>WMA</td>
<td>13,790-27,580</td>
<td>0.35</td>
</tr>
<tr>
<td>C</td>
<td>theopave</td>
<td>WMA</td>
<td>1,379-10,342</td>
<td>0.35</td>
</tr>
<tr>
<td>D</td>
<td></td>
<td>track soil</td>
<td>55</td>
<td>0.35</td>
</tr>
</tbody>
</table>

(Note: WMA = Warm Mix Asphalt.)

Poisson’s ratio. Differences between pavement N10 and the other two pavements lie in the first three layers of their respective profiles. Firstly, the surface thickness of N10 is different from that of other two pavements. For the second layer of N10, the material (Warm Mix Asphalt) is different from that of other two pavements, which is PG67-22. Even for the first layer, the material of N10 is PG67-22, while the material of other two pavements is PG76-22. Further, the third layer of N10 also has a different material from other two pavements, with a different elastic modulus. As Table 9.1 indicates, the elastic modulus is 13,790 ~ 27,580 MPa for the third layer of pavement N10, while the elastic modulus for the third layer of N5 and N6 is 1,379 ~ 10,342 MPa. Hence, the profile of N10 indicates an apparent difference with the other two pavements’ profiles, which is identified as the reason for the difference existed in their first principal component vectors. Based on these observations, the difference in the first principal component vectors may be due to the surface thickness, also, it is probably due to the subsurface structure. However, it represents the possibility that the PCA could differentiate the pavement subsurface structure.


9.2 Experimental Results and Discussions

Results from the above three pavements initiated a further study on the influence of pavement subsurface feature on tire/road noise. The pavements in the NCAT test were used for analysis. The investigation covered from the surface feature to subsurface feature. In this study, the surface feature was mainly characterized by MTD value and its appearance, and the subsurface features were concentrated on the layer thickness and stiffness. When focusing on a certain feature, other factors were kept to be the same. In addition, a special pavement section with and without debonding respectively in two parallel lanes was explored to seek the possibility of delamination detection from tire/road noise.

9.2.1 Different Surface

Previous study already proved that sound pressure level at low frequencies (below 700 Hz) is strongly related to pavement surface macrotexture. Two pairs of pavements shown in Figures 9.4 and 9.5 are consistent with the above conclusion. The pavement names are shown in Table 5.1. From Fig. 9.4 (left), one can conclude that Pavement W1 has larger MTD than Pavement W2 since the sound pressure level (SPL) of W1 before peak frequencies is much higher than that of W2. Similarly, the MTD of Pavement W10 should be larger than that of Pavement W6. The measured MTDs of these four pavements (Fig. 9.5) match with their corresponding frequency spectra. Moreover, Pavement W1 and W2 share the same subsurface profile based on NCAT data, so do Pavement W6 and W10. Hence, it confirms the statement again that the difference in pavement surface is mainly reflected in the frequency range below peak frequency area 700 ~ 1300 Hz.
9.2.2 First Layer

9.2.2.1 Thickness

Pavement W6 and S7 shown in Fig. 9.6 have the same subsurface profile and MTD except the thickness of the top layer, 10 cm (4 in.) for Pavement W6 and 5 cm (2 in.) for Pavement S7. However, the frequency spectra of both pavements are very similar to each other. No significant difference is detected. Sandberg and Ejsmont (2002) have investigated the influence of top layer thickness of porous pavement on tire/road noise. It concluded that the peak frequency will shift for different thickness. Nevertheless, for non-porous pavement, it seems that the thickness of the top layer has little influence on the frequency spectrum.
9.2.2.2 Stiffness

Nilsson and Zetterling (1990) have conducted an experiment to test if the top layer stiffness will influence the tire/road noise. A set of measurements of tire/road noise was collected on a thin grinding paper that was glued either directly on a smooth cement concrete base or on a rubber sheet that was placed on the concrete surface. The difference obtained was a 5 dB noise decrease at the peak frequencies 700 ~ 1300 Hz. Accordingly, it seems that the influence of pavement stiffness may be dramatic if a really soft surface like rubber is mainly used. The observations suggest a quite high stiffness effect when very soft surfaces are compared to conventional hard surfaces.

Figure 9.7 through Figure 9.10 shows four pairs of pavement from NCAT. The only difference for each pair of pavement lies in their surface material, i.e., the stiffness of top layer. Based on the conclusion from the experiment by Nilsson and Zetterling (1990), the SPL at peak frequency of Pavement S1 is higher than that of Pavement E3 (Fig. 9.7), which means the stiffness of stone matrix asphalt (SMA) is larger than that of epoxy. Hence, in Fig. 9.8, the SPL at peak frequency of Pavement E1 should be higher than that of Pavement E2 since the top layer of E1 is SMA while E2 is epoxy. Therefore, the conclusion that the top layer with larger stiffness produces larger amplitude of SPL at peak frequencies 700 ~ 1300 Hz is demonstrated by the consistent performance in Figures 9.7 and 9.8. Figures 9.9 and 9.10 lead to the same conclusion knowing that PG76-22 provides higher stiffness compared to PG67-22.
Figure 9.7 Frequency Spectra of Pavements E3 and S1

Figure 9.8 Frequency Spectra of Pavements E1 and E2
9.2.3 Second Layer

9.2.3.1 Thickness

For the influence of the second layer thickness on tire/road noise could be examined from Pavements N5, N6 and N10. Figure 9.3 indicates that both the second layer thickness and stiffness of N10 are different from the other two pavements. However, from the above discussion, the author believes that the difference is caused by the different stiffness in the first and second layer of pavements. The second layer thickness has little influence on the tire/road noise.
9.2.3.2 Stiffness

A frequency analysis of Pavement S3 and Pavement S4 indicates that the second layer stiffness could be reflected in the frequency spectra of tire/road noise (Figure 9.11), within 10 cm (4 in.). In the first 10 cm profile on the right of Fig. 9.11, the difference in the second layer causes the higher acoustic energy in high frequencies of Pavement S3 than that of Pavement S4. One possible reason is that the asphalt concrete mixed by SMA is usually harder than that mixed by Superpave (VDOT 2012).

![Figure 9.11 Frequency Spectra of Pavements S3 and S4](image)

9.2.4 Pavement with Delamination

A data analysis is done on the special lane test data collected at NCAT on the section named N5. There are two parallel lanes in this section. The profile of this special lane (left lane) has artificial debonding as shown in Fig. 9.12 for the first 12.7 cm. Ten subsections are included in this special lane. Subsection with red block indicates debonding, and subsection with blue block means partial stripping. The rest subsections are fully bonded. The other lane (right lane) is a healthy pavement whose profile is not displayed. The VOTERS vehicle drove over both lanes three times respectively with different speeds. The acoustic measurements of the microphone behind the driver side rear tire were collected.
Figure 9.12 First 12.7 cm Pavement Profile with Debonding Distribution

Figure 9.13 Distribution of Frequency at Peak Value for Normal and Debonding Pavement: (a) Time-Frequency Contour; (b) Frequency of Peak Value Distribution

Figure 9.13 (a) shows its time-frequency contour with the driving speed of 32 kph (20 mph). The x axis is the time. The bold black line divides the plot of “Normal” lane from “Debonding” lane. The frequency in y axis is from 0.25 kHz to 2 kHz. Yellow color means very high sound pressure level and the red color means lower sound pressure level. Fig. 9.13 (a) represents a clear yellow line at 0.8 kHz for the normal pavement, while the yellow line shifts to 0.6 kHz for the pavement with debonding. In order to make it clearer, the frequencies of peak values are plotted in Fig. 9.13 (b). As shown, the continuous line is at 0.8 kHz for normal lane and then shifts to 0.6 kHz for debonding lane. Referring to Fig. 9.12, the subsurface condition of the debonding lane switch
between “full bond” and “no bond” frequently, which leads to the frequency at peak SPL varies between 600 Hz and 800 Hz in the debonding lane part of Fig. 9.13 (b). Vázquez and Paje (2012) introduced an equation according to ISO 9052-1 (ISO 1989), which claimed that the resonance frequency increases along with the dynamic stiffness. Besides, the dynamic stiffness test on the SMA pavement samples (Vázquez and Paje 2012) leads to the same conclusion. Thus, assuming the dynamic stiffness of pavement is reduced due to subsurface delamination, the resonance frequency (i.e., the frequency at peak SPL) would decrease also, which explains why the frequency at peak SPL will shift from 0.8 kHz to 0.6 kHz due to delamination. In summary, this phenomenon indicates a potential for detecting the debonding with the shifting of the frequency at peak SPL.

9.3 Conclusions

The study on the influence of pavement subsurface features on tire/road noise indicates some potential for non-contact pavement subsurface monitoring with moving vehicle at real time. Generally, the stiffness of top layer pavement within 10 cm from surface could be sensed by microphone. The harder surface layer will produce higher amplitude in sound pressure level at peak frequencies 700 ~ 1300 Hz. The resonance frequency (frequency with peak SPL) will shift to a lower value when delamination appears under the pavement surface, which could be a strategy for detecting subsurface delamination. Moreover, this study is focused on the single microphone mounted behind the driver side rear tire. The microphone array as shown in Fig. 5.1 might contain more subsurface information.
10 Conclusions

This research uses the sound generated by tire-road interaction for pavement condition assessment and distress detection. It started from the frequency content of vehicle noise related to road features. Then the factors influencing road features were determined. Quantification approaches for road feature macrotexture depth (MTD) measurement were developed, in which a statistical method, Principal Component Analysis, was applied for noise removal from acoustic measurement. In addition, the applications of MTD and another acoustic parameter from tire/road noise were discussed. Finally, an exploration for pavement subsurface delamination detection through tire/road noise was conducted. So far, a preliminary system for pavement surface and subsurface condition assessment using tire/road noise is demonstrated.

Conclusions are drawn as follows:

1. Three factors play an important role in the pavement surface mean texture depth (MTD) estimation: tire/road noise level, vehicle driving speed, and acoustic sensor placement. Firstly, the acoustic energy of tire/road noise below 1 kHz has a positive and linear correlation with macrotexture MTD. Secondly, the sound pressure level increases with speed for the same pavement below 1 kHz, which will affect the acoustic energy calculated from the frequency spectrum of tire/road noise. Thirdly, the optimal acoustic sensor placement is behind driver side rear tire, which consistently represents the best linear correlation between MTD and acoustic energy from tire/road interaction.

2. Principal Component Analysis (PCA) is applied to acoustic measurement to keep the signal with most variation versus frequency and remove the other noise with little variation versus frequency, which matches the assumption that the variations of the road-feature-related signal and noise with respect to frequency are different. After PCA treatment, the first principal component vector is extracted to best represent pavement surface features. Meanwhile, noise that varies less with frequency is eliminated through PCA. Additionally, the speed effect can be reduced by the normalization step.
3. Pavement macrotexture (MTD) is successfully predicted through the tire/road acoustic energy of the first Principal Component over the frequency band 140 to 700 Hz. To simplify the model, Taylor expansion theory is applied to determine the variables including PCA energy and driving speed. The prediction range from 0.2 to 3 mm is validated by field test. The MTD can be predicted every 7.8 m at speed from 32 kph to 80 kph.

4. Experiments using different types of tire prove that no tire effect exists during the MTD estimation above 32 kph. First, the increase of sound pressure level caused by studs is minimized by the normalization in PCA treatment. Secondly, according to the studded tire generation mechanisms, the sound emission increase due to studs is concentrated at high frequencies above 6 kHz, which will not influence the low frequencies below 700 Hz.

5. The predicted MTD could be used for severity of pavement deterioration evaluation. The macrotexture is converted from a local scale (MTD) to a global scale (Texture Ratio) with the mixture type of pavement considered. With the Texture Ratio (TR), the difference caused by different pavement mixture design would be eliminated, and the pavement condition assessment would become more objective.

6. The STD of the amplitude of Fourier transform of acoustic measurements for road quality inspections has a linear correlation coefficient of -0.77 with PCI in this study. A linear regression equation is obtained for PCI prediction. Furthermore, The PCI could be processed in real time, 31.133 milliseconds for one second of data. Hence, the proposed approach is able to perform continuous network-wide health monitoring of roadways in real time and provide frequently updated condition information without stopping traffic. The MTD and STD of tire/road noise can be used to predict PCI accurately.

7. The study on the influence of pavement subsurface features on tire/road noise indicates some potential for non-contact pavement subsurface monitoring with moving vehicle at real time. Generally, the stiffness of top layer pavement within 10 cm from surface could be sensed by acoustic sensor. The harder surface layer will provide higher amplitude in sound pressure level at peak frequencies 700 ~ 1300 Hz. The resonance frequency (frequency with peak SPL) will shift to lower value when delamination appears under pavement surface, which means a detection of subsurface delamination.
Limitations and recommendations for future research are discussed below.

1. For the PCA Energy Method, since the parameter of the prediction model is determined based on NCAT test data, limitations may exist in the minimum and maximum driving speed and PCA energy used for the normalization of variables applied to the model. Hence the predicted MTD may be more accurate at the driving speed within 32 kph to 80 kph, and at a certain range of PCA energy. For speeds out of that range, or the PCA energy higher than the maximum one at NCAT test, the predicted MTD is still reliable but less accurate.

2. The predicted MTD might be less than 0.2 mm or larger than 3 mm. The pavement condition for this kind of situation needs to be defined after a thorough investigation of the relationship between MTD and pavement surface condition, i.e., raveling or bleeding.

3. It is not sufficient to use macrotexture estimated from tire/road noise only for friction prediction at current state, because the microtexture could not be measured directly from tire/road noise. Hence a library may be established to refer to the microtexture measurement in ASTM E1960 (ASTM 2011a) at certain tire/road noise level. Then it is probable to lead to the real-time pavement friction measurement from MTD and parameter from tire/road noise level.

4. The MTD predicted from PCA Energy Method is not a real MTD to some extent. It is related to the severity of pavement deterioration since it is obtained from acoustic measurements. It might be more reasonable to treat the predicted MTD as an index for the severity of pavement distresses, Macrotexture Index (MTI). MTI could be helpful in identifying pavement distress type under a certain PCI value. Thus, effective pavement treatments to a specific pavement distress type could be determined.

5. The influence of other regular tires with different tire treads on MTD prediction need be studied later to make a more convincing and completed conclusion on tire effect.

6. In the future, the microphone array and their phase difference might be applied for further subsurface analysis.

7. The use of a microphone is limited to certain weather conditions since it does not have a weather protection device. A better microphone with weather protection device is needed for everyday use.
11 References


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