Vehicle Axle Detection and Spacing Calibration Using MEMS Accelerometer

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ABSTRACT

Vehicle classification data especially trucks has an important role in both pavement maintenance and highway planning strategy. An advanced microelectromechanical system (MEMS) accelerometer for vehicle classification based on axle count and spacing was designed, tested, and applied to the pavement. Vehicle-pavement interaction was collected by the vibration sensor while vehicle axle count and spacing were calibrated later. Collected vibration data also used to analyze the pavement surface condition and compared with simulation using dynamic loading analysis. Laboratory tests using MMLS3 device to verify the accuracy of MEMS accelerometer and reaction under different surface condition were tested. An algorithm for calculating axle spacing and axle count was developed. Acceleration of different pavement surface condition were analyzed and compared with simulation results, the influence of surface condition to the pavement acceleration was concluded.

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1. Introduction

Background

Vehicle classification, especially truck and other heavy-loading vehicle, is considered significantly for transportation engineering and pavement health monitoring. Current classification technologies including intrusive and non-intrusive technologies. Intrusive technologies like piezoelectric sensors and inductive loop detectors have very high maintenance costs and complicit installation processes under pavement which may need lane closing and possibly cause both pavement and sensor damage in the further. Non-intrusive technologies like video imaging and ultrasonic sensors are sensitive to weather condition which may influence the accuracy. In this case, a convenient method which sensors installed on the shoulder of the pavement without subjecting to vehicle loading should be considered and tested. An accelerometer is a device that measures acceleration force which can be used to monitor the vehicle-pavement interaction. There are different kinds of accelerometers, most common used is piezoelectric crystal, however, they are too big to be used in several areas. MEMS accelerometer was developed and used widely due to their smaller size and higher compatibility. In our tests, an Omega-CP-Ultrashock-5 sensor is used to detect pavement acceleration which will be collected to analysis vehicle axle, axle spacing and speed under both laboratory tests and actual condition. At the same time, the pavement health condition is also very important to us. In my project, a slab with a 1 in wide and 1.5 in deep crack was tested compared to the slab without a crack. Besides laboratory tests, a dynamic simulation analysis using Abaqus was done to compare with our experiment tests.

Objectives

There were there main objectives in this research, the first objective was to verify the accuracy of using MEMS accelerometer to classify vehicles under both laboratory and actual conditions. The second objective was to develop an algorithm to count vehicle axles and to calculate axle spacing and speed. This essentially entails testing sensor under both laboratory and actual condition and collect data for analyzing, at the same time, compare our calculated results with actual situation. The last objective is to compare our simulation results with experiment tests when there is a crack or not. It will give a clear view of the response when the pavement condition is good or bad.

Outline of the Thesis

A literature review was conducted to investigate three main parts. The first part of it was discussion about the traffic monitoring theory and classification method. Second part was vehicle detection method and background information about MEMS accelerometer which was used in our project. Last part was about the development and currently used methods about dynamic loading analysis and its importance. And a summary of finding which about the importance of using MEMS accelerometers for vehicle classification and the necessity of using dynamic simulation was given.

Then the laboratory tests using MMLS3 was described first including tests strategy, test devices installation, and test procedures, data collection method. Then, an Omega CP-Ultrashock-50 Tri-axial Shock Recorder was described. Later the experiment setup was introduced about how to install the sensor on the plate and how to run the MMLS3. At

last, the test procedures of running the MMLS3 and MMLS3 speed correction was described.

Next part of the thesis focused on the test data analysis. First was about axle detection algorithm which explain the signal noise filtering and signal peaks locating. Then the axle spacing and speed analysis method was described. And the simulation results were analyzed and compared with our experiment data. Last part was about the comparison between experimental tests results and actual data to verify the accuracy of using MEMS accelerometer.

2. Literature Review

Instruction

Vehicle classification is extremely important to transportation department as they can determine the road maintenance method and select proper improvement that will be applied. Vehicles are typically classified into carrier of passengers and carrier of goods. One of the most common classify method is depending on the vehicle axle counts and spacing between axles.

Traditional vehicle classification method mostly rely on the sensors installed in the pavement, and several sensors along the traveling direction may needed to collect as much data to calibrate axle spacing and speed. In this case, it may be dangerous for sensor installation and data collection, at the same time, if the sensor installed improperly it may shorten the life of the pavement where the sensor placed. As a result, non-intrusive sensor that can be installed and maintained without entering the traffic lane becomes more important. In this paper, we used a 3-axle MEMS recorder to monitor the pavement acceleration which was installed under the MMLS3 to simulate the traffic. The sensor was located on the surface of the pavement just beside the wheel without subjecting to the loading or damaging the pavement.

This method releases us from entering the traffic lane to install sensors or collect data, meanwhile, a new algorithm is used to provide axle count and spacing information considering just the acceleration of the pavement which needs at most 2 sensors in actual condition. Laboratory tests using MMLS3 to simulate actual traffic was applied to verify

the feasibility of MEMS accelerometer monitoring the pavement vibration which located beside the road.

Reviews

Traffic Monitoring Theory

Vehicle classification data is very important to different users. Transportation agencies use it to plan, design, construct highway system, operate and maintain roadways. Decision makers use it to evaluate highway usage and optimize different resources on the road. The classification scheme is divided into two major categories depending on whether the vehicle carries passengers or commodities. Non-passenger vehicles are further subdivided by number of axles and units. The most commonly used algorithm used to interpret axle spacing information to correctly classify vehicles into different categories is based on the "Scheme F" developed by Maine DOT in the mid-1980s (FHWA 2013).

There are two general methods used to collect traffic data: automatic and manual. Automatic: refers to use automatic equipment to collect traffic data continuously and record the distribution and variation of traffic flow. Both permanent and portable counters can be included in the automatic method.

Manual: refers to visually observing number, classification, vehicle occupancy, turning movement counts, or direction of traffic. Methods include using tally sheets or electronic counting boards.

Equipment used for monitoring traffic data can be divided into four different kinds. One is Automated Traffic Recorder (ATR), which is a traffic counter placed at specific

location to record the distribution and variation of traffic flow by different time interval. It can be used continually or permanently to record data at certain location. Continuous Count Station (CCS) provides 24 hours a day and 7 days a week of data for every day of the year or at least a seasonal collection. Another type of collection equipment is Portable Traffic Recorder (PTR) which is portable and easy moved to different locations and not necessary installed in the infrastructure permanently. Weight-In-Motion (WIM) is a measuring device that can read the dynamic tire forces of a moving vehicle and estimate the corresponding tire loads of the static vehicle.

When install traffic recorder, specific point on the roadway may needed. This point also called "count station" or "site". The point always represents the characteristics of a road segment. Since collecting traffic data is not feasible on every possible point within a segment, traffic data collected and representing a point on a segment is extrapolated to represent the entire segment. The extrapolation of point data to the line segments is known as the traffic data and linear referencing system (LRS) integration process. There are two primary categories of traffic count method: continuous and short duration. Continuous may also be known as permanent and count may also means monitoring. A continuous count station uses an automatic traffic counter or in-pavement sensors and record traffic distribution and variation of traffic flow by hour of the day, day of the week, and month of the week. The purpose of this continuous count site is to record data 365 day of the year which will give a whole picture of the traffic information for the future maintenance and optimization. Those stations only collect continuous count data for part of the year due to weather and road condition may also be considered continuous count stations. Short Duration Count Station is a site using an automated traffic counter

and recording traffic distribution and variation for a certain time period. It can be permanently installed or moved to specific location to fit count requirements. The purpose of short duration count station is to collect data that can be used to analysis daily traffic number that represents a typical traffic volume any time or day of the year.

Vehicle Classification

The FHWA vehicle classification system separates vehicles into categories depending on whether they carry passengers or commodities (FHWA-Traffic Monitoring Guide-2013). Non-passenger vehicles are subdivided by the number of axles and the number of units. Axle-based automatic vehicle classification using algorithm to calibrate axle spacing then classify vehicles into certain classes. However, there is no specific algorithm or program that has been recommended by FHWA for analyzing axle spacing, and it may change among states for identifying vehicle classes. In this case, every agency has to develop and verify their own algorithm for vehicle classification.

Detection Methods

In the 1920s, when automatic signal control system replaced manual one, engineers start to find an automatic way to collect traffic data instead of obtaining it visually. The first traffic sensor was developed in 1928 by Charles Adler based on detecting acoustic energy from the vehicle's horn. (Traffic Detector Handbook, FHWA-HRT-06-108). Almost the same time, Henry A. Haugh developed the first in-roadway pressure-sensitive sensor which using two metal plates that worked as electric contracts. When vehicle passes, the two plates bought together and electric signal produced. This method had been used widely for over 30 years as the primary means of traffic detection. Today, the most

common traffic detection method is inductive-loop detector, other methods, like

magnetometers, magnetic sensors, video image processors, acoustic and passive infrared

sensors are also commercially produced and used for different traffic management

applications.

Table 1 compares the strengths and weaknesses of current used detection methods

including installation, data collection, accuracy and maintenance. Some of the sensors are

capable to work above or to the side of the roadway which made installation and

maintenance easier, while most of them need close roadway and pavement cut for

installation. Several technologies are able to support more than 1 lane or multiple

detection zones with limited number of sensors. These devices are good for the places

where need to monitor larger numbers of detection zones.

Table 1 Comparison between Different Methods

Technology	Strengths	Weaknesses
Inductive loop	- Flexible design to satisfy large variety of applications. Mature, well understood technology. - Large experience base. - Provides basic traffic parameters. - Insensitive to inclement weather such as rain, fog, and snow.	- Installation requires pavement cut. And improper installation decreases pavement life - Installation and maintenance require lane closure. - Detection accuracy may decrease when design requires detection of a large variety of vehicle classes.
Magnetic	- Can be used where loops are not feasible (e.g., bridge decks) - Some models are installed under roadway without need for pavement cuts;	- Installation requires pavement cut or boring under roadway - Cannot detect or classify stopped vehicles or axles unless special sensor

	however, boring under roadway is required • Insensitive to inclement weather such as snow, rain, and fog	layouts and signal processing software are used
Microwave radar	• Typically insensitive to inclement weather at the relatively short ranges encountered in traffic management applications • Direct measurement of speed • Multiple lane operation available	• Detector can miss occasional vehicles traveling side-by-side (occlusion) • Calibration and sensor position are crucial to proper operation • Does not detect axles
Laser Radar	• Transmits multiple beams for accurate measurement of vehicle position, speed, and class • Multiple lane operation available • Good motorcycle detection • Non-intrusive installation	• Operation may be affected by fog when visibility is less than ≈ 20 feet (6 meters) or blowing snow is present • Installation and maintenance, including periodic lens cleaning, require lane closure (should not require a lane closure for cleaning and maintenance of a side-fired laser)
Infrared Sensors	• Passive detection • Insensitive to precipitation • Multiple lane operation available in some model	• Cold temperatures may affect vehicle count accuracy • Specific models are not recommended with slow-moving vehicles in stop-and-go traffic • Cannot detect stopped vehicles, axles
Video image processor	• Monitors multiple lanes and multiple detection zones/lane • Easy to add and modify detection zones • Rich array of data available	• Installation and maintenance, including periodic lens cleaning, require lane closure when camera is mounted over roadway (lane closure may not

• Generally cost effective when many detection zones within the camera field of view or specialized data are required	be required when camera is mounted at side of roadway) • Performance affected by inclement weather such as fog, rain, and snow; vehicle shadows; vehicle projection into adjacent lanes; occlusion; day-to-night transition; vehicle/road contrast; and water, salt grime, icicles, and cobwebs on camera lens • Reliable nighttime signal actuation requires illumination • Requires 30- to 50-ft (9- to 15-m) camera mounting height (in a side-mounting configuration) for optimum presence detection and speed measurement • Cannot detect axle

Inductive-Loop Detectors: inductive-loop detector can detect vehicles passing or arriving at certain point. It senses the presences of a conductive metal object by inducing currents which will reduce the loop inductance. Inductive-loop detectors consist of four parts: a wire loop installed in the pavement, a lead-in wire connecting pull box with the wire loop, a lead-in cable connecting the pull box and the controller, and a terminal. When a vehicle passes over the wire loop or is stopped within the area, it reduces the loop inductance which results in increasing the oscillator frequency and detected by the electronic unit and considered as a vehicle.

Magnetic Sensors: magnetic sensors are passive sensors that detect magnetic anomaly caused by metal in the Earth's magnetic field. There are two kinds of magnetic field

sensors used for traffic monitoring, two-axis fluxgate magnetometer and magnetic detector. Two-axis fluxgate magnetometer detects changes in both vertical and horizontal components of the Earth's magnetic field caused by a ferrous metal vehicle. The magnetic field sensor referred to as an induction or search coil magnetometer. It detects the vehicle vibration by monitoring the distortion in the magnetic flux lines induced by the change in the Earth's magnetic field produced by a moving vehicle.

Video Image Processor: Video cameras were used for traffic monitoring and analysis based on their ability to collect vehicle image and transmit to a terminal for operation. A video image processor typically including more than one cameras, a terminal with microprocessor-based computer for analyzing the image, and software for interpreting and transforming them into traffic flow data.

Microwave Radar Sensors: Microware radar was first developed during World War II. It transmits a continuous wave Doppler waveform to monitor vehicle movement and provide information of vehicle flow and speed. While it is not able to detect stopped vehicle. Microwave sensors that transmit a frequency modulated continuous wave are able to detect both moved and stopped vehicles and provide measurement of vehicle flow, speed, and occupancy.

Infrared Sensors: Infrared sensors have active and passive types. Active sensors transmit low power infrared energy laser and collect backward energy laser reflected by moving vehicles. Passive sensors does not transmit energy of their own. They collect energy from (1) emitted from vehicles, pavement and other objectives within their view (2) emitted by the atmosphere and reflected by vehicles, pavement and other objects.

Infrared sensors can be used for signal control, occupancy, speed and class measurement; collect pedestrians movement.

Laser Radar Sensors: Laser radars are active sensor that can transmit energy near the infrared spectrum. They provide information of vehicle movements, volume, speed, length and classification. Modern laser sensor can collect 3-D image of vehicle for classification.

MEMS Accelerometer

An accelerometer is an electromechanical device that measures proper acceleration forces. These forces could be static or dynamic. Most of the accelerometer is based on the piezoelectric crystals, but they are too big to be used in some applications (Andrejaši 2008), in this case, researchers developed a smaller and more accuracy sensor using micro electromechanical systems (MEMS). The first MEMS accelerometer was developed in 1979 at Stanford University, but it took more than 15 years to be largely accepted and used (I. Lee 2005). MEMS accelerometers are advanced device that provide lower power, integrated and accuracy sensing and have huge commercial potential. Micro Electric Mechanical Systems or MEMS is a term provided around 1989 by R.Howe (F. Chollet 2008) referred to very small device merges mechanical elements, like cantilevers or membranes at a nano-scale using micro-fabrication technology. Typically MEMS components including MicroSensors, MicroActuators, MicroElectronics and MicroStructures. Microsensors and microactuators work as "transducers" which covert a measured mechanical signal into an electric signal.

Typical MEMS accelerometer measures acceleration by sensing changes in capacitance. Capacitive sensing is independent of the material and relies on the geometry of a

capacitor. When neglecting the fringing effect near the edge, the parallel-plate capacitance is (Lyshevski 2002):

$$C_0 = \epsilon_A \frac{A}{d} \qquad (1)$$

Where A is the area of the electrodes, d is the distance between them and ϵ_A is the permittivity of the material separating them. Typical structure of MEMS accelerometer is shown in figure 1, it is composed of moveable proof mass with plates which is attached to a reference frame using a mechanical suspension system. Moveable plates and fixed outer plates work as capacitors. By measuring the capacitance changes, the deflection of proof mass can be detected. The free-space (air) capacitances between the movable plate and two stationary outer plates C_1 and C_2 are functions of the corresponding displacements x_1 and x_2:

$$C_1 = \epsilon_A \frac{1}{x_1} = \epsilon_A \frac{1}{d+x} = C_0 - \Delta C \ , \ C_2 = \epsilon_A \frac{1}{x_2} = \epsilon_A \frac{1}{d-x} = C_0 + \Delta C \qquad (2)$$

If the acceleration is 0, $x_1 = x_2$ so $C_1 = C_2$. The proof mass displacement x corresponding to the acceleration, if x $\neq$ 0, the capacitance difference is

$$C_2 - C_1 = 2\Delta C = 2\epsilon_A \frac{x}{d^2 - x^2} \qquad (3)$$

Equation 3 can be written to

$$\Delta C x^2 + \epsilon_A x - \Delta C d^2 = 0 \qquad (4)$$

For small displacement, $\Delta C x^2$ is negligible, thus the equation can be simplified to

$$x \approx \frac{d^2}{\epsilon_A} \Delta C = d \frac{\Delta C}{C_0} \qquad (5)$$

It holds true that

$$(V_x + V_0) C_1 + (V_x - V_0) C_2 = 0 \qquad (6)$$

Where V_x is output voltage and V_0 is input voltage from oscillator. If we use equation 2

and 5, it can be convert to

$$V_x = V_0 \frac{C_2 - C_1}{C_2 + C_1} = \frac{x}{d} V_0 \qquad (7)$$

For an ideal spring, according to Hook's law, $F_s = k_s x$ where k_s is the spring constant.

Also from Newton's second law of motion, $ma = k_s x$. Thus, the acceleration is

$$a = \frac{k_s}{m} x \qquad (8)$$

Then using equation 7, the relationship between acceleration and voltage output is

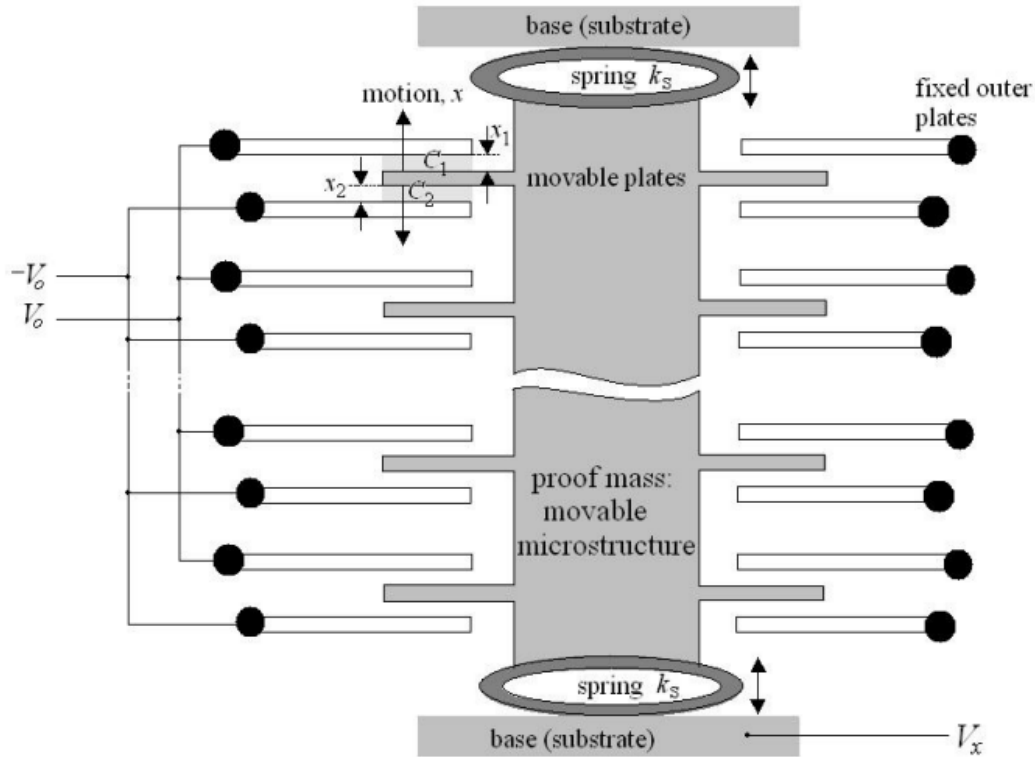$$a = \frac{k_s d}{m V_0} V_x \qquad (9)$$

Figure 1 Accelerometer Structure (S. E. Lyshevski, Mems and Nems: systems, devices

and structures, CRC Press LLC, USA,2002; Used under fair use, 2014)

Accelerometers are being used into more and more personal electric devices like smartphone which using accelerometers for step counts or tilt sensor for tagging the photos' orientation. Accelerometers can also be used in laptop protection when the device drops suddenly, the accelerometer detects it and switches the hard drive off to avoid crashing.

In infrastructure health monitoring area, accelerometer can be used to collect pavement or bridge acceleration to evaluate their health condition. In 2000, Wong et al using piezoelectric accelerometer to monitor Cable-Supported Bridges in Hong Kong. In 2012, Kim et al using a capacitive accelerometer to collect vehicle-bridge interaction in Yeondae Bridge, Korea. With the development of modern electric technology, it becomes possible that producing highly integrated MEMS board which can be used in different areas.

Dynamic Loading Analysis

Vehicle loading is commonly considered as static, actually pavement is subjecting to a moving loading especially when compared with MMLS3 which provides constant loading to the slab. In this case, it is necessary to do the dynamic loading analysis to simulate the response under MMLS3. Currently, there are two methods, 2-Dimensional and 3-Dimensional method, these two method have their own advantages and shortcomings when using in different conditions.

Two-Dimensional Dynamic Analysis: Sawant conducted 2-D dynamic vehicle–pavement interaction analysis by idealizing the underlying soil medium with elastic spring and dashpot systems (without considering the proper continuity between the spring-dashpot elements) and observed significant effect of velocity of moving load on pavement

response. The dynamic interaction between the moving load and the pavement was considered by modelling the vehicle by spring–dashpot unit. Sawant et al. conducted 2-D finite element analysis of rigid pavements under moving vehicular or aircraft loads. The analysis was based on the classical theory of finite thick plates resting on two-parameter elastic soil medium. However, the infinite plate elements were not included in the solution algorithm and also a proper study was not being conducted to investigate the effect of vehicle–pavement interaction on the dynamic response of rigid pavement. Huang and Thambiratnam proposed a procedure to investigate the dynamic behavior of the rectangular plate resting on an elastic Winkler foundation subjected to moving loads. They used the finite strip method and a spring system and showed that the velocity of moving load and elastic foundation stiffness have significant effects on the dynamic response of the plate.

Three-Dimensional Dynamic Analysis: To accomplish a comprehensive analysis of pavement behavior incorporating the pavement-soil interaction effects, it is necessary to model the pavement in the form of 3D elements and the supporting soil medium as 3D elastic continuum. In general, there are two important factors that should be considered in any dynamic pavement analysis: (1) The variation of the interaction load with time and space; and (2) the dependency of the material properties on the applied stress and the loading frequency.

Zaghloul and White considered several realistic conditions of the flexible pavement problem and using ABAQUS as an analysis tool. 3D analysis was used in which the asphalt concrete was considered viscoelastic, the base was treated by Drucker–Prager model and the subgrade by CamClay model. The load was simulated as a moving load. In

their model sensitivity analysis, they investigated the effect of deep foundation type, some other attributes of the pavement cross section, and the dynamic features of the traffic load on the pavement rutting. The results of surface deflection were correlated to the surface deflection results of the elastic analysis. Ioannides and Donnelly used the 3D models to simulate pavement problems concerning the effect of subgrade stress dependence. Wu and Shen presented the dynamic analysis of rigid pavements by modeling the pavement as 3D brick elements supported by spring and dashpots.

Uddin and Ricalde successfully implemented microcraking and crack propagation models into ABAQUS (with the help of the feature of user-defined subroutines) to simulate the viscoelasticity of the asphalt concrete layer. In their work, the pavement foundation was considered linear elastic, and 3D dynamic analyses were adopted.

Bassam et al using 3D dynamic FE analyses considering the granular base as elastic perfectly plastic (Druker–Prager) and the subgrade as elastoplastic strain hardening (Cam Clay) are carried out to investigate the effect of base thickness, base quality, and the subgrade quality on the fatigue of the pavement system, reflected by the maximum tensile strain at the bottom of asphalt concrete layer.

Al-Qadi et al developed a 3-D finite element model to predict the pavement responses to vehicular loading. The model was verified with in situ pavement responses to accelerated pavement loading. In their model, the measured 3-D tire–pavement contact stresses on a flat pavement are considered in the 3-D FE modeling. Hence, the dynamic loads would be simplified by the continuous changing of the loading amplitude within the tire–pavement contact area.

Comparison between 3D Analysis and 2D Analysis

Despite the fact that it requires considerably more computational time and computer memory, the 3D analysis is still considered superior to the 2D analysis. The necessity for adopting the 3D analysis arises from the following advantages.

1. It better reflects the complex behavior of the composite pavement system materials under traffic loads of different configurations.

2. It is preferred when verifying numerical model results with the laboratory or field test results.

3. It is capable of simulating the rectangular footprint of the loaded wheel In other words, when dealing with 2D analysis, the load shape is restricted to a circular (axisymmetric condition) or infinite strip load (plane strain condition), which is not realistic.

Summary of Findings

With an accuracy vehicle classification method, engineers can design a better maintenance programs, evaluate highway usage and plan the future development strategies. The vehicle-pavement interaction can be detected by accelerometer to classify vehicles. Currently, the vast majority accelerometers are based on piezoelectric crystal, however, they are too big and clumsy to be used in specific areas. In this case, researchers developed a more integrated and much smaller MEMS accelerometer. While in pavement monitoring area, it have not been used very often probability due to its higher cost. Traditional sensor installation needs pavement cut-off which will shorten the lifespan of the pavement, in other words, it will cause higher maintenance cost to ensure pavement serviceability. Also the device subjects to the traffic loading which will cause the device broken easily. To find a balance between cost and monitor efficiency, a

MEMS accelerometer installed beside pavement without subjecting to the traffic directly need to be considered. Pavement acceleration has not been much considered to monitor the health condition, and less researches have been done about the pavement acceleration under different conditions. In this case, it is real necessary to do the tests about the pavement response when it in a good or bad condition. At the same time, the simulation using dynamic analysis to verify the laboratory tests results is important too.

3. Laboratory Tests Using MMLS3

Before applying our sensor to the pavement, series laboratory tests were done to verify the feasibility and accuracy of the accelerometer monitor the wheel passing. A MMLS3 machine was used to simulate the actual traffic situation. Sensor was attached to the asphalt plate just next to the wheel. Four different speeds were conducted to test sensor reaction to different traffic conditions. Acceleration data was recorded by the sensor and transmitted to laptop through USB cable.

MEMS Accelerometer Selection

An Omega CP-Ultrashock-50 Tri-axial Shock Recorder with MEMS semiconductor to collect pavement acceleration data. It is a battery powered, stand alone and easy-installed sensor which also has a strong resistance to the outside environment influence. Its acceleration range is up to ±250 g and the calibration accuracy is about ±0.2 g, the recording interval is 64Hz.

Experiment Setup

To simulate actual traffic condition, laboratory tests using MMLS3 were applied to our MEMS accelerometer to verify the accuracy. Sensor was fixed to the asphalt plate using expansion screws, so that the sensor could vibrate with pavement. It located on the edge of the plate next to wheels without subjecting to the loading which also simulated our purpose of sensor installation next to the roadway. Figure 2 shows the fixed sensor and Figure 3 shows the broad view of plate under MMLS3. The MMLS3 shown in Figure 5 is a unidirectional, vehicle-load simulator which can simulate model or full-scale

accelerated traffic under both dry and wet condition. The MMLS3 device is 2.4 m (7.9 ft.) long by 0.6 m (2 ft.) wide by 1.2 m (3.9 ft.) high. This Accelerated Pavement Testing device has pneumatic tires which are 3/10 or approximately one-third the diameter of standard truck tires and apply a load on 300 mm (12 in) diameter. The MMLS3 has four wheels with a distance between centerlines of 1.05 m (3.4 ft.). It can provide up to 2.7 kN (607lbs or approximately one-ninth of the load on one wheel of a dual tire standard single axle) when simulate the traffic on pavement. A maximum of 7200 single-wheel load repetitions can be applied per hour at a speed of up to 2.6 m/sec (8.5 ft. /sec) that corresponds approximately to a 4 Hz frequency of loading for a measured tread length of 0.11 m (0.36 ft.) (de Fourtier Smit 1999).

Figure 2 Sensor Fixed to the Plate

Figure 3 Broad View of the Plate

To simulate real traffic situation and verify sensor sensitivity under different conditions, four different speeds (10, 20, 30, and 40) were applied. Wheel passes were recorded manually during every tests, so that can be compared with calculated axle count based on our output signal. Output data was collected by the Omega software through USB cable after the test was finished.

Figure 4 Slab with a Crack

To test the reaction of bad surface condition, a one inch wide 1.5 inches deep crack was
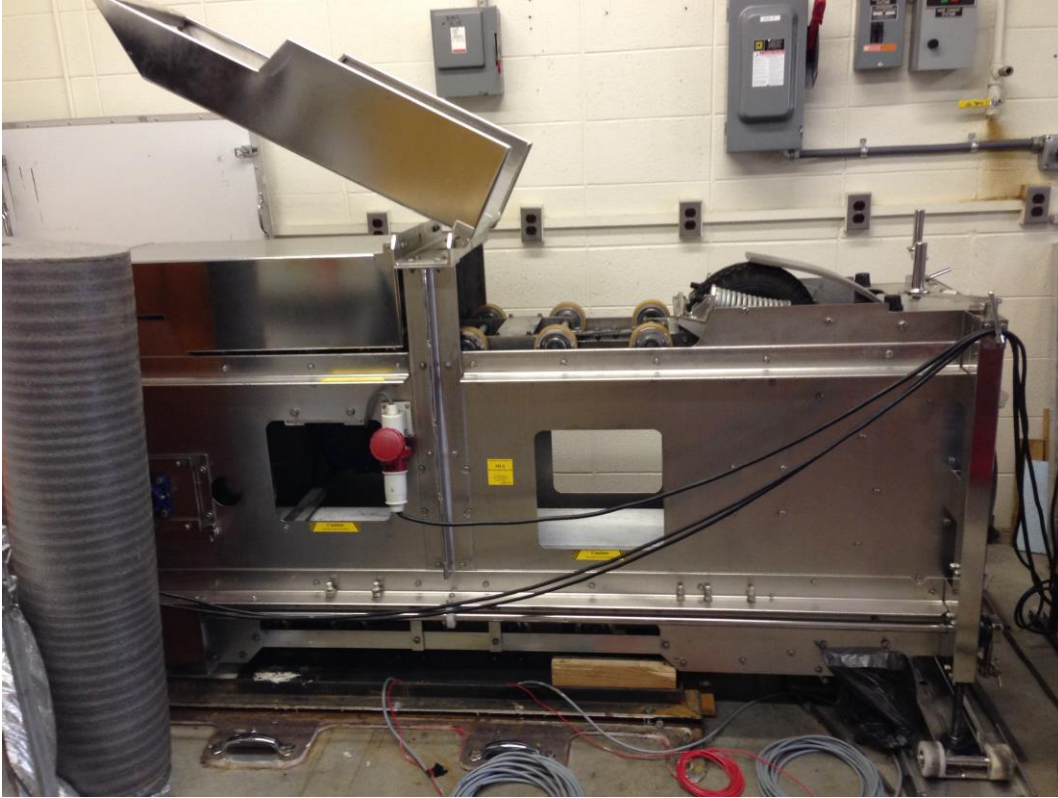
created just beneath the sensor.

Figure 5 Broad View of MMLS3

Test Procedures

Pavement Acceleration Tests

Once the sensor installed on the asphalt plate, it can be connected with personal computer using USB cable and controlled by OM Data Logger Software. To collect data, the software has to be open first and wake up the sensor by pushing start button, then it can collect pavement vibration while MMLS3 is running.

When the test is running, number of wheel passing the sensor has to be recorded manually. During the test, make sure that wheel loading is the only source for the pavement vibration.

Once the test finished, stop the sensor and download data to personal computer through the software, the download data was saved as an .mtff file including 3-axle acceleration and temperature, humanity and pressure. Since the purpose was to classify the vehicle and tests environment almost keep constant, only 3-axle acceleration data was exported and analyzed. Figure 6 shows the interface and output data of the software.
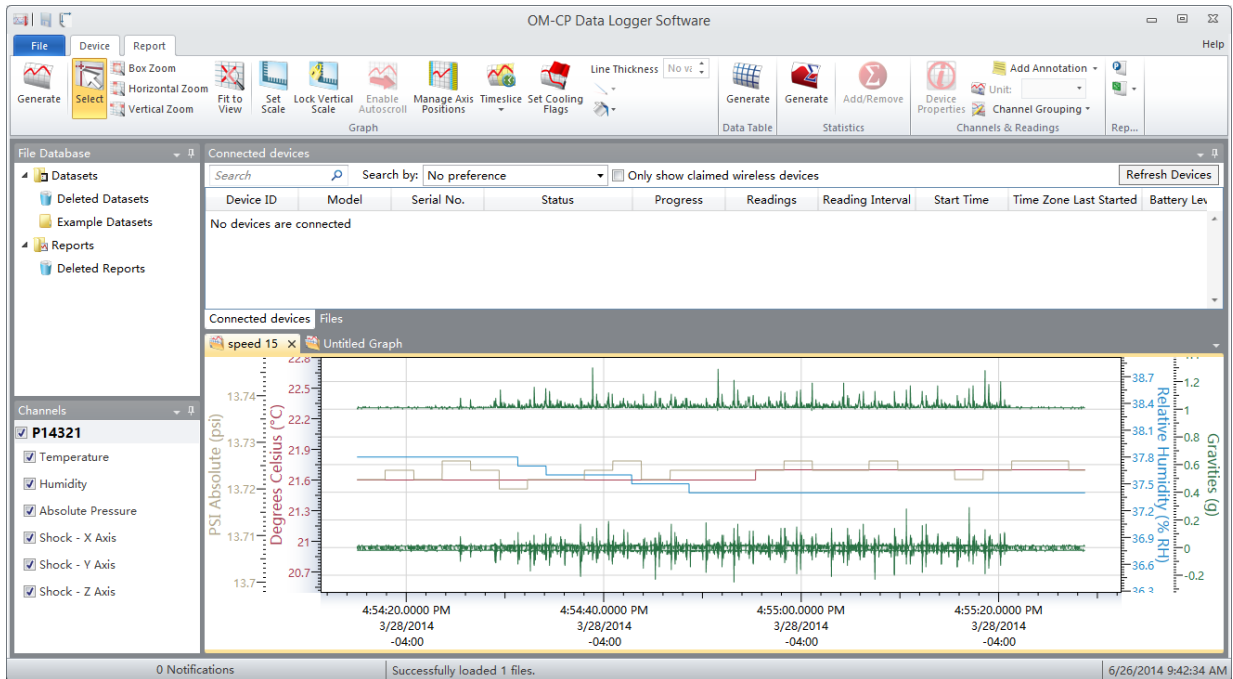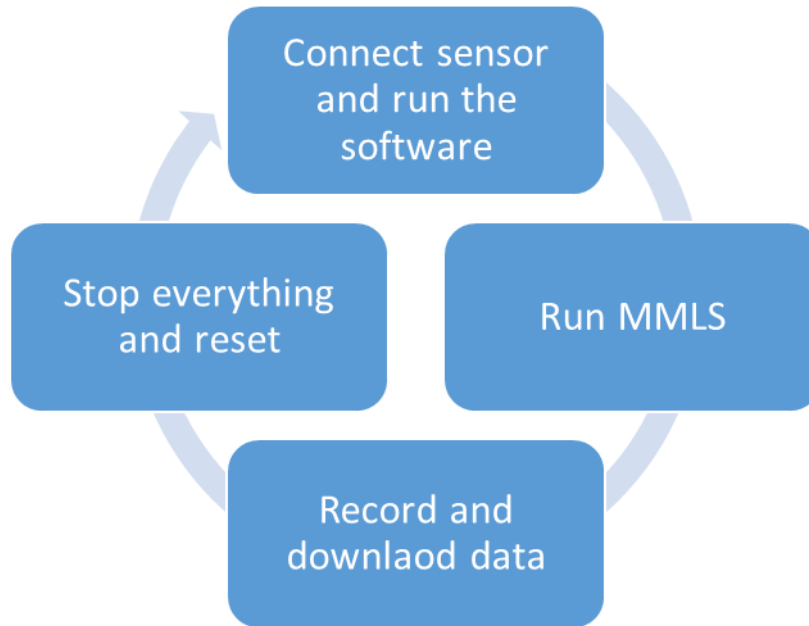

Figure 6 Interface of the Software

Figure 7 Flow Chart of Test Procedures

MMLS3 Speed Tests

Since the speed provided by MMLS3 does not use the common unit and increases non-linearly, speed correction is necessary for the further verification.

Distance between wheel centerline given by manufacturer is 1.05m (41 inch), when we record the time X of running Y cycles, speed could be calculated as

$$Speed = \frac{41 \times Y}{X} \text{ in/s}$$

In our tests, time spent of 50, 75, 100, 125 cycles has been recorded, and the calculated speeds are listed below:

Table 2 Correction Speed

MMLS3 Speed	Correction Speed (in/sec)
10	17.52137
20	36.18148
30	54.78869
40	72.1831

4. Dynamic Loading Simulation

Necessity of Using Dynamic Analysis

When considering the small traffic flow, low speed and light load, the linear elastic theory with static loads was adopted. Pavement dynamic responses may be larger than static responses and exacerbate pavement distresses. Therefore, when pavement dynamic responses are considered, the reliability and durability of pavement structure would be sufficiently evaluated. Along with the development of computational mechanic, the finite element method and the boundary element method broke the limitations of boundary conditions and load types in analytical methods. In our laboratory tests, the highest speed is about 72 in/sec which could be considered as a low speed loading, at the same time, the wheel passing is constant in MMLS3, in this case, dynamic analysis using finite element method gave us a straightforward view to monitor the pavement vibration and compare it with our sensor results.

Finite Element Model Geometry

To simulate the slab vibration with and without crack under MMLS3, ABAQUS Version 6.13 was used based on dynamic loading analysis. Since the slab size tested was fixed, the modeled domain is the same as the slab which is 12 inches long, 10.5 inches wide and 1.5 inch thick. Figure 8 is the 3-D finite element slab domain without a crack. The whole slab was divided into 1512 elements each is 0.5*0.5*0.5 inch.
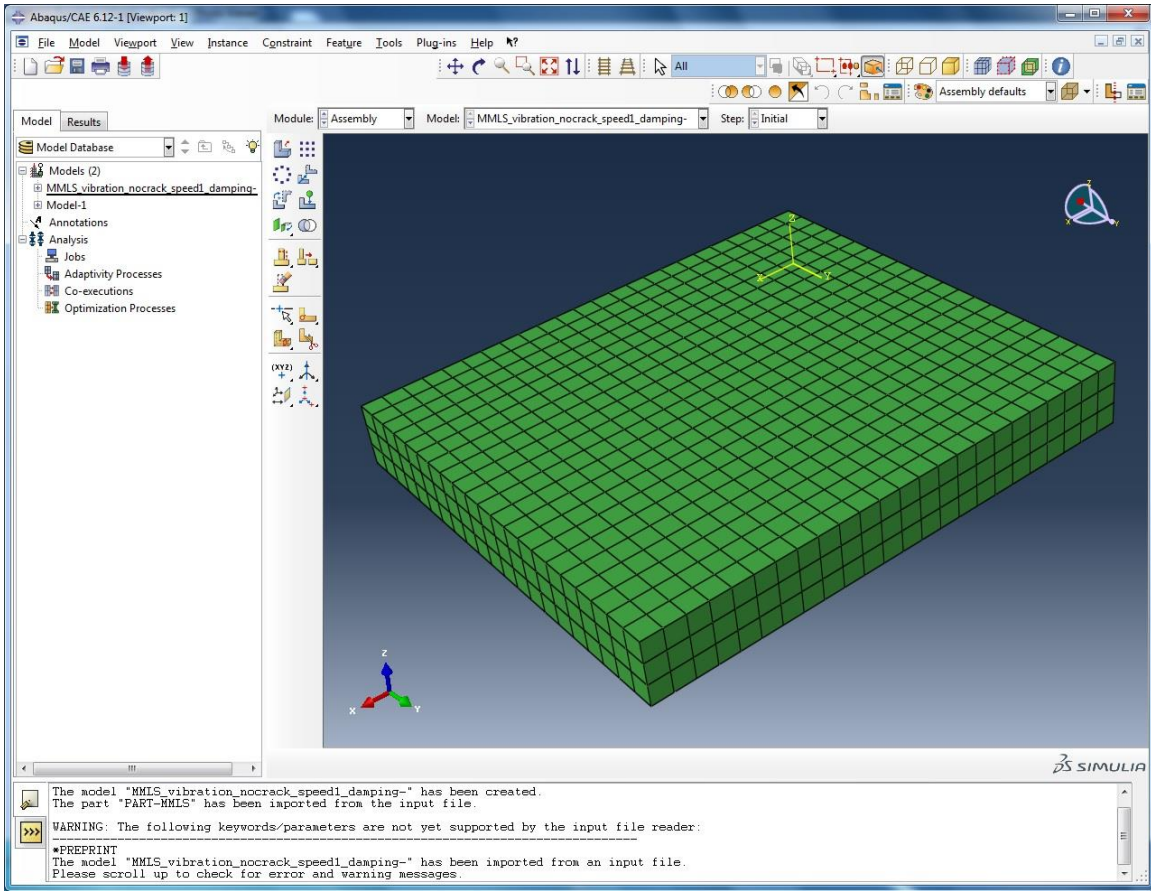
Figure 8 3-D Model of Slab without Crack

To create the model of slab with a crack, we did it into two parts separated by the crack

which shown in Figure 9. In this case, the boundary condition at the crack location is

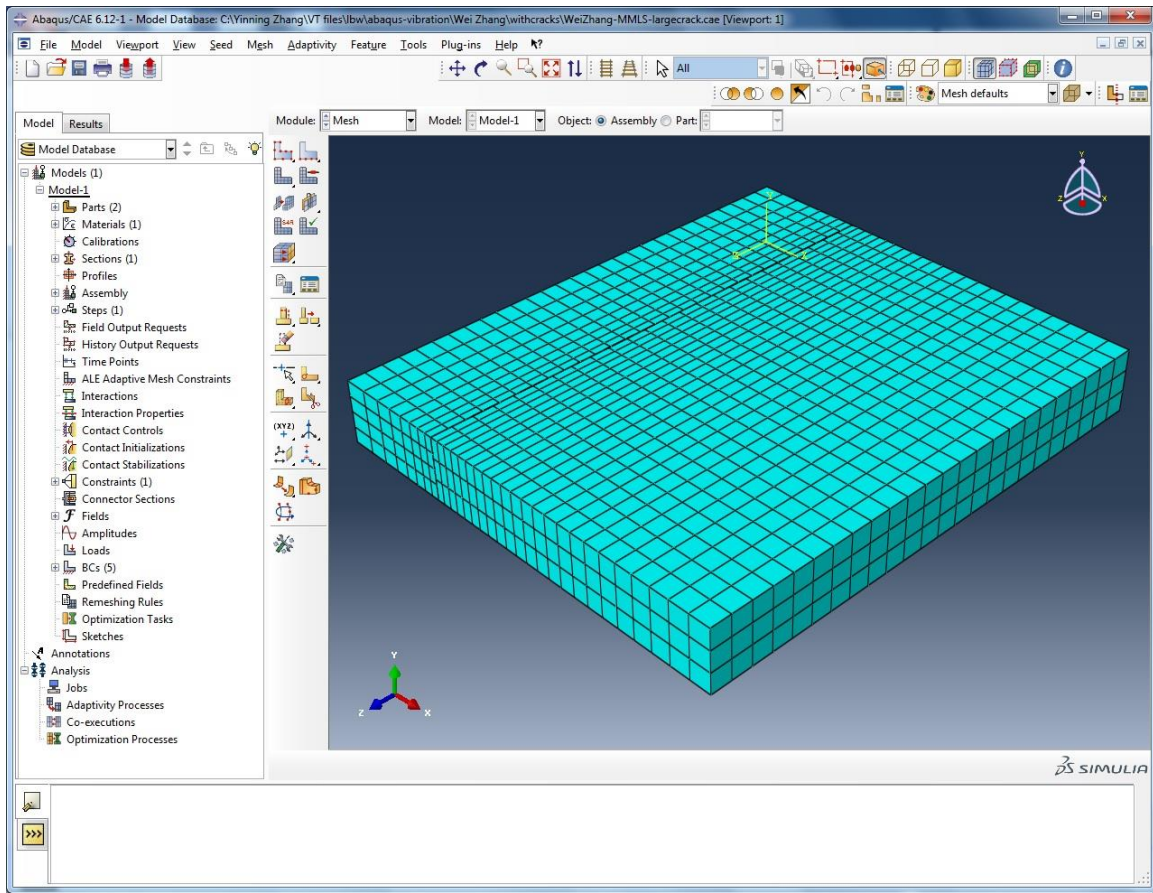different from other point where a roller support condition will be used.

Figure 9 3-D Model of Slab with Crack

Boundary Condition

Conventional kinematic boundary conditions are used while little different occurred when there is a crack. In good slab condition, fixed support on all four vertical boundaries and at the bottom of the mesh. While comes to the bad slab condition which has a crack in it, at the crack position, roller support was used since the crack made it possible to spin, on other four vertical boundaries and at the bottom of the slab still used fixed support.

Loading System

To simulate the loading effect of the MMSL3, the load value, configuration and shape are determined by MMLS3. It is a single wheel load of 2 kN, the contract pressure on the

29

slab is assumed to be the same as tire pressure which is 800 kPa in this analysis. Since

four different speeds were applied on the slab, the loading frequency changed among

different speeds. The distance between centerline of each wheel is 3.4 ft, and loading

frequency could be easily decided by distance/speed.

5. Experimental and Simulation Results Analysis

Axle Detection Algorithm

Based on Ravneet Bajwa et al. work, every moving wheel can be modeled as a moving impulsive force on the pavement. In this case, it can cause vibration of pavement together with sensor so that the acceleration could be recorded. It would be easy to spot different axles from our sensor signal if they have obvious differences in time, for example, the next axle arrives sensor when the whole decay of the last axle's signal. However, the actual highway traffic has a more complicit situation.

So a statistical method is needed to efficiently detect vehicle axle from sensor output signal. An appropriate approach can still filter axle form signal even moderate overlap exists. Our algorithm is based on the Ravneet Bajwa et al method and has been improved to fit our project.

Figure 10 shows the block diagram of signal analysis. It attenuates noise and amplifies useful signal, finally locates the peaks that are separated in time. Figure 11 shows part of the output signal form our sensor. It is hard to tell noise and axle signal from it, so the statistical method is important to spot axle and minimize noise. The signal a(n) is divided by 3 times the noise (given by sensor manufacture). This step ensures that signal without wheel loading is below 1. After that, the signal is squared to get the energy, this step further attenuates the noise and amplifies the useful signal which is greater than 1. Figure 12 is the signal chart after the first step. In this figure, noise has been attenuated and ranged between a very limited values, at the same time, several peaks are clearly appears.

The next step is passing the signal through a Moving Average Filter so that the signal could be smoothed and easily find their peaks. M(v) is the number of points in the average which determines the bandwidth of the filter, and the bandwidth need to be speed based. From other researches did before, the bandwidth is empirically defined as $M(v) = \frac{900}{v}$. In our laboratory tests, according to our MMLS3 running speed and actual traffic condition, 50 mph is used so that the filter tap is 18. This step further smoothed our signal and spotted signal peaks more effectively. Figure 13 is the signal chart after passing the moving average filter. In this figure, three peaks are clearly spotted.

The last step helps to filter peaks in the smoothed signal with a minimum time separation (ç (v)). This step ensures that local variations near peaks are not considered as an axle. In this case, space distance determines the time separation. In laboratory tests, distance between MMLS3 wheel centerline is about 42 inch, so assuming that axles are at least 40 inch apart. When applied to the actual vehicle situation, different axle distance has to be considered, typically, 6 ft is reasonable for time separation. If tandem axle which mostly consider as one axle want to be detected separately, 4 or 5 ft may be selected for the time separation.

$$\frac{(.)^2}{(3\sigma)^2}$$

Moving Average Filter

Peak Dector

Min Peak Seperation [ç(v)]

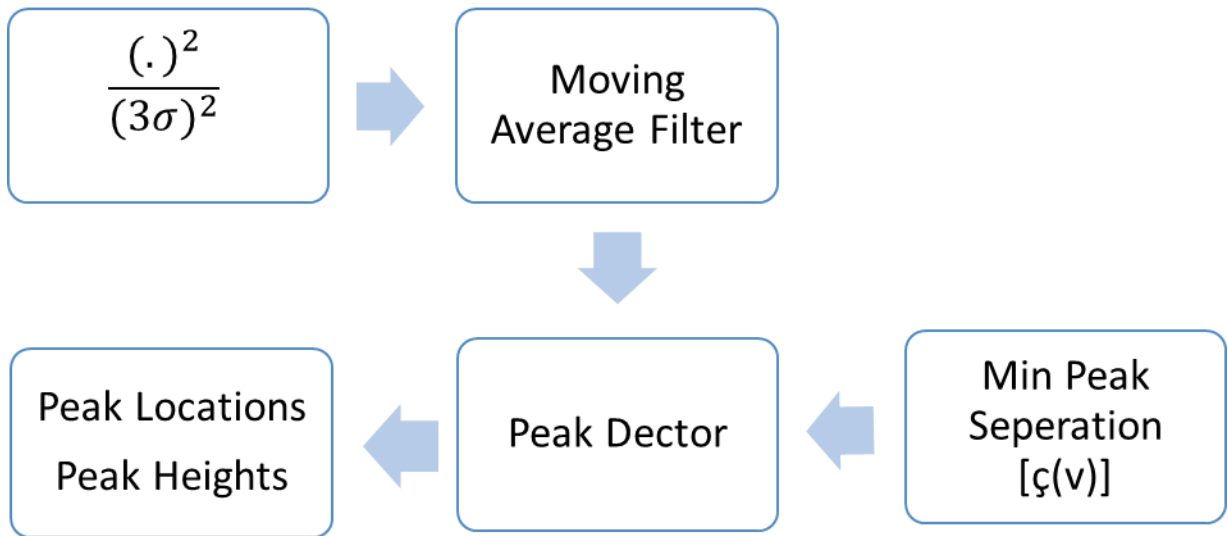Peak Locations

Peak Heights

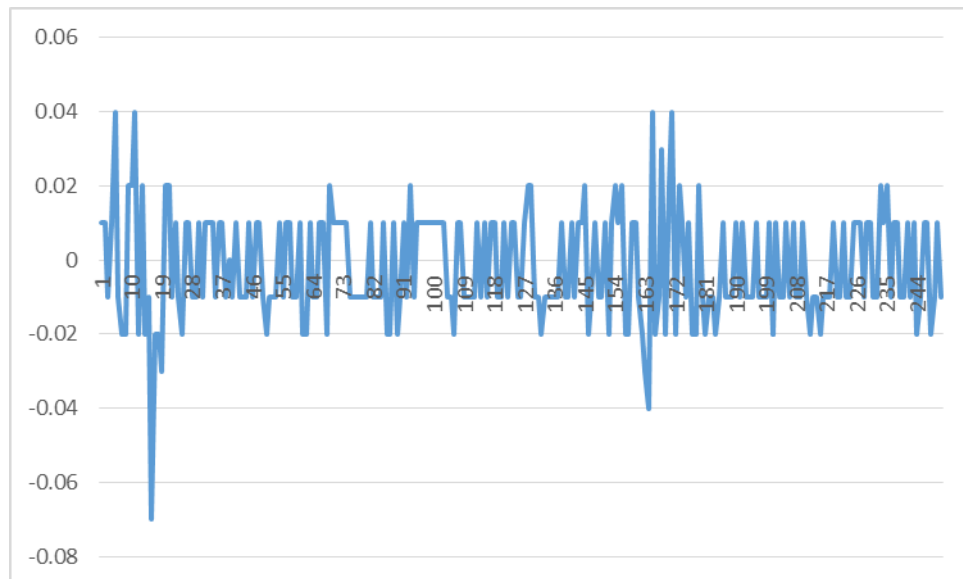Figure 10 Data Analysis Process
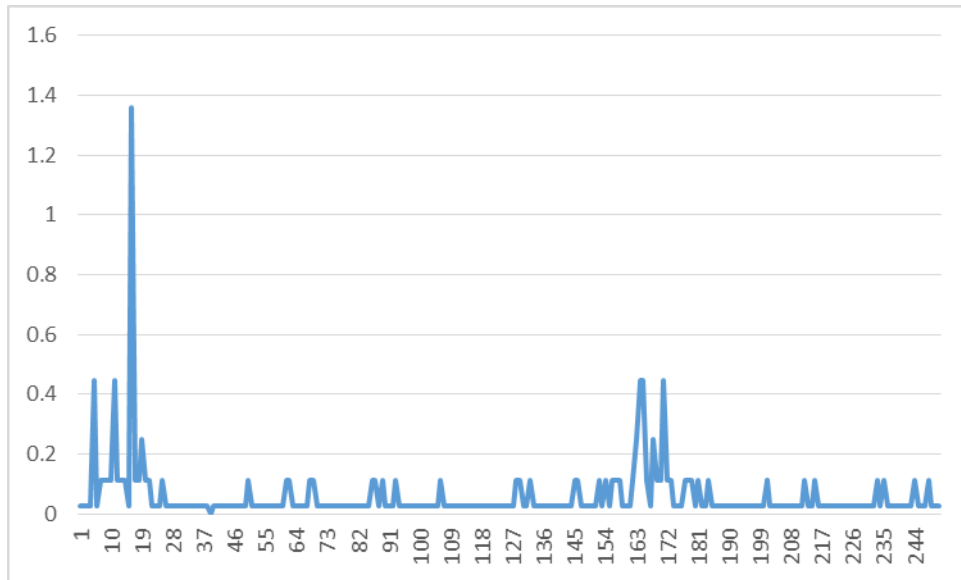

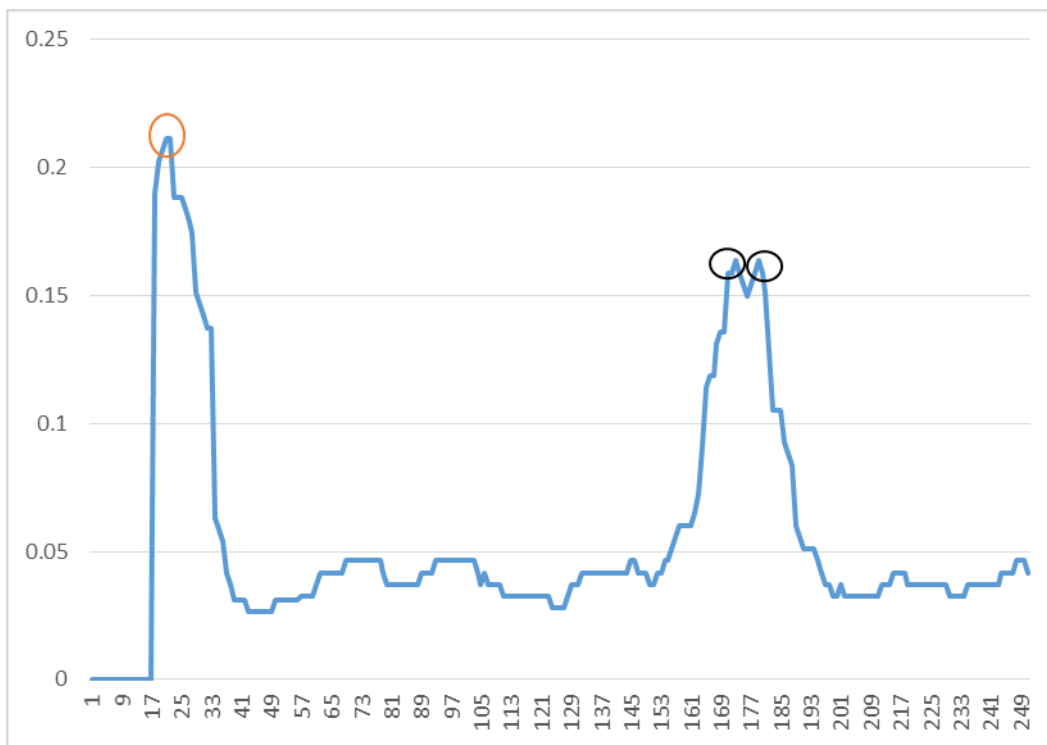Figure 11 Original Output Signal

Figure 12 Optimized Signal

Figure 13 Signal after Passing Moving Average Filter

In Figure 13, there are two peaks marked with black circles, according to our time separation theory, only one of them considered as an axle.

Axle Spacing and Speed Estimation

According to the product specification, it has a 64 Hz recording interval which means it records data every 0.015s, so every unit in the figure counts as 0.015s. From output signal, t_a refers to the peak time of axle a. In laboratory tests, as calculated before, the speed of MMLS3 is known and the axle spacing s_a between axles a and a+1 can be determined as

$$s_a = v(t_{a+1} - t_a)$$

On the other hand, the wheel spacing of MMLS3 is also known as s, the speed can be calculated as

$$v = s/(t_{a+1} - t_a)$$

Since the speed of wheel and the wheel centerline distance are both known in our laboratory tests, given any one of them can help to determine another one, in this case, we can verify the accuracy of sensor for detecting speed and axle spacing which will be explained later.

Experimental Results and Verification

One of the most important tasks in these research is to detect axle which reflects as a peak in output signal so that vehicle classification can be done. Sensor used in our test is a 3-axle accelerometer which has x, y and z-axle vibration data and all of them were analyzed to see the different and find out a better source for vehicle classification.

Sensor Performance

The noise of the sensor when there is no wheel passing was measured and listed below.

Table 3 Noise RMS and Signal Amplitude

	Noise RMS	Signal Amplitude
X-Axle	0.000131	>0.05
Y-Axle	5.477E-5	>0.1
Z-Axle	0.504	>1

According to our comparison between noise RMS and signal amplitude, x and y-axle have significant higher output than the noise while z-axle shows a slightly difference. However, the absolute value of z-axle accelerometer is greater than other two axles, the reason that causes little different between sensor noise and collect accelerometer is probably applied loading is not heavy enough.
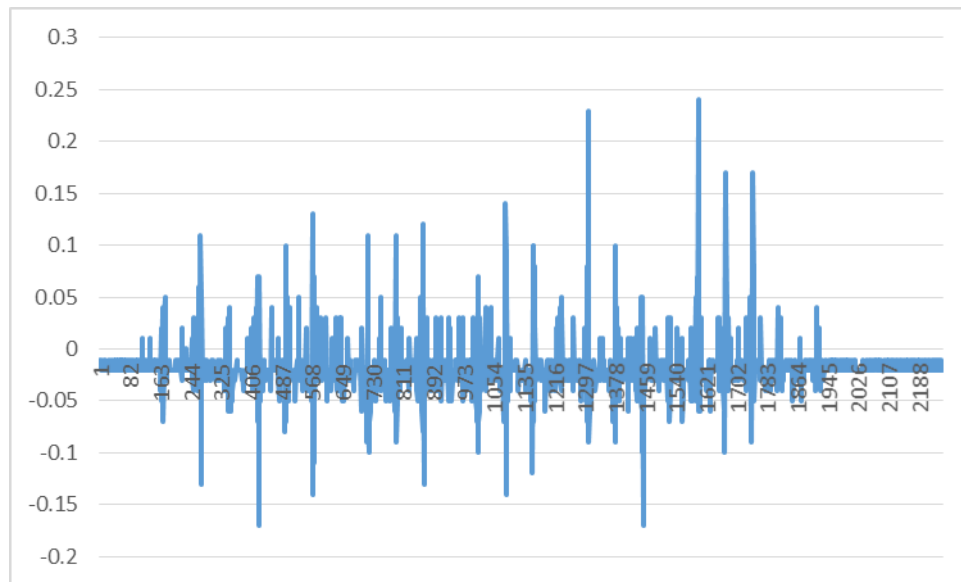

Figure 14 OM-CP-ULTRASHOCK-5 Shock Recorder Channel 4 Shock - X Axis (g)

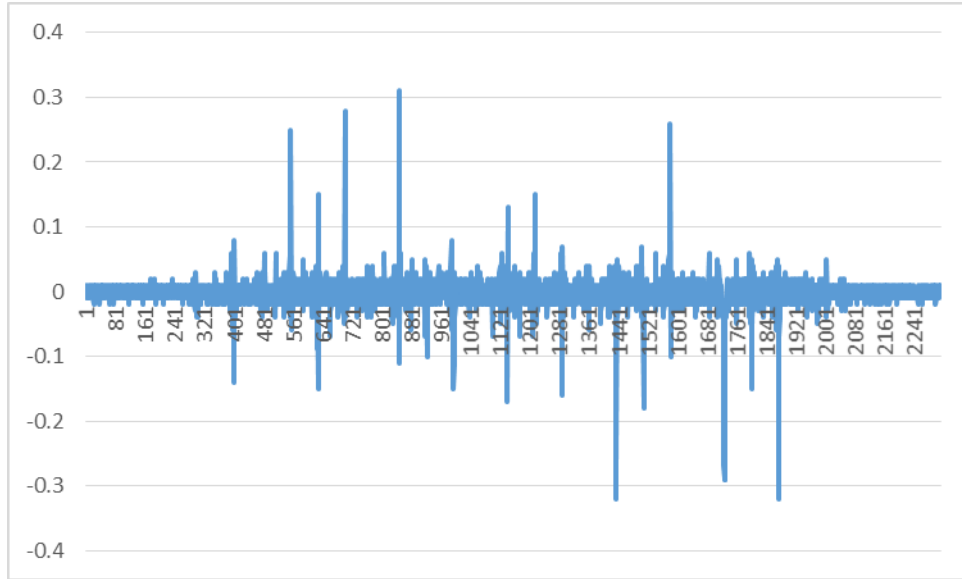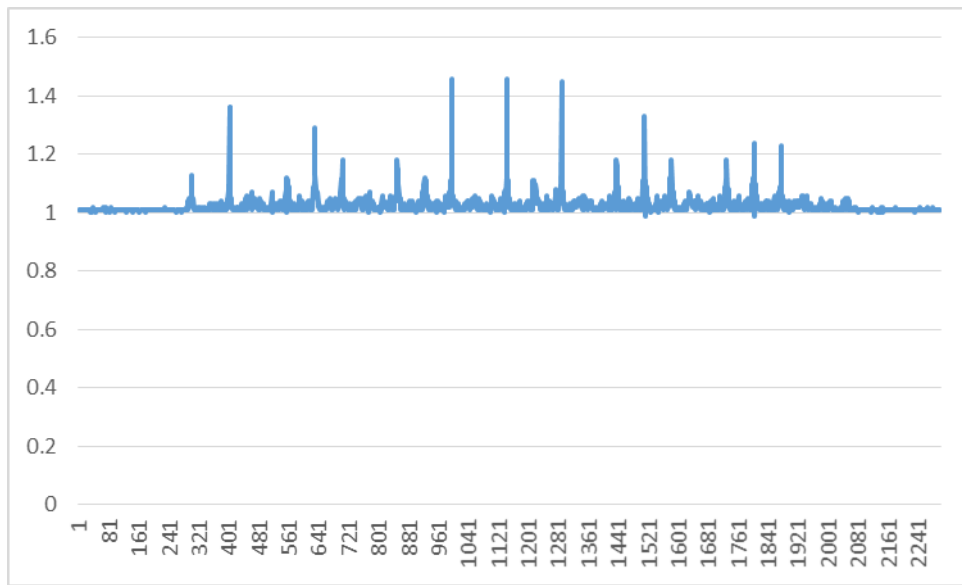Figure 15 OM-CP-ULTRASHOCK-5 Shock Recorder Channel 5 Shock - Y Axis (g)

Figure 16 OM-CP-ULTRASHOCK-5 Shock Recorder Channel 6 Shock - Z Axis (g)

Collected sensor output accelerometer of speed 20 are shown above, form the sensor output combined with our noise analysis, sensor spots peaks and decay between each wheels are clearly appeared. Next step is apply our data analysis algorithm which will be explained later.

Axle Count

To verify the sensor detection accuracy and our algorithm, calculated axles and manually counted axle which considered as the actual wheel passing were compared, table 4 to 6 summarized the performance of these two methods.

Table 4 Sensor Axle Count Performance(X-Axle)

X-Axle	Sensor Count	Manually Count
Speed 10	21	21
Speed 20	20	22
Speed 30	27	27
Speed 40	30	34
R^2	0.91933	

Table 5 Sensor Axle Count Performance(Y-Axle)

Y-Axle	Sensor Count	Manually Count
Speed 10	21	21
Speed 20	18	22
Speed 30	23	27
Speed 40	26	34
R^2	0.809101	

Table 6 Sensor Axle Count Performance (Z-Axle)

Z-Axle	Sensor Count	Manually Count
Speed 10	21	21
Speed 20	22	22
Speed 30	25	27
Speed 40	33	34
R^2	0.979644	

From tables above, X-axle and Z-axle have a R^2 greater than 0.9 which means sensor count match our actual axle passing. Even the lowest R^2 is greater than 0.8 which is still acceptable for axle counting. In axle count results, z-axle has a best match which is

reasonable that when wheel pass by the sensor, the vibration on the vertical direction should be strongest, this theory also supported by our actual pavement tests.

Axle Spacing and Speed Verification

Since only one sensor was used in laboratory tests, one of the two variables speed and axle spacing has to be fixed to calculate another one. With either of them determined from sensor signal, it could be verified with actual value. In our tests, both of them had been verified and explained below.

To verify the axle spacing calculated based on sensor data, wheel speeds mentioned before need to be used. With a fixed speed v and time between each peak t which is the distance between two orange line in figure 14, the space s could be calculate as s=v*t. Since the MMLS3 has a constant speed, in each speed group, average axle spacing was calculated and compared with actual wheel central line distance. Table 7 summarized axle spacing in different speed group.

From the comparison results, when the speed is slower the sensor has a better sensitivity to the axle and calculate the axle spacing more accuracy which has error about 0.6%. While as speed increased, the accuracy of sensor became lower and the highest error percentage locates on the speed 40 which is about 7%. However, in a whole picture, the sensor and our calibration algorithm did very well to collect and analysis the data, axle spacing mostly within the tolerance range and useful for vehicle classification.
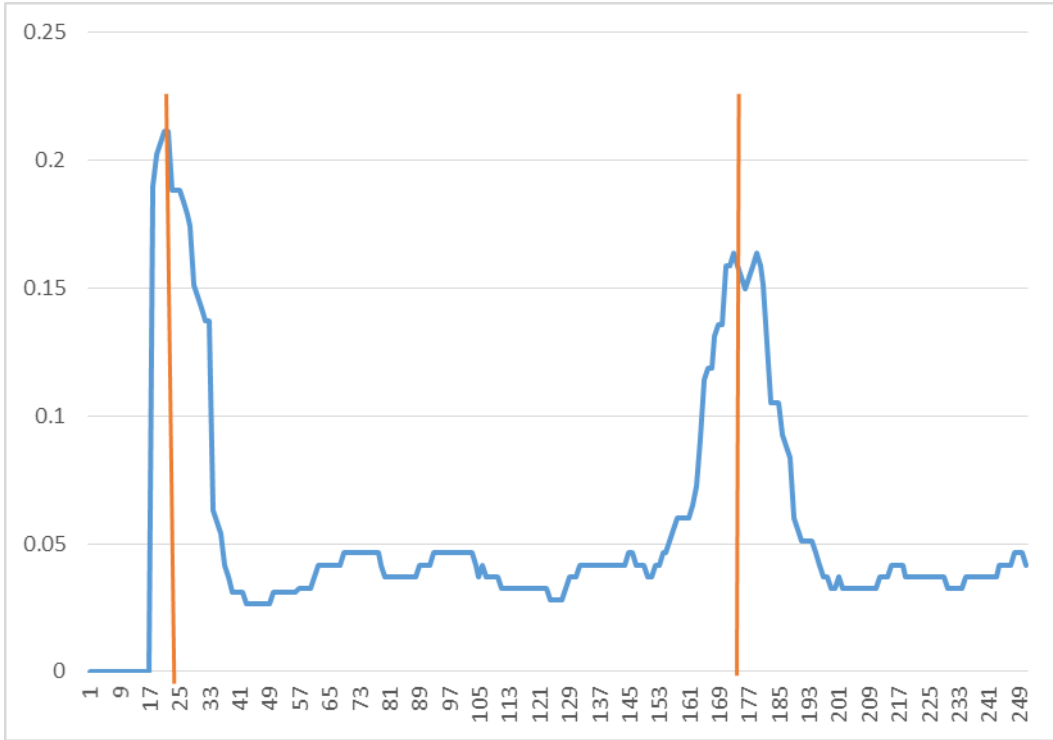
Figure 17 Axle Spacing

Table 7 Axle Spacing Summary

	Calculated Average Axle Spacing (inch)	Wheel Center Line Distance (inch)	Error Percent (%)
Speed 10	41.27	41	0.6
Speed 20	39.59	41	3.4
Speed 30	38.46	41	6.2
Speed 40	37.89	41	7

Table 8 Speed Verification Summary

MMLS3 Display Speed	Correction Speed (in/sec)	Speed Calculated According to Sensor Signal (in/sec)	Error Percentage
10	17.52137	17.40	0.6
20	36.18148	36.50	0.9
30	54.78869	58.40	6.5
40	72.1831	75.09	4.0

When using a fixed axle spacing which is the wheel center line distance to calculate the speed and compare with our correction speed, it could tell the accuracy of our sensor and calculation algorithm. Table 8 listed the correction speed and speed calculated based on sensor output data. According to the results, our calculated speeds are almost the same as the correction speed, the highest error is about 6.5% which is still within the tolerance range.

Sensor Performance with a Crack on Slab

A slab with a 3 mm wide and 38 mm deep crack beneath the sensor was tested to compare with the sensor performance without crack. Figure 18 and Figure 19 showed sensor performance under speed 30, from these two pictures, it is easily tell that when there is a crack on the slab, the acceleration will be bigger and more noise signal appears. The statistical analysis of the magnitude of acceleration gave the same conclusion when calculate the standard deviation and maximum acceleration.
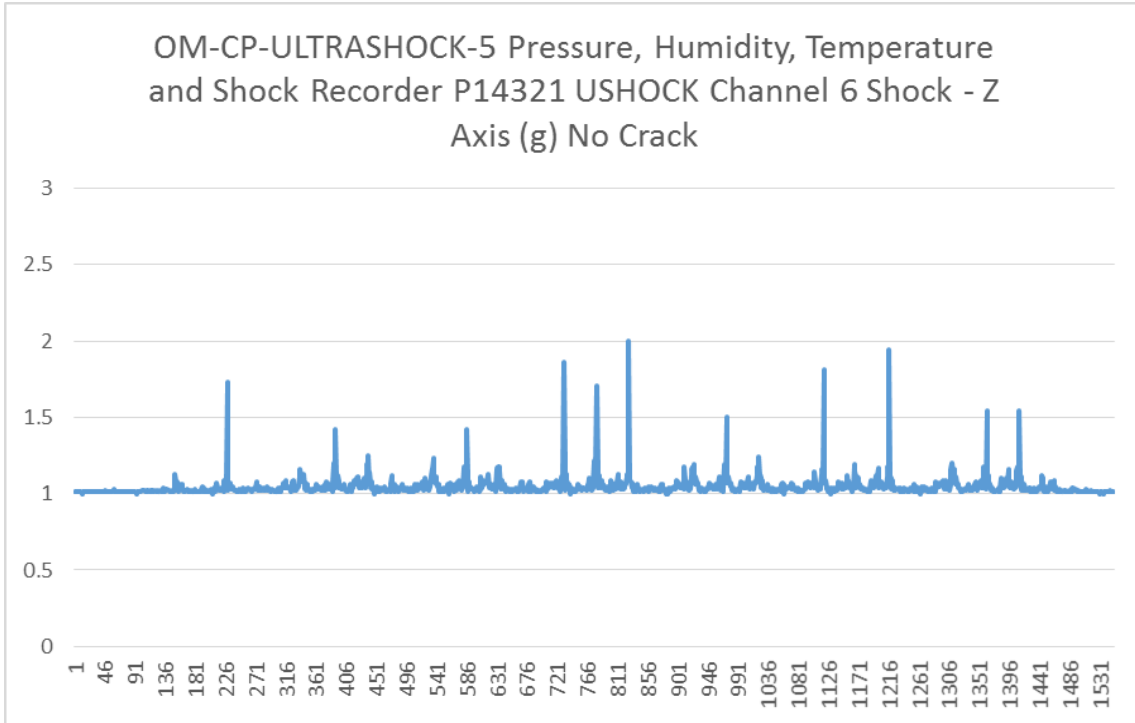
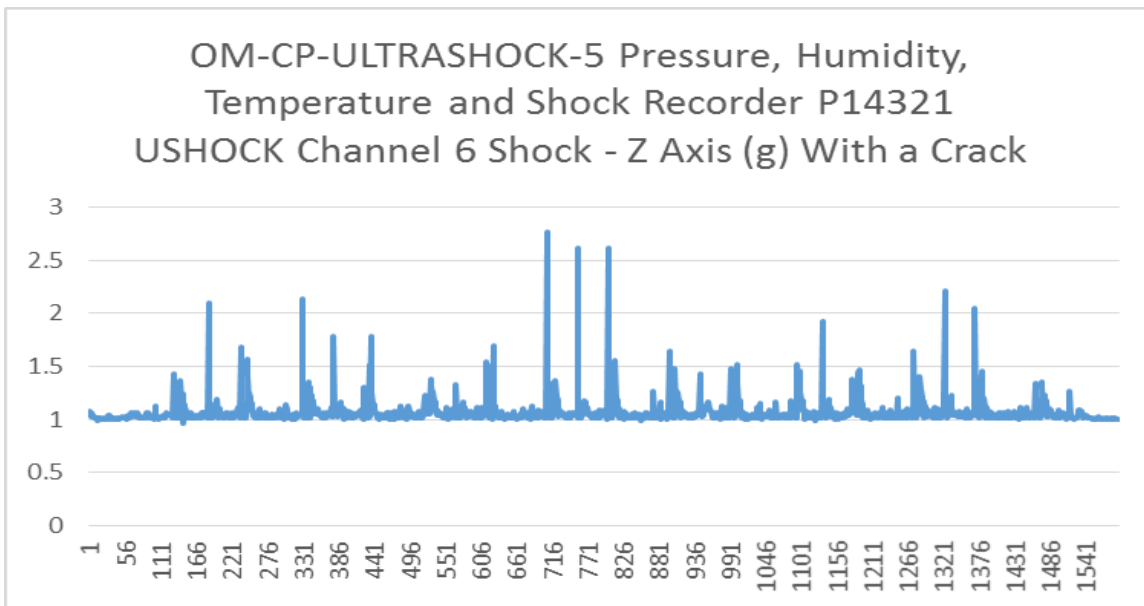Figure 18 Sensor Performance with No Crack

Figure 19 Sensor Performance with a Crack

The fact that the mean value and the minimum acceleration are almost the same among different speeds when the slab with or without a crack. But the standard deviation is a strong indicator of the slab condition. Below are the distribution of acceleration with and

without a crack when speed is 30. The standard deviation of the acceleration for the better

slab condition is about 0.06g, while the standard deviation for the slab with a crack is

0.126g which is about two times than the good condition. From Table, we have a same

conclusion whatever the speed is. Also from the table, as the speed increases, the

standard deviation increases as well.

Table 9 Standard Deviation Comparison

Speed	Crack	Non-Crack
10	0.01709	0.009538
20	0.060055	0.033347
30	0.125708	0.059857
40	0.100644	0.053885

Sp 30

Quantiles

100.0%	maximum	1.86
99.5%		1.5046
97.5%		1.17
90.0%		1.09
75.0%	quartile	1.06
50.0%	median	1.04
25.0%	quartile	1.02
10.0%		1.01
2.5%		1.01
0.5%		1
0.0%	minimum	1

Summary Statistics

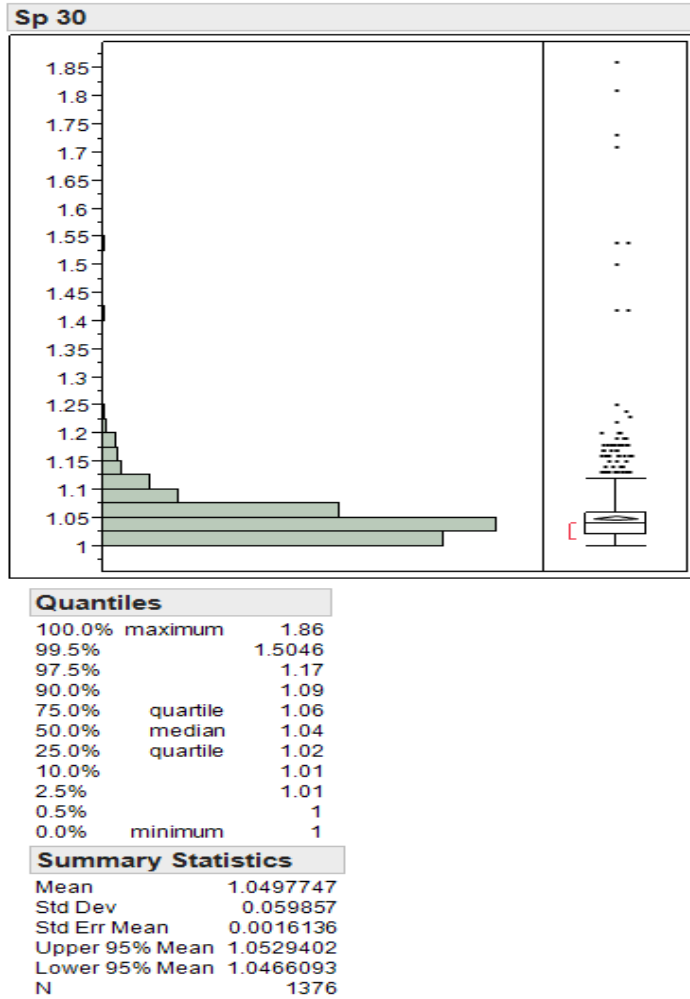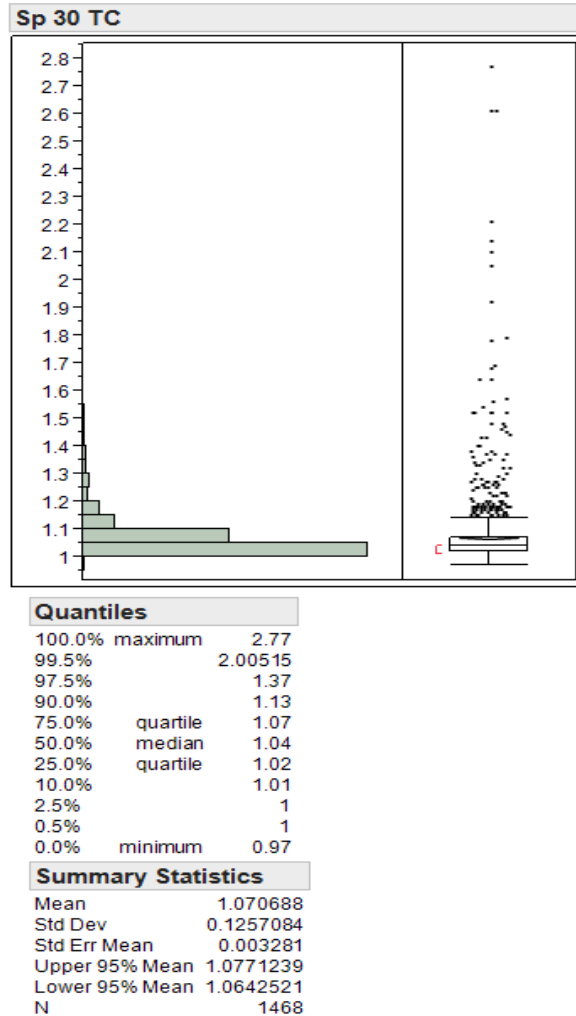|	
Mean	1.0497747
Std Dev	0.059857
Std Err Mean	0.0016136
Upper 95% Mean	1.0529402
Lower 95% Mean	1.0466093
N	1376

Figure 20 Slab without Crack

Figure 21 Slab with a Crack

From the sensor collected data, compared to the results when there is no crack on the

slab, slab with a crack has a larger maximum value which indicates a wider range of

acceleration. In this situation, data distributed among a larger area and make it harder to

tell the noise and useful signals. There is a same conclusion when considering the

standard deviation among two different conditions, a larger standard deviation appears

when the slab has a crack, and it is a more straightforward value which shows us the data

distribution. With a larger standard deviation, there are more noise signals distributed

along the actual peak location which will reduce the accuracy of detecting the wheel passing.

Simulation Results Analysis

The vertical direction was directly subjected to the moving loading and it has least influence by other vibration sources. In our simulation analysis, the vertical acceleration was considered as the primary factor and compared with laboratory tests results. Figure 22 is the vertical acceleration distribution when a wheel passing certain location. There are two direction acceleration from our simulation, one is created by wheel passing another one is the decay after wheel passed which is in the opposite direction. While our sensor collected data is only in one direction since the self-weight of sensor offset the vibration after the wheel passing. In our future analysis, only one direction acceleration will be considered and analyzed.
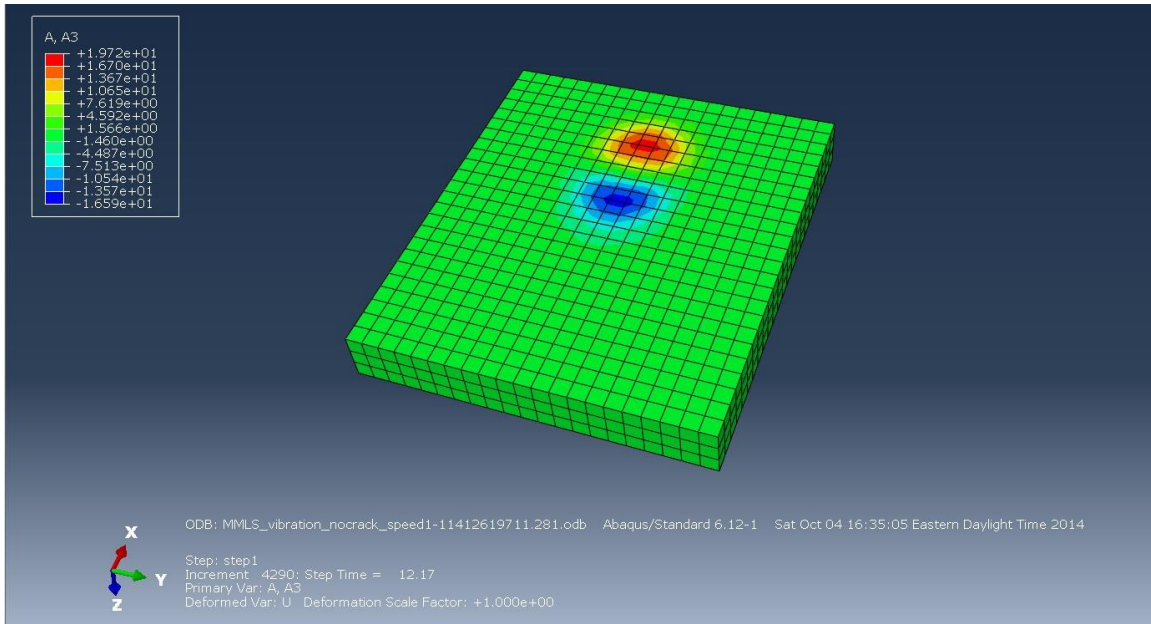
Figure 22 Vertical Acceleration

Simulation Results without Crack

Simulation using dynamic loading method is a more idealized situation, from the simulation results listed below, Figure 23, we can see that loading is the only vibration source and the acceleration between each peak is almost zero which is quite different from our sensor collected data. It is reasonable since the tests under MMLS3 have a lot of facts that cause our slab to vibrate during the time interval when there is no directly wheel passing.
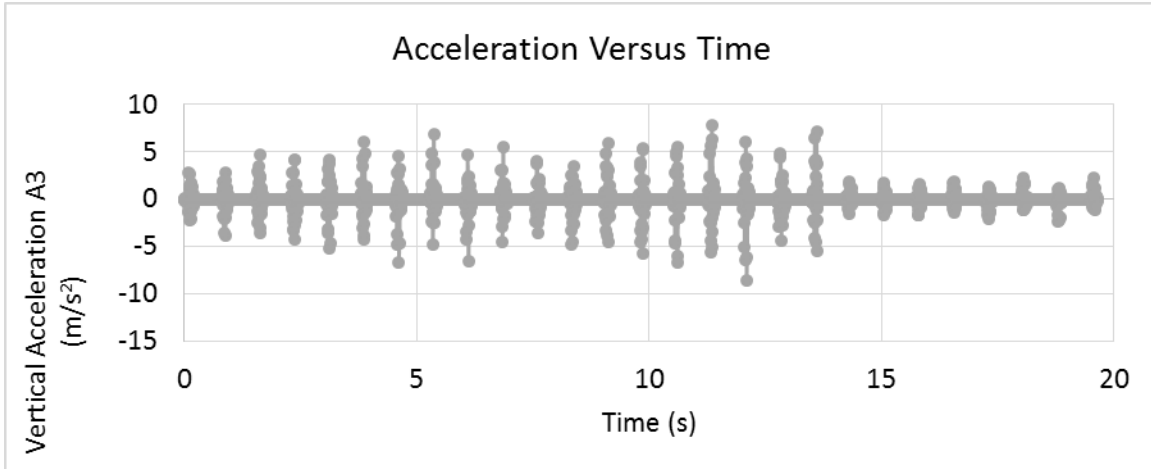
Figure 23 Simulation Results of Acceleration

But when we look detail into the certain period when the wheel loading is the primary

vibration source, both the laboratory tests and simulation results have better match to

each other. A single wheel passing was selected and compared below. Both of the

simulation and sensor represented a peak value for a wheel passing. Compare to sensor

collected data, the simulation results show a more sensitive response to the wheel

passing, before the wheel arrived the recording point, there are vibrations at the recording

point. While the sensor had less reaction to it since the sensor its weight which offset this

vibration. This also explained the sensor signal decayed faster than the simulation, due to

the sensor weight, it forced sensor back to its original position and offset the vibration
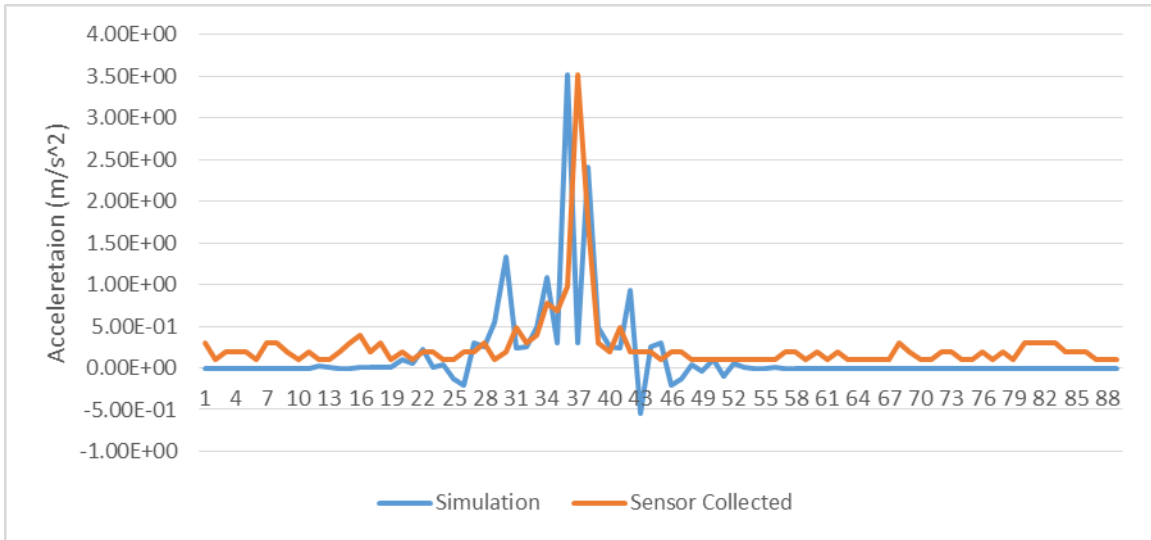
from wheel passing.

Figure 24 Single Wheel-Passing Comparison between Sensor and Simulation

Simulation Results with a Crack

To estimate the influence of pavement condition to the vibration, a simulation of slab reaction to the wheeling passing with a crack in it was conducted and compared with laboratory tests.

Figure 25 is the simulation results of a slab with a crack in it. The maximum acceleration is about 3 times larger than the slab in a good condition. Compared to the sensor data, the simulation results are more accuracy since the wheel passing is the only vibration source. In our laboratory tests, other factors like machine vibration would influence the actual vibration of the slab.
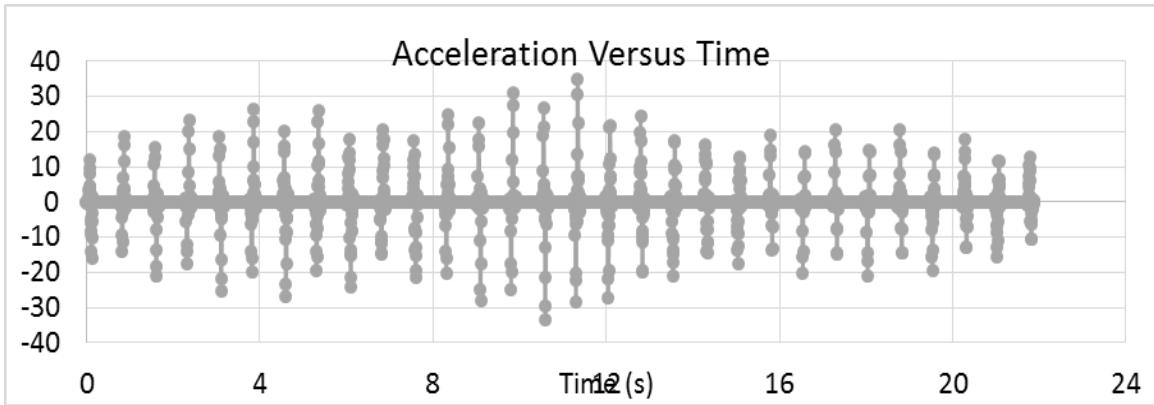
Figure 25 Simulation Results of Acceleration

But when we look detail into the single peak which represents a wheel passing and

compare it with our labortoray results, shown in Figure 26, they are very similar to each

other since the wheel passing is the primary vibartion source.

However, with a crack in the slab, around sensor collected peak location, our simulation

results have more than one peaks. In this case, other peasks will decrease the accuracy

detecting the actual wheel passing. From the figure we can also see that, after the wheel

passing, the accelaration decay is much slower than the no crack condition, some

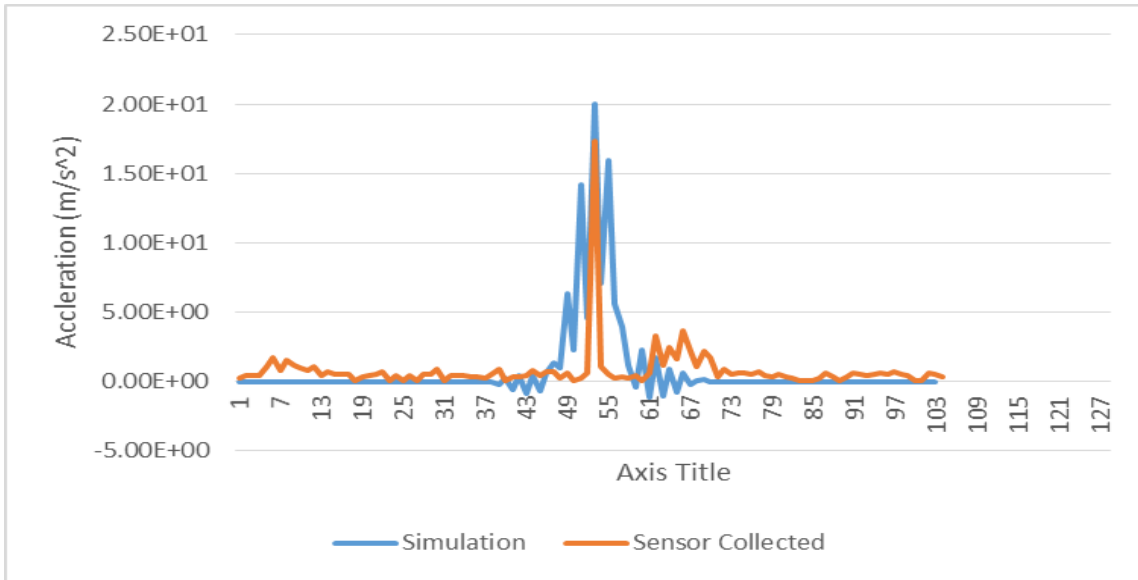vibrations even exist few seconds after the peak.

Figure 26 Single Wheel-Passing Comparison between Sensor and Simulation

To tell the pavement condition from our acceleration data is another important task. From our laboratory tests, good condition slab has a much smaller standard deviation than bad condition. In our simulation results, there is a same conclusion. As speed increases, the standard deviation of acceleration will increase. Comparing crack and non-crack slab, the standard deviation is bigger when crack exist.

Table 10 Standard Devotion Comparison from Simulation

Speed	Crack	Non-Crack
10	1.1377926	0.225157
20	1.7782633	0.298548
30	3.77777	1.2116992
40	5.617622	4.5438817

6. Deployment on Plantation Road

To verify the accuracy of the sensor when used on the pavement to monitor actual pavement-vehicle interaction, a test was done on Plantation Rd, vehicle used was GMC Sierra 2500 HD truck. Due to the speed limit, truck moved around 35 mph and the accurate speed was detected by handheld speedometer.

Installation Procedures

As shown in figures, four holes were drilled first and fixed sensor using expansion screws just as we installed under MMLS3 which could make sensor and pavement vibrate together. The distance between sensor and vehicle outside wheel is about 1 meter.

Figure 27 Sensor Installed on Pavement

Figure 28 Sensor Location on Pavement

Test Results and Analysis

Z-axle acceleration was used for analyzed since it had a better sensitive to the vehicle-pavement interaction. The same algorithm was used in processing the data.

The noise of static sensor were tested first, from the output results, the noise keeps at a constant value. Compared with laboratory test noises, pavement noise seems stable and easy to tell, in this case, an easy step could be used to analyze our output signals to detect axles.

Since the actual pavement noise locates between a certain values, after filter those noise within that range, the useful signal could appear clearly. Figure 29 shows the original

output signal form the sensor. Figure 30 shows the noise of the sensor when there is no traffic.
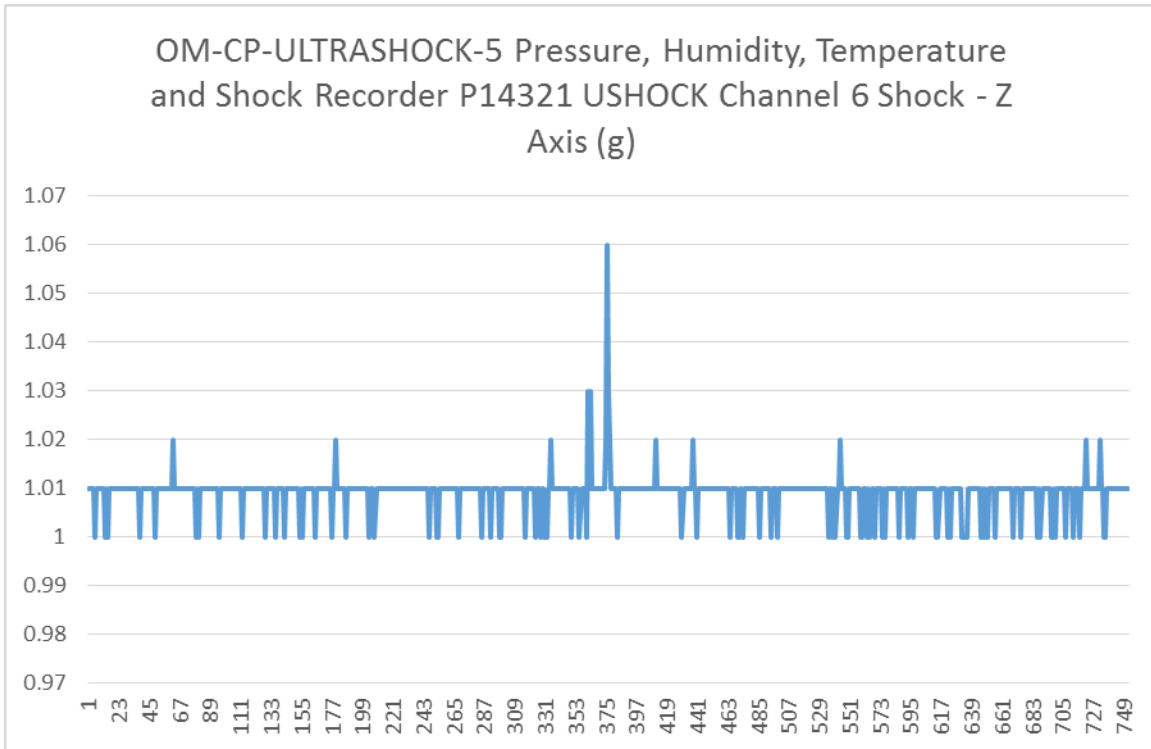

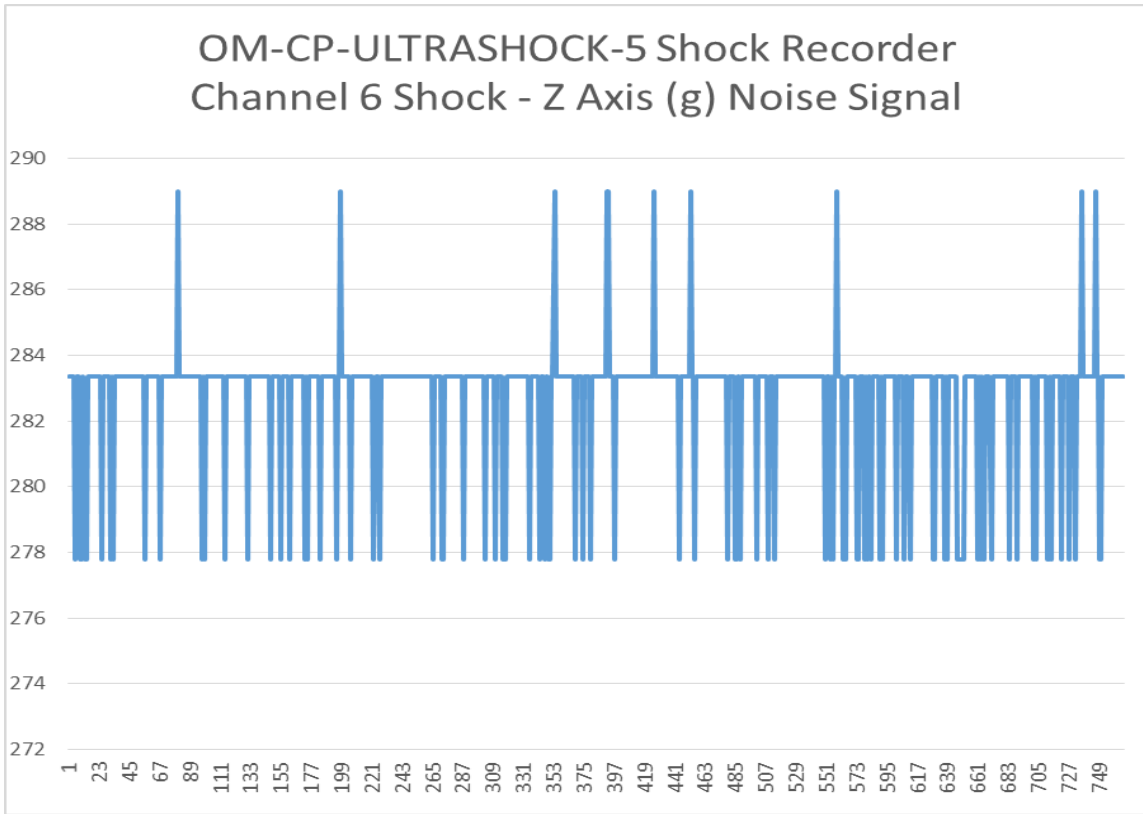Figure 29 Z-axis Acceleration from Pavement Test.
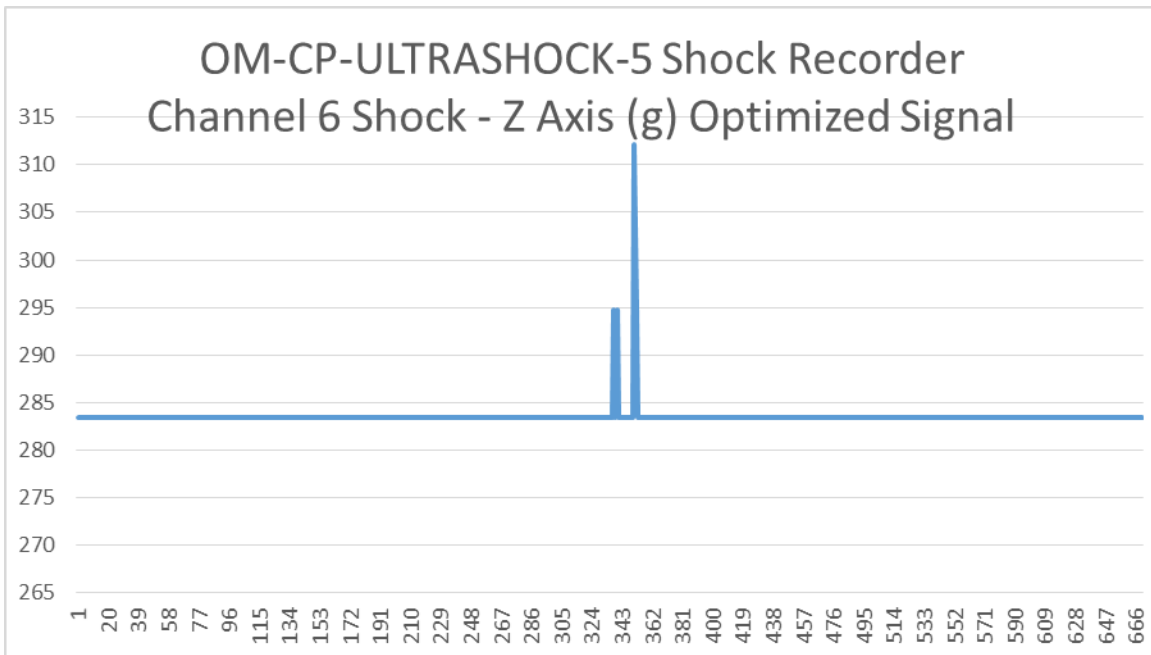
Figure 30 Static Noise Signal

Figure 31 Optimized Signal

From the figures 31, two peaks are clearly appeared which reflect as two axles. According to the actual condition, the truck used for our experiment has two axle just as our sensor monitored.

Time interval between two peaks were calculated as 0.195 sec. the speed detected by handed speedometer was 35 mph. So the axle spacing monitored by sensor was 10 feet. The official wheelbase given by GMC is 11.14 feet. The error rate is only about 1% which is accurate for vehicle classification.

Due to the limitation of field, only one kind of truck was tested and only 35 mph was applied. Higher speed cannot be tested because of the speed limitation. In the future, more kinds of vehicles and more speeds may be conducted. However, the test results were quite well and prove the feasibility of using MEMS accelerometer for vehicle classification.

7. Conclusions and Future Work

Vehicle Classification Based on MEMS Accelerometer

The first object of this project was to verify the feasibility of using MEMS accelerometer to classify vehicle based on axle count and spacing. A laboratory test was designed, conducted and applied to pavement. MMLS3 was used during the laboratory test to apply four different speeds to see the reaction of sensor. From output signal, the sensor had a good reaction to the wheel-pavement interaction, almost every axle passing showed a peak on the signal. The installation compared to existing methods has many advantages, since it located beside the pavement which without subjecting to the traffic loading directly will have a long-lifespan than traditional technologies. Also, this non-destructive method without cutting the pavement will protect the pavement form potential damage caused by improper installation. The data collection will be convenient and safe for engineers because they do not need to close traffic lanes or enter lanes. The laboratory test certify the feasibility of using MEMS accelerometer for vehicle classification.

The second object was to develop an algorithm to analysis the test data. The algorithm including a moving average smoothing filter and peak detector that could successfully locate every axle and report the time interval between two axles. The lowest error rate of this algorithm could be 0.7% for spacing and 0.6 % for speed calculation which are quite satisfactory. This method also used on the pavement test and output an accuracy axle detection result which could be easily used for vehicle classification.

Since all the tests did under relative low speed condition compared to actual traffic, also form our results, the accuracy has a decreasing trend as speed increases, in the future,

sensor will be installed beside a local highway to see the reaction. In our project, only one sensor was used to monitor the vehicle-pavement reaction, so we have to fix one variable to verify another. For example, when we want to know the accuracy of calculating the axle space, speed has to be fixed. In the future test, more sensors could be used, once the distance between each sensor is known, either speed or spacing can be calculated through sensor output data.

Currently, we have not considered the multi-lane condition whether the vehicle vibration on the further lanes could be collected by the sensor or the vibration from other lanes may affect the signal collection. A better way to avoid this is installed on a weigh station where only one lane open to trucks so that an accuracy signal could be collected.

Even though the installation and data collection method are more convenient and safer than traditional technologies, it still could be improved by adding a wireless transmission device which will release engineers from tedious data collection work and save lot of cost. In the future, we will try to develop an integrated sensor system to fulfill these requirements.

Pavement Condition Analysis Based on Acceleration

In this project, two different kinds of slab condition were tested and simulated to find the difference on acceleration output. In the future, we can use the acceleration data to tell the pavement condition. Based on our test results, compared good and bad slab condition, when a crack exist, the standard deviation of acceleration is larger which could up to two times the no-crack condition. This conclusion is also proved by our simulation results. Also if there is a crack in our slab, when a wheel passing, the acceleration occurred more

strongly and decay slower which means the vibration lasts longer and definitely caused

more damage to our slab.

References

R. Bajwa. *Weigh-in-motion system using a mems accelerometer. Technical report*, EECS Department, University of California, Berkeley, 2009.

S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C.-W.Tan, and P. Varaiya. *Traffic measurement and vehicle classification with single magnetic sensor*. Transportation Research Record: Journal of the Transportation Research Board, 1917:173-181, 2006

S. E. Lyshevski, Mems and Nems: systems, devices and structures (CRC Press LLC, USA, 2002)

Ravneet Bajwa, Ram Rajagopal, Pravin Varaiya and Robert Kavaler *In-Pavement Wireless Sensor Network for Vehicle Classification,* Information Processing in Sensor Networks (IPSN), 2011 10th International Conference on , vol., no., pp.85,96, 12-14 April 2011

Federal Highway Administration s (FHWA) *Traffic Detector Handbook: Third Edition—Volume I*, Publication No. FHWA-HRT-06-108 October2006

Federal Highway Administration s (FHWA) *Traffic Monitoring Guide 2013*

Pravin Varaiya, *A Low-cost Wireless MeMS System for Measuring Dynamic Pavement Loads,* California PATH Research Report, UCB-ITS-PRR-2008-36

Amy L. Epps, Tazeen Ahmed, Dallas C. Little, and Fred Hugo, *PERFORMANCE PREDICTION WITH THE MMLS3 AT WESTRACK,* FHWA/TX-01/2134-1, 2001

David CEBON (1989) V*ehicle-Generated Road Damage: A Review, Vehicle System Dynamics*: International Journal of Vehicle Mechanics and Mobility, 18:1-3, 107-150

Ravneet Bajwa, Pravin Varaiya, *Weigh-In-Motion System Using a MEMS Accelerometer,* Electrical Engineering and Computer Sciences University of California at Berkeley, Technical Report No. UCB/EECS-2009-127

Andrejaši, Matej. 2008. "MEMS ACCELEROMETERS."

de Fourtier Smit, A., F. Hugo, and A. Epps. 1999. Report on the First Jacksboro MMLS3 Tests. Center for Transportation Research.

F. Chollet, H. Liu. 2008. Short Introduction to MEMS.
http://memscyclopedia.org/introMEMS.html.

I. Lee, G. H. Yoon, J. Park, S. Seok, K. Chun, K. Lee. 2005. "*Development and analysis of the vertical capacitive accelerometer*", Sensors and Actuators A 119 (2005) 8–18

Lyshevski, S. E. 2002. *Mems and Nems: Systems, Devices and Structures* . CRC Press LLC, USA.

C. Sun and S. Ritchie. *Heuristic vehicle classification using inductive signatures on freeways*. Transportation Research Record: Journal of the Transportation, Research Board, 1717(-1):130-136, 2000

R. Rajagopal. *Large Monitoring Systems: Data Analysis*, Deployment and Design. PhD