Final Technical Report TNW2009-15

Research Project Agreement No. 61-7167

Low-Cost, Distributed, Sensor-based Weigh-in-Motion Systems

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A report prepared for

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December 2009

TECHNICAL REPORT STANDARD TITLE PAGE

1. REPORT NO.	2. GOVERNMENT ACCESSION NO.	3. RECIPIENT'S CATALOG NO.
TNW2009-15		

4. TITLE AND SUBTITLE	5.REPORT DATE
Low-Cost, Distributed, Sensor-based Weigh-in-Motion Systems	December 2009
	6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S) Gregory Miller, Yinhai Wang, Peter Mackenzie, Genevieve Farrar, Chia-So Chuang	8. PERFORMING ORGANIZATION REPORT NO. TNW2009-15
9. PERFORMING ORGANIZATION NAME AND ADDRESS Transportation Northwest Regional Center X (TransNow) Box 352700, 129 More Hall University of Washington Seattle, WA 98195-2700	10. WORK UNIT NO.
	11. CONTRACT OR GRANT NO. DTRT07-G-0010
12. SPONSORING AGENCY NAME AND ADDRESS United States Department of Transportation Office of the Secretary of Transportation 1200 New Jersey Ave, SE Washington, D.C. 20590	13. TYPE OF REPORT AND PERIOD COVERED Final Research Report
	14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES

ABSTRACT

Monitoring truck weights is essential for traffic operations, roadway design, traffic safety, and regulations. Traditional roadside static truck weighing stations have many operational shortcomings, and so there have been ongoing efforts to develop and implement Weigh-In-Motion (WIM) systems to make vehicle weight monitoring and enforcement more automatic, unobtrusive, and cost-effective. Current WIM systems typically rely on a transverse, instrumented beam installed in the roadway itself, which then can act as a transducer system whose response can be related to vehicle weights via calibration and basic principles. These systems work reasonably well, but they are still relatively costly to install and maintain since they require nontrivial modification of the roadway itself, and there are limitations on where and when they can be installed. The work aims to investigate an approach to WIM systems that can greatly reduce costs and increase flexibility and reliability by using the fact that the unmodified roadway pavement/foundation subsystem itself can be viewed as a transducer system amenable to direct characterization and calibration. Rather than using a relatively expensive, obtrusive single sensor system, the proposed approach would use a large number of inexpensive, self-powered, unobtrusive wireless sensor devices that would work together at a given location to achieve reasonably accurate vehicle weight measurement without modifying the roadway itself. The fundamental technologies and theoretical building blocks underlying the proposed approach all exist, but research is needed to answer a number of technical and practical questions to enable the development of a deployable system. To this end, we propose the development of both virtual and physical prototype systems that we will use to investigate the feasibility, suitability, accuracy, and generality of the proposed technology as a future heavy vehicle weight monitoring system.

17. KEY WORDS	18. DISTRIBUTION STATEMENT
Weigh in motion, weight measurement, monitoring	

19. SECURITY CLASSIF. (of this report)	20. SECURITY CLASSIF. (of this page)	21. NO. OF PAGES	22. PRICE
None	None	30	

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1 Introduction

This study involves a preliminary investigation into the feasibility of estimating weights of passing vehicles using roadside sensors rather than invasive, in-road techniques as is the current norm for Weigh-In-Motion (WIM) systems [1, 2]. Avoiding the need to install sensors across traffic lanes can potentially offer many advantages in regards to installation costs and traffic disruption, ongoing calibration and maintenance of the sensors themselves, and roadway life. If one can reduce the overall direct and indirect costs per sensor enough, then the advantages of increased numbers of sensors both locally (using redundancy to improve accuracy) and globally (increased data for understanding and operating roadway systems) can be exploited. This can give rise to dramatically increased sensor densities, enabling the generation of much richer data sets for operations, research, and maintenance. The general trend in sensor technology is such that costs are likely to continue to go down, and so it is worth considering the fundamental feasibility of roadside sensing of vehicle weight.

The general approach in this study has been to investigate mechanisms for sensing roadway deformations in the vicinity of, but outside of lanes of wheel travel. In the scope of this study pilot results have been obtained for passing vehicle characteristics on a local road circling the University of Washington campus. This road contains sections with rigid pavement and sections with flexible pavement, carries a variety of vehicles, and has a regular schedule of heavy vehicle use in the form of buses. Low-cost sensor prototypes capable of high-sensitivity rotation (and horizontal acceleration) measurement have been developed and used to gather a suite of preliminary data suitable for addressing fundamental questions such as whether vehicles can be detected, how sensitive instruments need to be, whether signals show repeatable patterns for different classes of vehicles, and whether signals can be correlated to vehicle weights, and so on.

In addition to collecting these initial sets of data, simple analytical and numerical models have been developed to help understand the measured responses, and to provide an initial framework for estimating weights from observed sensor signals. This part of the study is intended to be indicative rather definitive—the task of turning sensor signals into reliable weight estimates is a complex challenge for any WIM system, and requires extensive

testing, calibration, and validation, and ultimately relies on a high degree of empiricism. However, it is still useful to show that a physically-based fundamental approach generates reasonable results, both to lay the groundwork for more refined weight estimation schemes, and to provide confirmation that the sensor measurements are consistent with expectations.

This presentation focuses on single sensors, but a primary long-term goal is to leverage the low-cost aspect of the approach to allow for increased redundancy, and to thereby obtain improved estimates via multiple observations (see e.g., [3, 4]). More fundamentally, because of the nature of the use of the roadway itself as the sensing mechanism, multiple sensors would be needed to separate out the effects of multi-vehicle interactions in many instances. There also is potential for determining broader vehicle characteristics via this kind of sensing technology, including the possibility of vehicle tracking in the case of dense sensor arrays.

2 Background

Assessing vehicle weights is a key component of roadway system operations, both for regulating and understanding the frequency and effects of large vehicle loads. Traditional static truck weighing stations have many operational shortcomings, and so there have been ongoing efforts to develop and implement Weigh-In-Motion (WIM) systems [2] to make vehicle weight monitoring more automatic, unobtrusive, and cost-effective.

Weigh In Motion (WIM) Systems have been used for a number of years (the earliest systems dating to the 1950s [5], and there are numerous resources available presenting system descriptions, background and operating guidelines (see, e.g., [6, 7, 8, 9, 10, 11]. There are many different technologies that have been developed and tested (see, e.g. [12, 13, 14, 15]), with a relatively small subset of systems finding their way into commercial-scale use. Virtually all commercial systems are based on transducer devices that are installed in the roadway itself, and that measure tire loads via direct, in-lane contact. The load transducing system is typically coupled with loop detectors or other supporting technologies that are used to classify vehicles and and derive other vehicle characteristics beyond weight.

The optimal system would be one that renders highly accurate mass measurements for any desired range of speeds, without significant effects from arbitrary vehicle, roadway,

and environmental conditions. Because the vehicle mass is fundamentally independent of these effects, it should be possible in theory to build such a system. However, virtually all existing approaches rely on what is ultimately a generalization of a static scale device which functions via a localized snapshot of a dynamic process. This snapshot-like strategy is conceptually straightforward, but is inherently susceptible to errors caused by mass-independent effects. This means that such systems require significant effort to control roadway and traffic conditions, and to compensate for dynamic and environmental phenomena. An approach that captures a fuller picture of the dynamic process of vehicle motion and roadway system response integrated over time can offer large potential gains in terms of separating out mass-independent effects, and thereby allow more robust and accurate measurements with many fewer restrictions. By distributing numerous sensors in suitable arrays, it should be possible to overcome the problems existing systems exhibit in regards to high sensitivity to location, vehicle characteristics, calibration drift, and environmental factors. However, this requires the development of suitably low-cost, unobtrusive sensors such that large numbers can be installed cost-effectively, and this has motivated the present study.

As mentioned in the introduction, the key concept explored in this work has been to consider the use of sensors outside the lanes of traffic, essentially using the roadway/foundation system's deformations as the primary load transducer. This approach has the potential for particularly low-cost installation and maintenance, and increased flexibility in regards to location and density, but it also brings with it technical challenges as discussed in the next section.

3 Problem Statement

Roadway deflections and deformations due to traffic loading are generally quite small, and so one of the principal challenges is to have a means of observation that is sufficiently sensitive to detect vehicle-caused deformations without requiring complicated, intrusive or a priori installation. Measuring roadway vibration using accelerometers is one possible approach that was considered (in fact, United States Patent 6692567 describes a Seismic Weigh-In-Motion system based on a geophone sensor with some similarities to this approach), but based

on preliminary testing, the lower frequency signals associated with global pavement surface rotations were considered likely to be easier to work with on several levels. However, existing low-cost MEMS accelerometers were found to not have the sensitivity/noise floor required to capture the rotation signals in question, and larger accelerometers and seismometers were deemed too costly to fit the kind of low-cost model needed to allow broad and/or dense installation. This led to the need to identify or develop a suitable system providing low-cost, high sensitivity performance.

In particular, the work presented here is based on adapting a simple seismometer concept [16] to develop an inclinometer device capable of measuring the small rotations caused by passing vehicles, and suitable for low-cost, distributed installation. Figure 1(a) shows the basic principle on which the inclinometer works: a graphite rod with diamagnetic properties is held in suspension by the magnetic field from neodymium cylindrical magnets whose poles are oriented through the diameter of the cross section. When placed on a ferrous base, the magnets rotate as indicated in the figure, and this provides a sufficiently strong oriented field to levitate the rod. Longitudinal (i.e., out of the paper for Figure 1) vibration or ground rotation results in longitudinal motion of the graphite rod, and the non-contact nature of the suspension makes for a simple but sensitive sensor mechanism. Eddy current damping can be achieved by wrapping aluminum or copper foil around the graphite rod.

The motion/displacement of the rod can be measured in various ways, with a simple light-blocking optical scheme having been used in [16]. This kind of approach has been shown in other contexts to be capable of detecting motions on the order of 10^{-8} meters [17], which corresponds to a high sensitivity in regards to overall sensor performance. The approach used here is related to but somewhat different from that described in [16]. In particular, Figure 1(b) shows a schematic in which a pair of LEDs are aligned with the ends of the graphite rod, which is in turn inside a cover that both keeps the rod in place during transport, etc., and also provides a slit through which the light from the LEDs can pass. The rod effectively blocks this slit along its length, and so as the rod moves longitudinally, the amount of light passing through the lists at each end of the rod changes, increasing one end and decreasing on the other. As shown in the figure, light sensitive resistor (LDR) photocells are placed opposite these slits to respond to this light change. Placing these LDRs

in a half-bridge Wheatstone circuit leads to a classic push-pull amplification scenario, which can then be furthered amplified with typical bridge amplifier techniques.

During the course of this study a number of variations on this sensing device were developed and used [18], beginning with separate amplification, wired connectivity, and external A/D conversion, and evolving from that point towards the current configuration shown in Figure 2. This figure shows the current prototype and its components, which together provide standalone wireless measuring capabilities. In particular, the microprocessor/wireless module is an off-the-shelf, open source FunnelIO [19] board running the open source Arduino operating system [20], and powered by a lithium polymer battery. The microprocessor provides A/D conversion, communications support, and processing, and the wireless transmission is routed through a Digi Xbee module [21]. The sensing mechanism and supporting circuitry shown in Figure 2 correspond to that described above, and this has been implemented on a simple prototype circuit board as shown. Depending on amplification settings and other configuration details, sensor performance ranged from about 400-4,500 V/g with sufficiently low noise to enable useful data to be observed.

There is still significant room for further integration and improvement of this specific configuration—its main purposes have been to determine the feasibility of this kind of measurement, to provide a test bed for investigating fundamentals of the approach, and to enable the next stage of broader field testing. In this regard it should be noted that the results reported below have come from various prototypes that differ in some details from that shown in Figure 2, but all of which function on the same basic principles.

4 Objectives

To address the basic feasibility issues associated with roadway-response-based weight estimation, a series of fundamental pilot tests were conducted. The primary objectives of this pilot test program are enumerated below:

1. Determine the sensor sensitivities required to detect vehicles.

2. Investigate the range of vehicles that can be detected via roadside sensing.

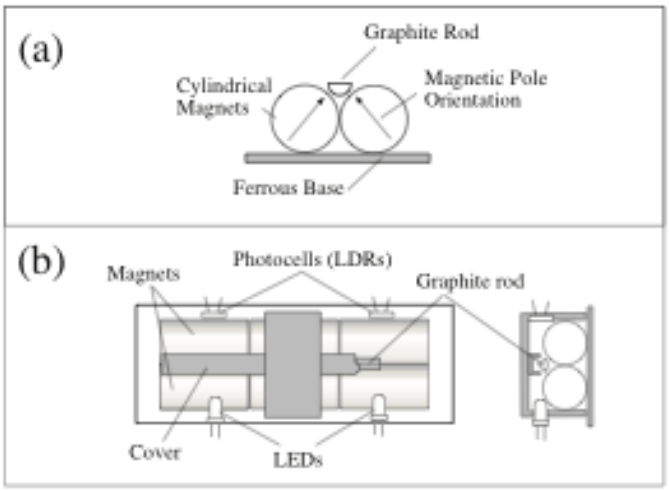

Figure 1: Schematic of the principal sensing mechanism: (a) shows the basic levitation arrangement; (b) shows the implementation.

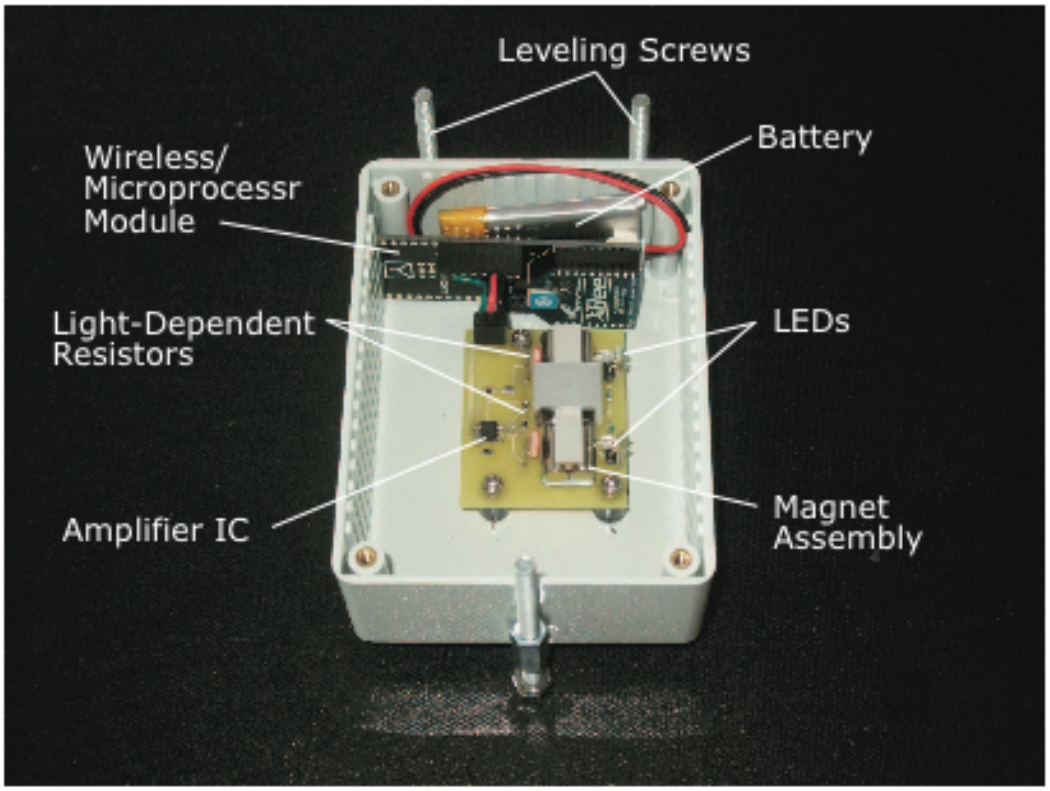

Figure 2: Interior of sensor box showing data acquisition components

3. Consider the effect when vehicles run over different pavement types.

4. Gather preliminary data to see if roadside-collected data for heavy vehicles show consistent patterns.

5. Estimate baseline system component costs.

6. Identify strategies to estimate weights based on measured signals.

7. Investigate simple numerical models that can be used for simulation.

Test data were gathered at several locations along the main perimeter road (Stevens Way) on the University of Washington campus. This road contains sections with jointed rigid pavement and sections with flexible pavement, carries a variety of vehicles, and has a regular schedule of heavy vehicle use in the form of 2- and 3-axle buses. There are a number of parking turnouts to allow for variation in the distance to the vehicle lanes, as well as allowing for relatively unobtrusive installation. The speed limit is a relatively slow 20 mph, which limits the role of dynamic effects in the observed responses, but which provides a good starting point for the basic feasibility testing presented here. Figures 3 and 4 show typical sensor locations for both rigid and flexible pavement cases.

5 Field Test Results

Preliminary data collected with an early prototype showed basic detection of a variety of vehicle types, ranging from buses and trucks down to bicycles. Figure 5 shows an overlay of representative plots. These data were collected on a section of jointed rigid pavement. At this particular site, vehicle signals exhibited sharp peaks which correspond to the impact of the tires with the edge of each subsequent slab of rigid pavement. As expected at a qualitative level, heavier vehicles caused a proportionally greater response, and different vehicle types caused different signal patterns. Although not evident from this single plot, patterns were repeatable even in this relatively complex environment.

The early sensor prototype used to capture the results in Figure 5 had a variable amplification scheme and a wider voltage range than the current device, and was capable of

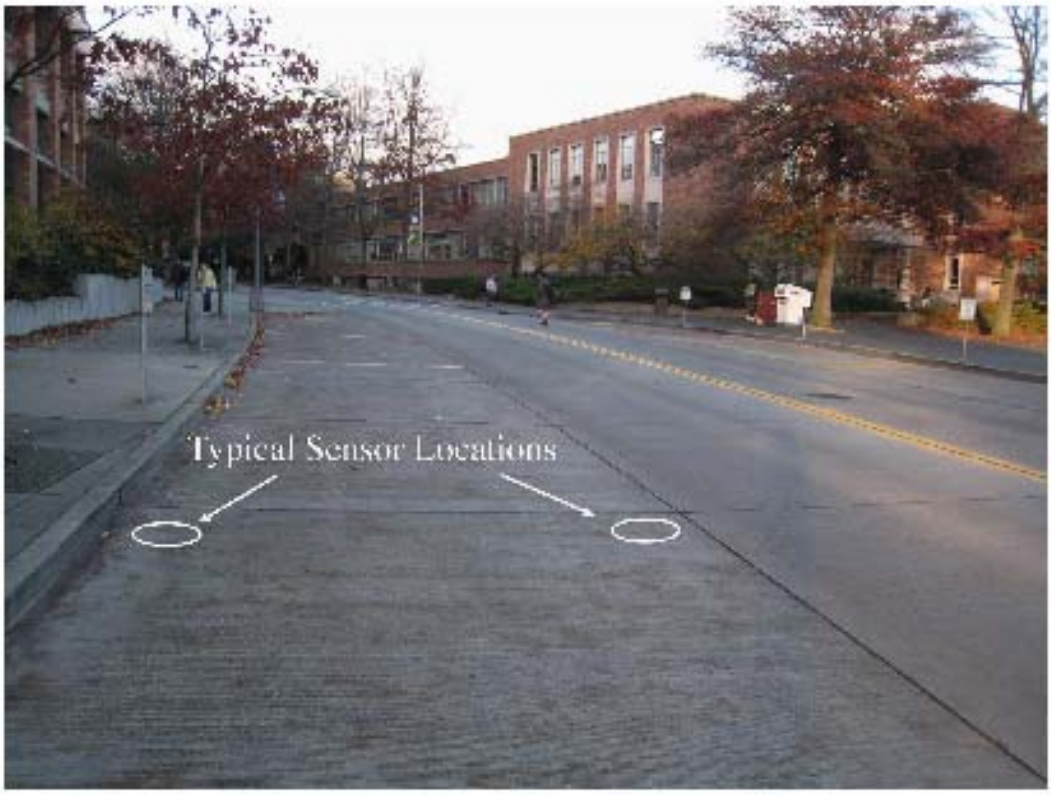

Figure 3: Photo of typical sensor locations in a parking pullout for rigid pavement (sensors not shown).

Figure 4: Photo showing typical near-curb sensor location for flexible pavement (sensor itself not shown).

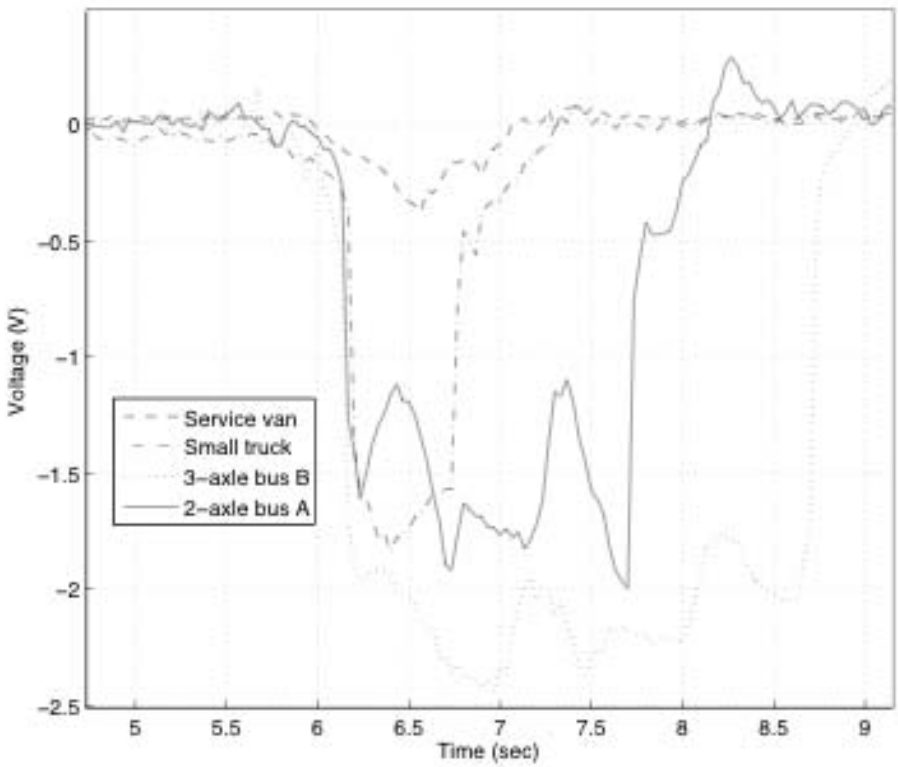

Figure 5: A set of signals corresponding to various vehicle types (rigid pavement).

collecting data for a wide range of vehicle weights (all the way down to bicycles in some cases). The fully wireless prototype has a more limited dynamic range currently (lower resolution A/D and smaller voltage range), and so has been tuned for the purpose of collecting the signals caused by two-axle and three-axle buses. Figure 6 shows two 2-axle bus signals and two 3-axle bus signals for a flexible pavement condition, collected with the current prototype.

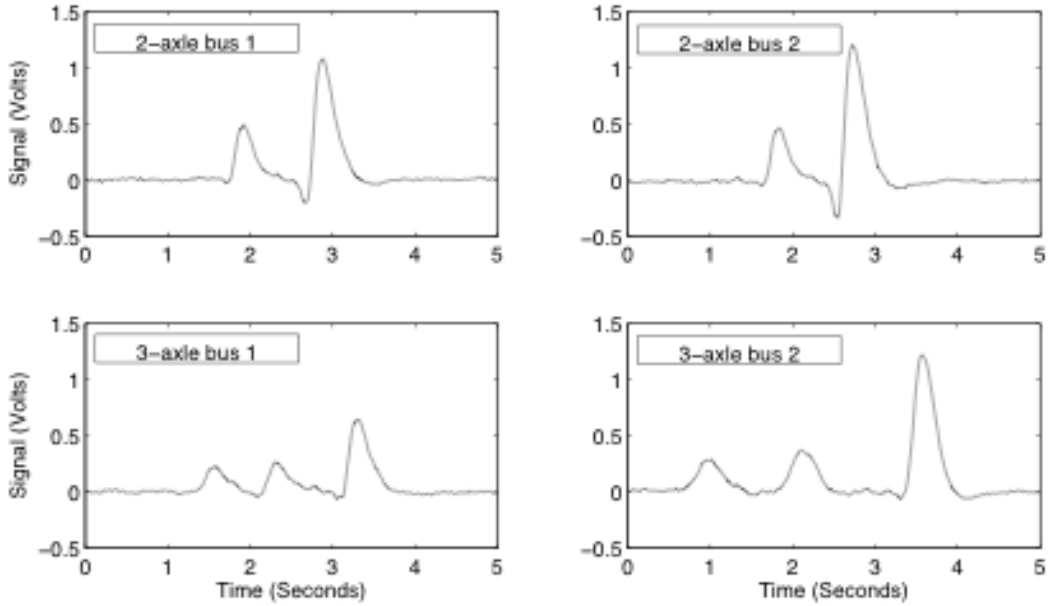

Figure 6: Signals for two 2-axle buses and two 3-axle buses on flexible pavement

Several qualitative observations can be made from the data in Figure 6.

1. Vehicles of a given type appear to cause a repeatable and recognizable signature for a given pavement condition. The 2-axle bus signals look remarkably similar. The 3-axle bus signals have the same basic pattern with some variation in both magnitude and width.

2. Each axle causes an individually recognizable response.

3. The magnitude of an axle's response shows general consistency with expected relative axle loads. Within the signal for a given vehicle, the individual axle response with the

largest magnitude corresponds to the heaviest axle of the bus.

4. Relative speeds are also apparent. For two vehicles of the same type traveling with different speeds, as is the case for the two three-axle cases shown above, the signature of the faster vehicle will be compressed in the time domain.

One clear anomaly in these particular preliminary flexible pavement data is the fact that the 3-axle bus signals indicate a smaller overall response than the 2-axle bus signals. Given the respective weight ranges of these classes of vehicles, this is not an expected outcome (and it can be seen to run counter to the jointed pavement observation shown in Figure 5). Because of the limited number of observations made to date, it is difficult to identify conclusively what is causing this, but one likely source of the anomaly is the distance to the sensor from the passing vehicle. It also can be seen from Figure 4 that this sensor location is on a downhill curve, which complicates these kinds of measurements. These are expected sensitivities, but this still requires further study in a context with many more observations involving measured sensor distances and known axle loads.

6 Method of Analysis and Analysis Results

Various procedures have been investigated for estimating static vehicle weights in weigh-in-motion systems. Broad summaries of previous work in WIM estimation methods have been assembled in various contexts [1, 2, 6, 22]. The aim of this study was to apply a few types of currently used WIM estimation methods to the small data sample obtained in the pilot study for purposes of validating the use of the types of sensors developed as prototypes, and to determine the best weight estimation methods for use with the collected pavement tilt data. The use of measured roadway deformations to estimate vehicle weights has been researched since at least the early 1990's [23], using deformation parameters such as pavement strain rather than pavement surface tilt. Numerous methods for calibrating weight estimates from signals have been developed. For example, calibration based on least squares procedures has been used in many contexts in the field of WIM [24, 25, 26]. Other procedures based on influence lines concepts [6], and other parameters such as the peak of the signal have

also been investigated in the context of weigh-in-motion. In this study, a few estimation and calibration methods were applied to a the sample data in order to make some general observations about what methods may yield the best estimates for the case of pavement surface inclinometer data.

It is important to note the many calibration/estimation-influencing effects present in WIM systems which were not taken into account in the models used for estimation and calibration in this preliminary study. Pavement temperature can have a significant effect on pavement deformations [26], especially for flexible pavements. Dynamic effects caused by the bounce of the vehicle suspension system, the sway of the vehicle, and the pavement roughness are magnified at higher speeds [7, 26, 27]. The somewhat viscoelastic behavior of flexible pavements can result in magnified deformation responses for slower vehicles [28]. Also, in most real-life cases there are several additional vehicles on the road at the same time, further complicating the measured signals.

A nonlinear least squares algorithm [29] was investigated as a preliminary estimation procedure for correlating sensor signals with vehicle weights. The physics of the system can be modeled with parameters such as vehicle weight, vehicle speed, the distance from the vehicle to the sensor, etc. The error between the measured signal and the curve created with the parameters is then minimized to obtain the best estimates of the parameters for the given modeling assumptions. The simple roadway response model described below is based on static analysis assumptions and does not include dynamic effects caused by the bounce of the vehicle suspension system, the vehicle sway, or the pavement roughness. Since these effects are known to be less of a factor for vehicles moving at slow speeds, and given that the speed limit on the road where data was collected is only 20 mph, the simple model was deemed adequate for assessing the basic feasibility of the Nonlinear Least Squares procedure for estimating vehicle weights from the collected inclinometer data.

For this estimation procedure, the relationship between the signal and the roadway tilt was modeled with a simple single degree of freedom spring-mass-damper system. While the movement of the graphite rod as a result of roadway tilt is actually governed by the magnetic field it is suspended in, the sensor dynamics appear to behave much like a simple

linear oscillator:

$$\ddot{u} + 2\xi\omega_n\dot{u} + \omega_n^2 u = g sin(\theta(t)) \approx g\theta(t) \tag{1}$$

in which $u(t)$ is the sensor output, ξ is the damping ratio, ω_n is the natural frequency, and $\theta(t)$ is the roadway tilt.

The relationship between the vehicle loads and the roadway deformation will be given by a simple analytical model. The wheel loads were approximated as moving point loads. The Boussinesq solution for the vertical displacement of the surface of an elastic half-plane due to four rectangularly-arranged moving point loads [30] can be written as

$$\begin{aligned} v_z &= \frac{(1-\nu)P_1}{2\mu\pi\sqrt{a_1^2+(b_1-ct)^2}} + \frac{(1-\nu)P_1}{2\mu\pi\sqrt{a_2^2+(b_1-ct)^2}} \\ &+ \frac{(1-\nu)P_2}{2\mu\pi\sqrt{a_1^2+(b_2-ct)^2}} + \frac{(1-\nu)P_2}{2\mu\pi\sqrt{a_2^2+(b_2-ct)^2}} \end{aligned} \tag{2}$$

in which ν and μ are the Poisson's ratio and shear modulus of the elastic sub-base, and c is the vehicle speed. The parameters a_1, a_2, b_1, b_2 are identified in Figure 7. The two front wheel loads are assumed to be equal (P_1) and the two rear wheel loads are assumed to be equal (P_2).

The tilt of the roadway surface perpendicular to the direction of the moving loads is $\partial z/\partial a$:

$$\begin{aligned} \theta(t) &= \frac{a_1(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_1^2+(b_1-ct)^2)^{3/2})} + \frac{P_2}{(a_1^2+(b_2-ct)^2)^{3/2}}\right) \\ &+ \frac{a_2(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_2^2+(b_1-ct)^2)^{3/2}} + \frac{P_2}{(a_2^2+(b_2-ct)^2)^{3/2}}\right) \end{aligned} \tag{3}$$

The relationship between the measurements and the parameters of interest was obtained by substituting the above expression for the tilt into the first expression for the sensor dynamics.

$$\begin{aligned} \ddot{u} + 2\xi\omega_n\dot{u} + \omega_n^2 u &= \frac{g\,a_1(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_1^2+(b_1-ct)^2)^{3/2})} + \frac{P_2}{(a_1^2+(b_2-ct)^2)^{3/2}}\right) \\ &+ \frac{g\,a_2(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_2^2+(b_1-ct)^2)^{3/2}} + \frac{P_2}{(a_2^2+(b_2-ct)^2)^{3/2}}\right) \end{aligned} \tag{4}$$

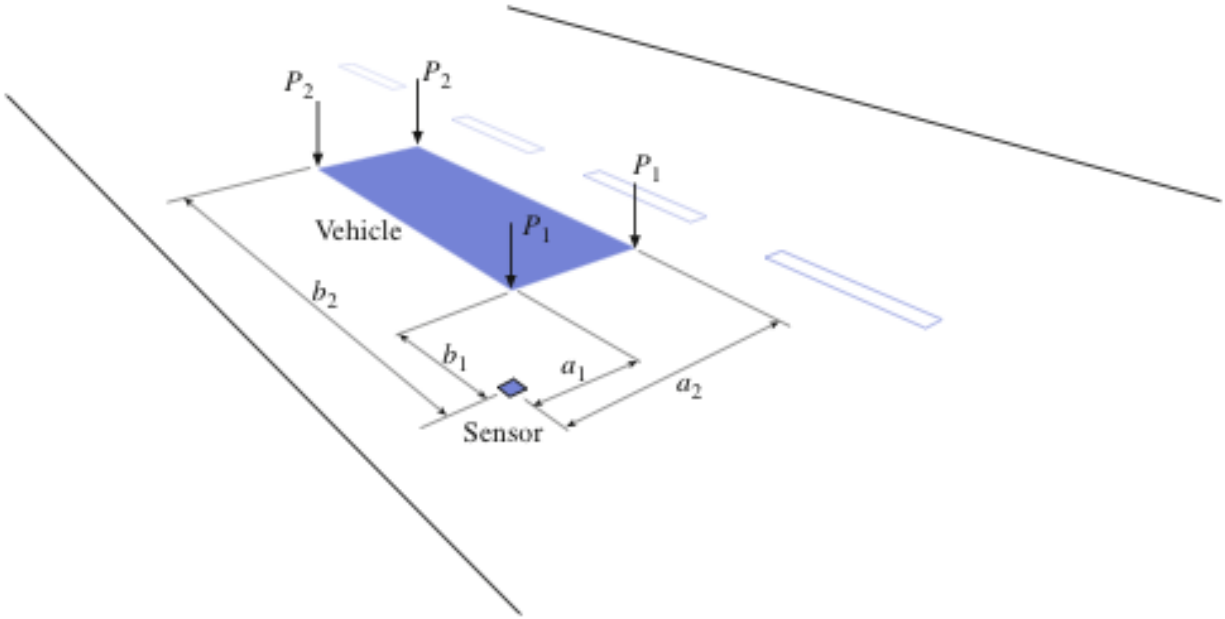

Figure 7: Model of vehicle loads on pavement used for Nonlinear Least Squares estimation

Centered difference approximations were used to obtain $\dot{u}$ and $\ddot{u}$ from the measurements u.

$$\dot{u}_k = \frac{1}{2\Delta t}\left(u_{k+1} - u_{k-1}\right) \tag{5}$$

$$\ddot{u}_k = \frac{1}{\Delta t^2}\left(u_{k+1} - 2u_k + u_{k-1}\right) \tag{6}$$

The model is then:

$$\begin{aligned} u_k \;=\; & \frac{1}{\frac{1}{\Delta t^2} + \frac{\xi\omega_n}{\Delta t}}\left[\frac{g\,a_1(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_1^2 + (b_1 - ct)^2)^{3/2})} + \frac{P_2}{(a_1^2 + (b_2 - ct)^2)^{3/2}}\right)\right. \\ & + \frac{g\,a_2(1-\nu)}{2\mu\pi}\left(\frac{P_1}{(a_2^2 + (b_1 - ct)^2)^{3/2}} + \frac{P_2}{(a_2^2 + (b_2 - ct)^2)^{3/2}}\right) \\ & \left.\left(\omega_n^2 - \frac{2}{\Delta t^2}\right)u_{k-1} - \left(\frac{1}{\Delta t^2} - \frac{\xi\omega_n}{\Delta t}\right)u_{k-2}\right] \end{aligned} \tag{7}$$

The above is the expression for the modeled curve $\hat{u} = f(\mathbf{x})$, in which

$$\mathbf{x} = [\nu, \mu, a_1, b_1, c, P_1, P_2, \xi, \omega_n]^T. \tag{8}$$

The standard nonlinear least squares algorithm [29] was then performed by minimizing the error between the modeled curve and the measured curve in order to obtain the parameters that lead to the closest match. The same basic procedure was used for the the case of 3-axle vehicles using six point loads rather than four.

This approach, appropriate for use after data collection, was carried out for the four sensor signals shown previously. An overlay of the modeled curves and the measured data is shown in Figure 8.

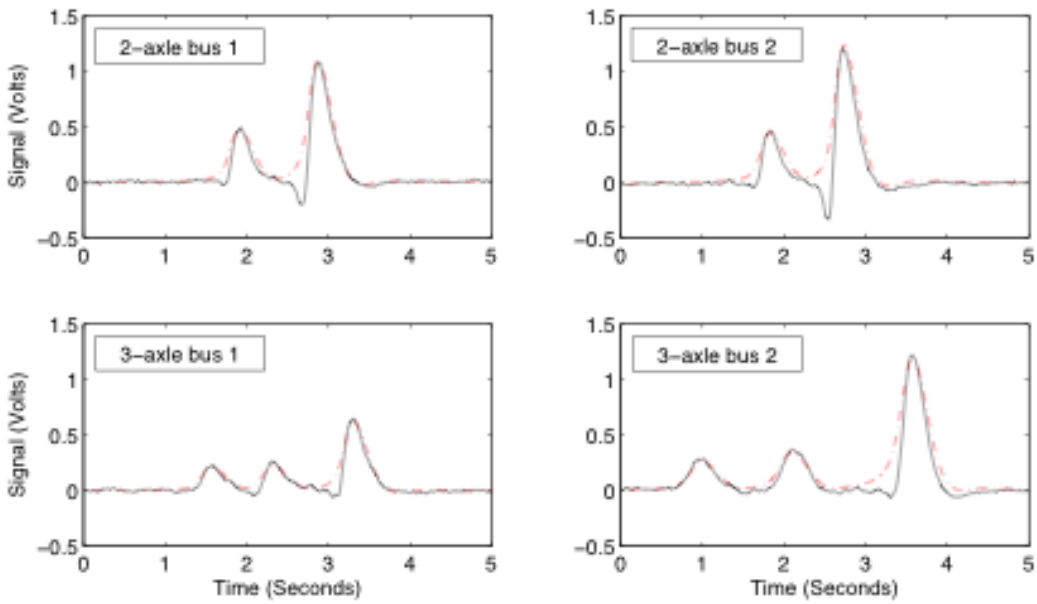

Figure 8: Overlay of the measured signals and the curves modeled with Nonlinear Least Squares estimation.

At this point, actual known vehicle weights have not yet been included in this study, but some basic analysis of the signals can be performed using expected weights. The expected total weights for 2-axle buses are between 28,240 lbs and 39,440 lbs, and the expected total weights for 3-axle buses are between 43,700 lbs and 66,600 lbs. The expected individual axle weights for 2-axle bus are about a 1-to-2 ratio for the first and second axle. If the total weight is assumed to be 33,000 lbs, for a medium-full bus, then axle weights of 10400 lbs and 22600 lbs are reasonable assumptions for the axle weights. For purposes of basic signal analysis,

the 2-axle bus 1 signal was assumed to correspond to a bus with these weights. Using these weights as fixed parameters, the Nonlinear Least Squares approach was used to determine the effective material parameters of the modeled elastic base and other parameters. The results were: $\nu = 0.17$, $\mu = 740$ psi, $a_1 = 1.47$ ft, vehicle speed $c = 17.73$ mph, natural period $T = 0.81$ sec, and $\xi = 0.67$. While the vehicle speed and distance a_1 correspond to the actual physical properties, the dynamic properties of the sensor and the material properties of the modeled elastic base are essentially "effective parameters", in that they are not describing true physical properties (because the model is very simplified), but they are parameters that can be "tuned" for calibration of data taken at a specific site.

The bus dimensions used in this study were based on standard bus data from King County Metro [31]. The longitudinal distance $b_2 - b_1$ between wheel loads for the 2-axle buses was set to 25 ft. The distances $b_2 - b_1$ and $b_3 - b_2$ for the 3-axle buses were set to 18 ft and 24 ft, respectively. These are essentially averages of the local bus dimensions. Given that the total width of the Seattle Metro Transit buses is on the order of 102 inches to 109 inches, the width between wheel loads $a_2 - a_1$ was set to 96 inches. Since the far-side wheels have very little effect on the sensor response relative the near-side wheels, basic approximations for this parameter were deemed adequate for the purposes of this study.

The Nonlinear Least Squares weight estimation procedure then was carried out for all four sample signals using fixed values for the effective material properties of the modeled elastic base of $\nu = 0.17$ and $\mu = 740$ psi, which were determined from the assumed-weight calibration. The results of this procedure are shown in Table 1.

Some general patterns can be noted from these results. The effective dynamic properties of the sensor came out reasonably consistent, as expected. The vehicle speeds of the two 2-axle buses were estimated to be quite similar, which makes sense considering that those two signals look very similar. As expected from the longer duration of the 3-axle bus 2 signal, its speed was estimated to be significantly slower than that of 3-axle bus 1. As expected from the relative heights of the peaks of the signals, the total weight of 3-axle bus 2 was estimated to be greater than that of 3-axle bus 1, and the total weight of 2-axle bus 2 was estimated to be greater than that of 2-axle bus 1. The ratios of the individual axle weights for the 2-axle bus signals also appear to be reasonable. As mentioned before the ratio for

Table 1: Least Squares Estimation Results

	2-axle bus 1	2-axle bus 2	3-axle bus 1	3-axle bus 2
T (sec)	0.82	0.83	0.81	0.86
Damping Ratio	0.67	0.62	0.61	0.57
Vehicle Speeds (mph)	17.7	18.7	16.5	11.1
axle 1 (lbs)	10,337	8,677	7,227	6,584
axle 2 (lbs)	22,502	25,819	7,875	7,844
axle 3 (lbs)	–	–	29,313	35,992
Total Weight (lbs)	32,841	34,497	34,645	38,423

the 2-axle buses is about 1:2 for the first and second axles.

The weight estimates for 3-axle buses exhibit the same issues seen qualitatively in the raw data in regards to overall magnitudes, but also in regards to relative response seen for each axle. While the ratios of the axle weights is expected to be about 4:5:8 (actual values depend on loading), the estimates given by this method show a ratio more like 1:1:4, with the third axle being significantly heavier than the other two. Closer examination shows this is again generally consistent with the data signal itself in regards to relative peak heights, and so the estimation procedure itself is not introducing undue skewing on its own.

Another method currently used in WIM technology [6] for estimating static vehicle weights is based on the concept of influence lines or Green's functions. The basic idea is to the express the variation of any force or displacement quantity at a specific location in a body due to a unit load at some other arbitrary location as an influence function, and then use this function to model the effects of multiple loads and/or moving loads. This is illustrated in Figure 9 for the common case of a simple beam structure and surface-loaded foundation. In particular, in each case the rotation at an observation point is expressed in terms of a load magnitude and an influence function, G.

For the case of two point loads moving across a simple beam at a fixed interval a, the

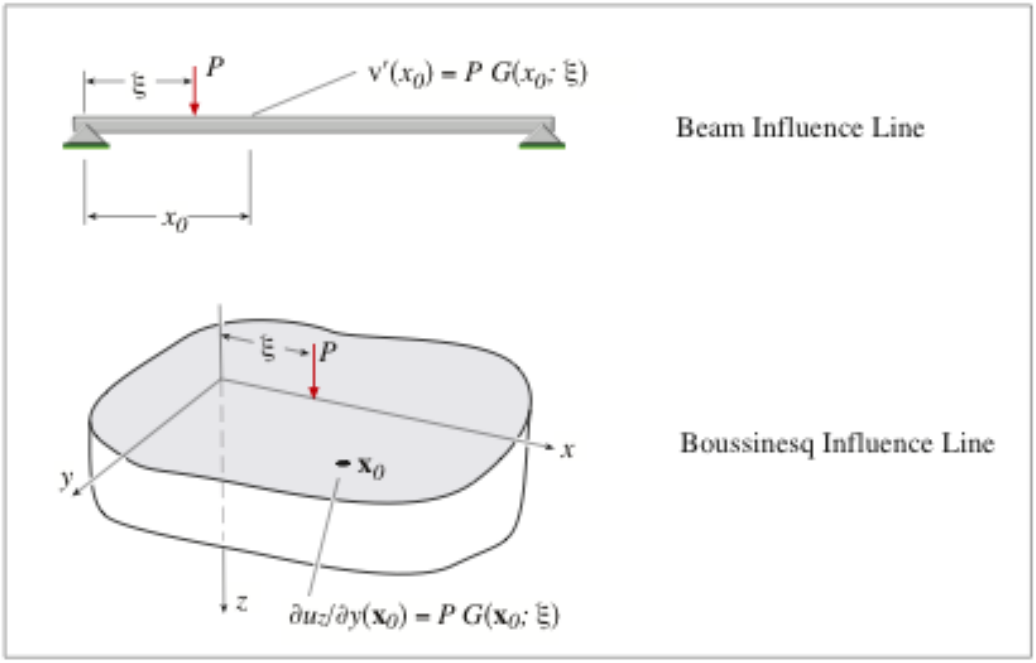

Figure 9: Rotation influence function definitions for some simple linear systems.

rotation $\theta = v'$ of the beam at a location x_0 can be written as

$$\theta(x_0) = P_1 G(\xi_1, x_0) + P_2 G(\xi_2, x_0) \tag{9}$$

$$\theta(\xi_1, x_0) = P_1 G(\xi_1, x_0) + P_2 G(\xi_1 + a, x_0) \tag{10}$$

Taking the integral of both sides leads to

$$\int_{-a}^{L} \theta(x_0, \xi_1) d\xi_1 = P_1 \int_0^L G(\xi_1, x_0) d\xi_1 + P_2 \int_{-a}^{L-a} G(\xi_1 + a, x_0) d\xi_1 \tag{11}$$

$$\int_{-a}^{L} \theta(x_0, \xi_1) d\xi_1 = (P_1 + P_2) \int_0^L G(\xi_1, x_0) d\xi_1 \tag{12}$$

Since the distance ξ is equal to the speed c of the moving load times time t, the combined weights can be calculated as

$$P_1 + P_2 = \frac{c \int_{-a}^{L} \theta(x_0, \xi_1) dt}{\int_0^L G(\xi_1, x_0) d\xi_1} \tag{13}$$

This concept can be extended to the Boussinesq case as shown below.

$$\frac{\partial v_z}{\partial y} = \theta(\mathbf{x_0}) = P_1 G(\xi_1, \mathbf{x_0}) + P_2 G(\xi_2, \mathbf{x_0}) \tag{14}$$

$$\theta(\mathbf{x_0}, \xi_1) = P_1 G(\xi_1, \mathbf{x_0}) + P_2 G(\xi_1 + a, \mathbf{x_0}) \tag{15}$$

$$\int \theta(x_0, \xi_1) d\xi_1 = (P_1 + P_2) \int G(\xi_1, x_0) d\xi_1 \tag{16}$$

$$P_1 + P_2 = \frac{c \int \theta(\mathbf{x_0}, \xi_1) dt}{\int G(\xi_1, \mathbf{x_0}) d\xi_1} \tag{17}$$

Analytically, in this simple model the denominator on the right hand side is only a function of the time t, the speed c of the load and the location $\mathbf{x_0}$ of the sensor, and could be calculated explicitly. The true system, in reality, will be affected by many additional factors which are not known a priori. A more "true" $G(\xi_1, \mathbf{x_0})$ would also be a function of many variables including site specific pavement conditions and weather conditions. But because it is only the integral that is of interest, this quantity can be considered to be a site-specific calibration factor. Thus, the influence lines approach essentially relates the area under the curve of the signal to the total vehicle weight via a calibration factor

$$Q(c, \mathbf{x_0}, \ ...) = \int G(c, t, \mathbf{x_0}, ...) \ c \ dt$$

It is important to note that unlike the Least Squares approach, this simple model neglects the dynamic properties of the sensor. When the method is applied, it is assumed that the measured quantity is the true surface rotation (rather than the response of a dynamic system to the pavement rotations). Despite this inherent shortcoming, the attraction of this kind of method in the current context is that the algorithm is sufficiently simple to be amenable to implementation within the sensor microprocessor itself, and thus to allow realtime embedded estimation. Among other things, this can reduce the amount of data to transmit, and this can significantly reduce power demands.

Proceeding along this line, a calibration factor Q can be determined from the signal caused by a vehicle of a known weight traveling at a known constant speed. If 2-axle bus 1 is assumed to be 33,000 lbs, as before, and the vehicle speed determined by the Nonlinear Least Squares estimate is assumed to be correct, the calibration factor Q is calculated as

$$Q = \frac{29.10 \text{ V} \cdot \text{sec} \times 17.7 \text{ mph}}{33000 \text{ lbs}} = 0.0156 \tag{18}$$

Weight estimates for all four sample signals calculated with this calibration factor are shown in Table 2.

Table 2: Estimation Based on Influence Lines

Influence Lines Estimation				
	2-axle bus 1	2-axle bus 2	3-axle bus 1	3-axle bus 2
Total Areas (V·sec)	29.1	23.4	22.6	41.2
Weights (lbs)	33000	28035	23891	29300
Peak Values Estimation				
	3-axle bus 1	3-axle bus 2	2-axle bus 1	2-axle bus 2
axle 1 (lbs)	10299	9774	4729	6054
axle 2 (lbs)	22701	25223	5570	7777
axle 3 (lbs)	–	–	13662	25748
Total Weight (lbs)	33000	34997	23962	39579

There are a few things to note about the results of the Influence Lines estimation. First, the 2-axle bus 2 receives a lower weight estimate than 2-axle bus 1 even though it has higher peaks. This is because it also has larger negative values in the dip between the peaks. Since the Influence Lines approach does not take into account the dynamic properties of the sensor, it assumes that rotation measurements will only be positive. This issue can be dealt with in various ways. For example, a low-pass filter may be able to remove the negative dip between peaks. Although it might also reduce the height of the peaks, that effect would be applied to all data samples including the one used for calibration, and will be investigated in future work.

Another even simpler estimation method used in some WIM systems is simply based on relating the peaks of the response to the corresponding axle weights. If again the 2-axle bus 1 weight is taken to be 33,000 lbs, then, with the two peaks of the signal equal to 0.49 volts and 1.08 volts, the calibration factor is 0.04757. This factor was applied to all four sample signals, and the results are shown in Table 2.

Unlike methods based on areas, this method directly gives larger weights for larger signal magnitudes. However, because this method does not take vehicle velocity into account,

the issue of the second 3-axle bus weight being significantly greater than the first is a potential drawback of this method. Again, there are various statistical/empirical methods one could use to address this shortcoming, although the the key would be to try to achieve embeddable algorithms, if possible.

7 Conclusions and Recommendations

As mentioned earlier, this has been a preliminary study, and so the conclusions to be drawn are more indicative than definitive. Nevertheless, there are several basic conclusions to be drawn from the results of this work:

1. The sensors developed for this study have the required sensitivity to measure pavement deformations caused by passing vehicles.

2. Different pavement types create different dynamic response for the same vehicle type. In particular, jointed rigid type pavement can create significant effects when vehicles pass over the joints.

3. The signals obtained show clear patterns for facilitating vehicle classification. Vehicles of different types produce noticeably different signatures. Different signals caused by the same vehicle type have the same basic shape, showing repeatability.

4. Vehicle speed can be estimated from the signals.

5. Weight estimation techniques similar to those used for other sensing devices can be used effectively.

6. Vehicle distance from the sensor is a key parameter for flexible pavement.

7. The cost is well under $100 per sensor, so deploying larger numbers of these sensors in the future is feasible.

The overriding conclusion at this point, though, is that much more refinement, testing, and observation is required to develop a practical system, and the real key will be to implement arrays of such sensors to obtain the benefits of multiple observations. Although

not presented here, more refined versions of the sensing devices used to date have been developed recently that would be well-suited to larger scale production. Also, Hewlett-Packard is currently developing a MEMS sensor with specifications that may be adequate for this application, and so the initial goal of using existing MEMS technology may come back on the table. With larger numbers of sensors available, field tests with accurately known weights, dimensions, and geometries must be conducted with a range of vehicle, roadway, and ambient conditions. This having been said, the ability to gather weight-related and other kinds of vehicle data on the kind of scale that such a low-cost approach would make possible makes a compelling case for pursuing this line of research further.

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