2008 American Control Conference
Westin Seattle Hotel, Seattle, Washington, USA
June 11-13, 2008

Friction Coefficient Measurement System for Winter Maintenance Vehicles

G. Erdogan, L. Alexander, R. Rajamani, *Senior Member, IEEE*

Abstract—**Real-time measurement of tire-road friction coefficient is extremely valuable for winter road maintenance operations. In winter maintenance, knowledge of tire-road friction coefficient can be used to optimize application of deicing and anti-icing chemicals to the roadway.**

In this paper, a wheel based tire-road friction coefficient measurement system is developed for snowplows. Unlike a traditional Norse meter, this system is based on measurement of lateral tire forces, has minimal moving parts and does not use any actuators. Hence, it is reliable and inexpensive. A key challenge is quickly detecting changes in estimated tire-road friction coefficient while rejecting the high levels of noise in measured force signals. Novel filtering and signal processing algorithms are developed to address this challenge including a biased quadratic mean filter and an accelerometer based vibration removal filter.

Detailed experimental results are presented on the performance of the friction estimation system on different types of road surfaces. Experimental results show that the biased quadratic mean filter works very effectively to eliminate the influence of noise and quickly estimate changes in friction coefficient. Further, the use of accelerometers and an intelligent algorithm enables elimination of the influence of driver steering maneuvers, thus providing a robust friction measurement system under all operating conditions.

I. Introduction

Determining the optimum amount of chemicals that need to be applied for maintaining a safe road surface condition in winter is an application where measurement of tire-road friction coefficient could be utilized effectively. Many highway agencies in Europe, Japan, and the U.S. have come to believe that surface friction measurements may form the basis for improved winter maintenance operations and mobility [1]. Efficient use of deicing material, correct road location and time for the maintenance, minimum environmental damage and minimum cost are the main goals for the design of an advisory or automated system.

Several research papers [5-8] have been published so far about vehicle-based tire road friction coefficient estimation systems. These systems are based on measurement of the vehicle's motion through sensors such as GPS, lateral and longitudinal accelerometers, wheel speed and yaw rate. However, most of these proposed systems require a certain minimal amount of slip of the vehicle's tire, either through acceleration-deceleration maneuvers or else through steering maneuvers. The friction coefficient cannot be estimated when neither acceleration, deceleration nor steering occurs [3].

Wheel based friction measurement systems utilize a redundant wheel and are appropriate for heavy duty trucks such as snowplows. The Norse meter is a commercialized wheel based system which is used in winter road maintenance. The Norse meter requires a dedicated operator and an actuator to skid the additional wheel on the roadway at timed intervals. The new wheel based system described in this paper for the same purpose has several advantages over this traditional system.

The wheel based system developed in this paper employs an additional wheel which is at an angle with the travel direction of the snowplow. Due to this angle, namely the slip angle, a continuous lateral force is generated at the tire. The continuous force signal enables the design of an autonomous system which is very beneficial for the maintenance of roadways. The measured lateral force signal is filtered and processed in real time with the help of some novel algorithms developed for reliably estimating the tire-road friction coefficient. The road surface condition is precisely evaluated with the tire-road friction coefficient and a control signal is sent to the winter chemical applicator using the output of a change detection algorithm.

II. New Friction Measurement System

A. System Specifications

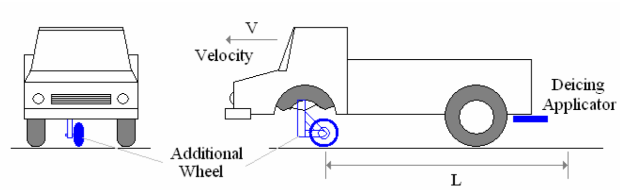

Fig. 1. Winter Road Maintenance System.

The designed Automated Winter Road Maintenance System is composed of an additional wheel, a load cell, a

This research was supported in part by a contract from the Minnesota Department of Transportation.

G. Erdogan is with the University of Minnesota, Minneapolis, MN 55455 USA (phone: 612-626-2010; e-mail: gurkan@ me.umn.edu).

L. Alexander is with the University of Minnesota, Minneapolis, MN 55455 USA (e-mail: alex@ me.umn.edu).

R. Rajamani is with the University of Minnesota, Minneapolis, MN 55455 USA (phone: 612-626-7961 e-mail: rajamani@ me.umn.edu).

data processing unit and the deicing applicator of the snowplow. The additional wheel is located near the front axle of the snowplow, while the deicing applicator is located at the back as in figure 1.

Since a real-time system is desired, only a limited time is available for data processing. The available data processing time depends up on the vehicle's speed and the distance from the front wheel to the deicing applicator. In other words, after the additional wheel passes over a road surface transition, the processor has a total time of L/V seconds to send a control signal to the applicator. Minimum available time occurs at the highest snowplowing speed and the goal is to keep the data processing time less than the minimum available time. Various snowplowing speeds and corresponding available times are listed in table 1.

Truck Speed [mph]	Available Time [msec]
20	671
30	447
40	336
50	268

Table 1. Truck Speeds vs. Available Times for Data Processing

B. *Description of Friction Coefficient Measurement System*

A top view schematic and a side view photo of the developed wheel based system are given in figure 2. The additional wheel is oriented at an angle to its traveling direction. This angle is called the tire slip angle and it causes the tire to generate a lateral force continuously [3]. A pneumatic dashpot with a constant air pressure applies a constant normal force to the wheel. Since the normal tire force is fixed and since the slip angle is large ($\alpha \sim 5^o$) enough, the lateral force is proportional to the tire-road friction coefficient. By measuring the lateral tire force and after adequate signal processing, one can estimate the tire-road friction coefficient.

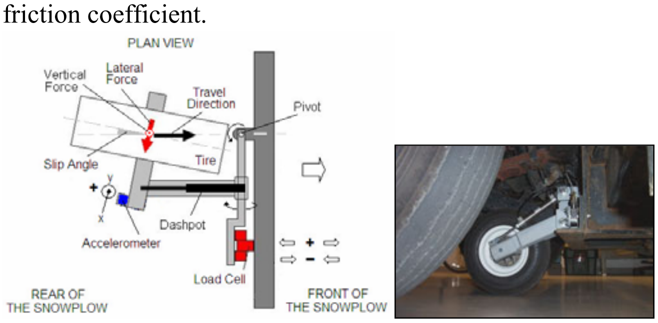

Fig. 2. Wheel Based System

A pancake type load cell is used to measure the lateral force through the moment arm turning about the pivot as indicated in figure 2. The load cell produces a negative voltage under compression forces and a positive voltage under tension forces. Only the lateral tire forces at the contact patch are measured by the load cell since the centerline of the contact patch is aligned with the vertical hinge. An inexpensive, two dimensional MEMS accelerometer is used to detect and filter out the noise on the force signal. The X axis accelerometer measures the lateral acceleration while the Y axis accelerometer measures the vertical acceleration of the center of the additional wheel. The vertical axis of the accelerometer produces a positive voltage while accelerating in the upward direction and a negative voltage while accelerating in the downward direction.

III. Fundamental Technical Challenges

A. *Technical Challenges*

There are two main technical challenges to be addressed in developing a friction estimation algorithm with the proposed redundant wheel based system.

1) *Enormous Noise on the Force Signal*

A major technical challenge in the design of the wheel based system is the excessive noise on the load cell signal mainly caused by the oscillations of the truck body or by the excitations from the bumps and dips on the roadway. Due to the high variance of the noise on the force signal, it is hard to detect any change on the road surface by using the raw force signal, as seen from figure 3.

2) *Variations due to Steering*

When the driver is steering, the lateral force measured by the instrumented wheel changes. It is important to compensate for these steering induced changes in order to correctly identify the tire-road friction coefficient.

B. *Physical Interpretation of Noise Generating Mechanism*

A typical force signal measured by the load cell and an arithmetic mean (AM) filtered version of it are shown in figure 3. The force is measured while the snowplow is traveling on a dry asphalt road in the first four seconds and on an icy road in the following four seconds. The step change due to the road surface transition at the fourth second cannot be easily distinguished because of the high variance of the noise, especially on the dry asphalt region. A careful analysis of the system and the force signal reveal some clues about the dominant noise generating mechanism and the associated frequency bands.

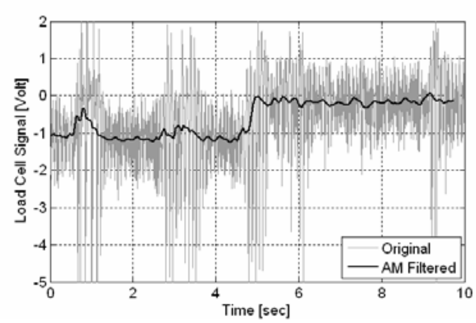

Fig. 3. Typical Force Signal

When we take a closer look at the noise on the dry asphalt region, we see that the signal is negatively skewed, meaning that the tail of the distribution under the mean is longer than the tail of the distribution over the mean. We can also see that the absolute mean value of the signal decreases as the variance of the signal increases. The physical interpretation of this type of behavior is explained in the following paragraphs and the disturbances coming from the roadway play an important role as a noise generating mechanism in this interpretation.

As we have mentioned previously, the wheel based system is designed in such a way that the load cell only measures the lateral tire force (F_{lat}) which is a function of both the tire-road friction coefficient (μ) and the normal tire force (F_N):

$$F_{Lat} = \mu \times F_N \tag{1}$$

The pneumatic dashpot applies a constant normal force to the additional wheel, but does not really help to reduce the tire deflections due to the disturbances coming from the roadway. So, the roughness of the roadway introduces a high frequency noise on the normal tire force which engenders a similar type of noise on the lateral tire force according to the equation 1.

Each time the additional wheel passes over a relatively bumpy spot on the roadway, it vertically starts to vibrate between the ground and the dashpot. The negative skewness of the lateral tire force is due to the transient normal forces occurring as the wheel bounces from the ground, while the reduction of the absolute mean value of the signal is due to the low impedance of node on the dashpot side. In other words, the vertical vibrations of the wheel loosen the contact patch between the tire and the road, causing a reduction in the lateral force. This slower change in the lateral tire force can be seen on an arithmetic mean filtered force signal as in figure 3. In summary, as an inherent property of the designed system, the absolute mean value of the force signal decreases whenever the variance of the force signal increases.

This interpretation can best be proved by the high correlation coefficient observed between the vertical acceleration and the load cell signals at high frequencies. This will be discussed in more detail in the following sections.

C. *Frequency Content of Force Signal*

The FFT spectrum of a typical force signal measured on a dry asphalt road is given in figure 4. By using this frequency spectrum we can clarify what a meaningful signal is and define which frequency ranges correspond to low and high frequency noise.

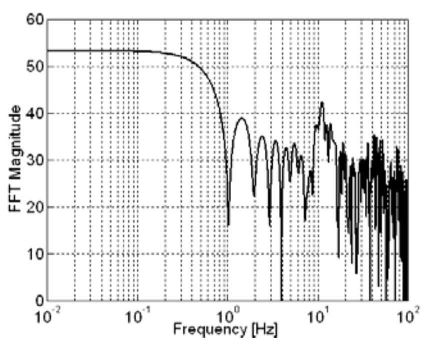

Fig. 4. FFT Spectrum of a Typical Force Signal

A meaningful signal is a change in the force signal only due to a road surface friction condition change. We assume that the frequency content of the noiseless signal is very close to zero frequency, i.e. to the DC component. Low frequency noise will correspond to the frequencies lower than 1 Hz excluding the DC component, whereas high frequency noise corresponds to the frequencies higher than 1 Hz. The energy of the high frequency noise of a typical force signal is mainly centered between 10 Hz and 20 Hz as seen in figure 4.

IV. Filter Development

A. *Low Pass Filter Performance*

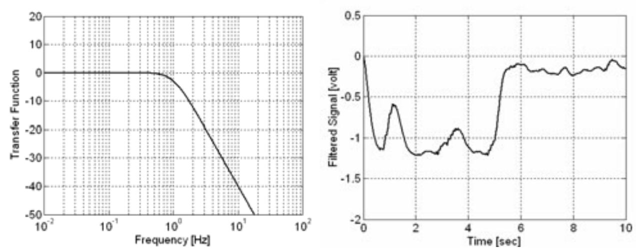

Fig. 5. 2nd Order Butterworth Low Pass Filter and the Filtered Signal

Ideally, a filter with a cut off frequency close to zero frequency (~0.1Hz) and with a sufficient amount of noise reduction (~25dB) at low frequencies (~0.5Hz) is required.

It is not possible to design a linear low pass filter that could meet both the filtering specifications and the data processing time constraint due to the real-time requirements of the system. As an example, a 2nd order Butterworth low pass filter is designed in MATLAB. The frequency response of the designed filter is given in figure 5. The cut-off frequency is picked as 1 Hz so as to meet the real-time requirements of the system. However, the filter does not meet the filtering specifications, as seen in figure 5 where significant low frequency oscillations can be seen in the signal. Consequently, new filtering algorithms need to be developed for removing very low frequencies in reasonably quick time.

B. *Design Based on Biased Quadratic Mean Filter*

A new filter is designed based on a modified quadratic mean filter (QMF) by exploiting the relationship between the mean and the variance of the force signal which is inherent in the dynamics of the proposed friction coefficient measurement system as discussed previously. The variance takes care of filtering the low frequency oscillations on the force signal, leading to a faster and better filtering performance at low frequency bands.

The definition of a QMF is given in equation 2, where x_i is the sampled signal, m is the number of samples in a moving time window and N is the size of the sampled signal.

$$y_j = \sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} (x_i)^2} \qquad j = 1 : N-(m-1) \tag{2}$$

The output of QMF is nothing but the (moving) root mean square (RMS_j) of the signal which can be written in terms of the moving average (μ_j) and variance (σ_j^2) of the signal as in equation 3 [4].

$$y_j = RMS_j = \sqrt{\mu_j^2 + \sigma_j^2} \qquad (3)$$

The quadratic mean filter can be modified to utilize the dynamic relationship between the mean and the variance for removing the low frequency oscillations. The new biased quadratic mean filter algorithm introduces a constant bias (K) which is unique to the measurement system and valid for all snowplow speeds.

$$y_j = -\sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} (x_i + K)^2} - K \quad j = 1 : N - (m-1) \qquad (4)$$

From equation 4, the following relation between the moving average (μ_j) and the variance (σ_j^2) can be deduced:

$$y_j = -\sqrt{\sigma_j^2 + (\mu_j + K)^2} - K \quad j = 1 : N - (m-1) \qquad (5)$$

The proof of this relation is given in equation 6.

$$\begin{aligned} y_j &= \sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} (x_i + K)^2} \\ &= \sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} x_i^2 + \frac{1}{m}\sum_{i=j}^{j+(m-1)} 2x_i K + \frac{1}{m}\sum_{i=j}^{j+(m-1)} K^2} \\ &= \sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} (x_i - \mu_j + \mu_j)^2 + 2K\,\mu_j + K^2} \\ &= \sqrt{\frac{1}{m}\sum_{i=j}^{j+(m-1)} (x_i - \mu_j)^2 + 2\mu_j^2 - \mu_j^2 + 2K\,\mu_j + K^2} \\ &= \sqrt{\sigma_j^2 + (\mu_j + K)^2} \end{aligned} \qquad (6)$$

As we have explained previously, the absolute mean value of the force signal decreases/increases whenever the variance of the force signal increases/decreases according to the physical interpretation of the system. This implies that the low frequency oscillation on the square mean value (μ_j) signal is approximately 180^o out of phase with the low frequency oscillation on the variance (σ_j^2). Hence, an appropriate bias value should be chosen so that the oscillations on both signals cancel out each other. If the magnitude of the square mean value oscillations is less than the magnitude of variance oscillations, K should have the same sign as μ_j.

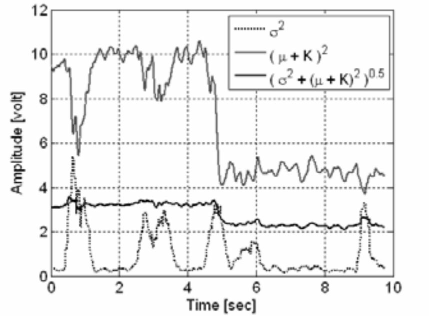

Fig. 6. Biased Quadratic Mean Filter

If we assume that the oscillations on the $(\mu_j+K)^2$ signal and the variance have the same magnitude and are perfectly out of phase, by adding them up we can completely remove the low frequency oscillations and find a constant output such as $y_j=A$ which only changes with respect to the friction coefficient as is shown in figure 6.

We can write the mean value as a function of the standard deviation.

$$\mu_j = \sqrt{(A+K)^2 - \sigma_j^2} - K \qquad (7)$$

We could solve equation 7 for the bias value, if we know the noise statistics and the exact value of the current friction coefficient. Alternately, we can also use the statistics and the mean value over a long period of time to update the value of the bias.

A Hann type weighting function is used while averaging the time windows. The Hann window is mostly effective in the filtering of high frequency bands rather than the low frequency bands.

C. New Filter Design Aided by Accelerometer Measurements

An alternate new filter, aided by accelerometer measurements, is designed to remove both low and high frequency noise from the signal. An accelerometer, measuring the vertical accelerations, is located at the center of the additional wheel as shown in figure 7.

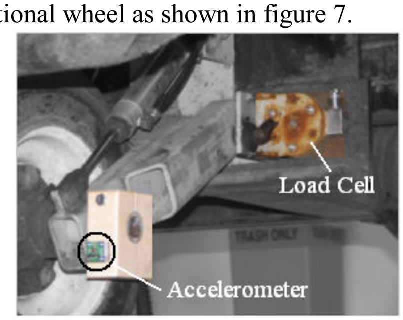

Fig. 7. Accelerometer and Load Cell Locations

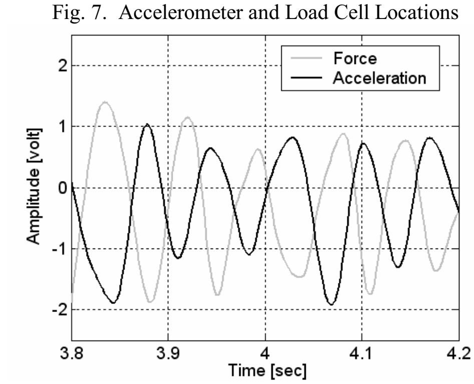

Fig. 8. Force and Acceleration Signals

Smoothed force and acceleration signals are plotted together and zoomed in for a 400 msec time span in figure 8. This plot clearly shows that the high frequency noise (~10Hz) on the force and the vertical acceleration signals are inversely correlated. This also supports the assumption that the high frequency content of the measured lateral force signal is mostly due to the high frequency changes in the normal tire force caused by roughness of the roadway. The acceleration signal can be utilized to remove the noise since it is related to the variance of the noise while being indifferent to step changes in the force signal. When we look at the force and acceleration signals together, we see a certain amount of time delay between them. Because of this time delay and the excessive noise, the raw signals do not seem to be correlated enough to be utilized directly in a filter design. However, the correlation coefficient between the signals can be increased significantly by simply smoothing the two signals and shifting them with respect to each other.

After smoothing out both signals with an arithmetic mean filter using a Hann window, the shifting process is applied. The shifting algorithm is defined as follows;

- Predefine a set of time (time-step in discrete time) delays as in equation 8.

$$P = \{-3,-2,-1,0,1,2,3\} \tag{8}$$

- Shift the accelerometer signal as much as the time delay values in the set, once at a time.
- Calculate the correlation coefficient between the force and the shifted accelerometer signal for each and every time delay in the set p.

$$C_{yf}(p) = \frac{\sigma_{yf}(p)}{\sqrt{\sigma_{yy}\,\sigma_{ff}}} \tag{9}$$

- Find the required shift corresponding to the time delay that maximizes the correlation coefficient

$$\overline{p} = \{p : p \in P \quad \& \quad C_{yf}(p) = \max[C_{yf}(p)]\} \tag{10}$$

The time delay set can be expanded according to the anticipated time delay range and the capacity of the processor. There is no unique time delay between the signals, so we have to update the time delay between the signals in every time step. However, this updating process can be done less frequently, if the desired data process time is exceeded.

Finally, the algorithm requires the addition of smoothed and shifted versions of accelerometer and load cell signals in every time step to cancel out noise on the force signal. The sum is passed through a secondary arithmetic mean filter to remove the higher frequency components of the noise.

D. Comparing Filter Performances

A performance metric can be defined for assessing the filter performances in terms of the main goal of the system. Signal-to-noise ratio, as it is given in equation 11, is one way of defining such a metric. In this formula, “high” and “low” subscripts indicate two different levels of the signal, namely the dry asphalt and icy road regions respectively. The signal-to-noise ratio basically gives an idea how reliably a filtered signal could be used in a change detection algorithm

$$SN = \frac{\mu_{high} - \mu_{low}}{\sigma_{high} + \sigma_{low}} \times 100 \tag{11}$$

The signal-to-noise ratio comparison of the filters is presented in table 2. The cut-off frequency of the Butterworth filter in this table is set to 1Hz, so that it is fast enough to be within the limits of the real-time system and comparable with the designed filters.

Low Pass Filters	Signal to Noise Ratio
Butter Worth Filter	1.9
Quadratic Mean Filter	4.0
Accelerometer Aided Filter	7.8

Table 2. Performances of Different Filters

Results show that both of the designed filters perform better than a typical linear low pass filter. Further, the vertical acceleration signal seems to contribute to the filtering performance significantly. The experimental results provided in the following sections at various snowplow speeds are very compatible with this ranking.

V. Snowplow and Experimental Hardware

The vehicle used to conduct the experiments is a full sized snowplow manufactured by Navistar International Truck Company as shown in figure 9.

Fig. 9. The SAFEPLOW used for the experiments

The front axle of the snowplow had Goodyear G159 11R24.5 tires while the rear axle had dual Goodyear G124 11R 24.5tires. A computer data acquisition, signal processing and real-time control system were utilized. The real-time software consisted of C-code written for quasi real-time operation in the Windows operating system with a sampling frequency of 400 Hz. A PCI Sensorray 626 data acquisition system was utilized. A Sensotec load cell for force measurements and dual axis accelerometers from Analog Devices were the primary sensors that were used.

VI. Detailed Experimental Results

Several tests are done to evaluate the performance of the designed autonomous road maintenance system. First, the effects of acceleration, deceleration and steering maneuvers on the measurement system are examined. And then, the developed filtering algorithms are tested on a skid-pad having a surface transition from dry asphalt to ice, at different snowplow speeds.

A. Effects of Acceleration, Deceleration and Steering

Due to lack of space, experimental results on the effect of acceleration, deceleration and steering are not discussed in this conference paper. Algorithms have been developed and implemented to remove the influence of both longitudinal and lateral maneuvers on the force signals measured by the instrumented wheel.

B. Skid-Pad Tests

The test environment is a special, closed-to-traffic roadway with a length of approximately 0.5 km. Two thirds of the road surface is dry asphalt, while the rest is covered with hard ice. The transition from dry asphalt to icy road does not occur abruptly, rather gradually through a road surface composed of a mixture of wet asphalt and soft ice.

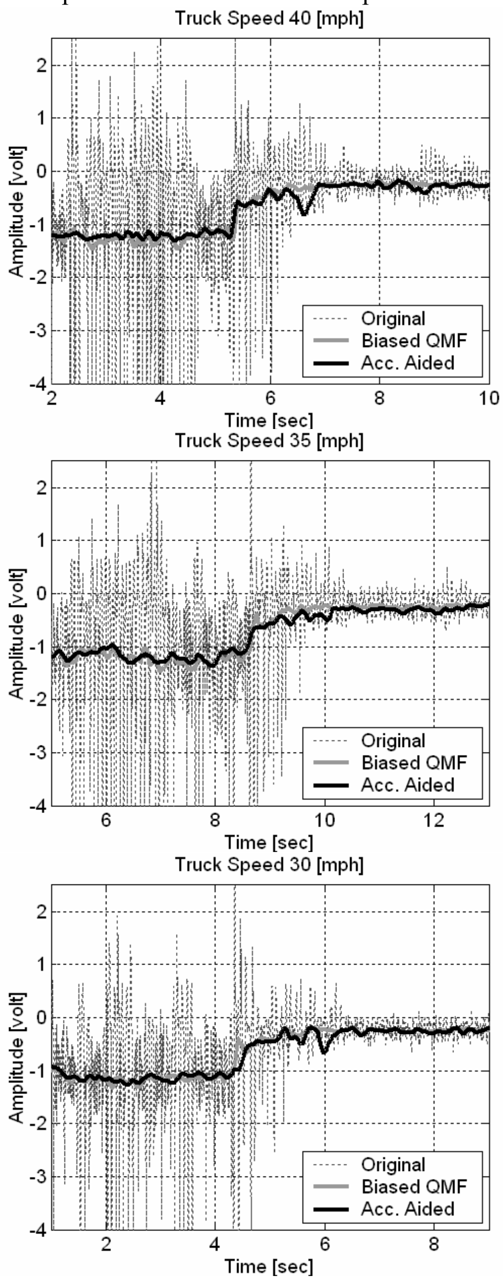

Fig. 10. Test Results at Various Truck Speeds

The original force signal and the performances of the developed filters at different snowplow speeds are presented in figure 10. The speeds, ranging from 10mph to 40mph, cover the speed range in which the snowplows operate in real-life during application control. The variance of the excessive noise on the original force signal tends to increase as the speed of the snowplow increases. Both filter algorithms perform well and operate fast enough to satisfy the real-time requirements of the system at different speeds.

However, in some of the measurements, it is observed that after a few seconds when the snowplow passes over the asphalt-to-ice transition, the output of the accelerometer aided filter falls remarkably. This type of behavior can be seen in the 30mph and 40mph plots, in figure 15. A bumpy spot is determined on the icy roadway where this incident happens according to the time axis. The reason for the poor performance of the accelerometer aided filter in this bumpy spot on the icy road is the reduction of the tire-road friction coefficient. The accelerometer measurements are highly affected by the vertical force oscillations coming from the roadway, but only a small portion of these vertical tire force oscillations are converted into the lateral tire force oscillations through equation 1 since the friction coefficient of the icy road is low. Because of the disproportional amplitude of vertical acceleration and lateral force signals, the accelerometer aided algorithm does not perform very well during this bump while removing the excessive noise.

On the other hand, the biased quadratic mean filter performs better than the accelerometer aided filter, when the wheel passes over such a bumpy spot on the icy roadway. The reason for this is that the biased QMF uses the variance of the original force signal rather than the accelerometer signal to quantify the noise. In other words, the algorithm does not rely on equation 1 and so is not affected by any reduction of the friction coefficient.

In general, the accelerometer aided filter performs better on dry asphalt road with high noise levels, while biased QMF performs reasonably well on both dry and icy roads. Since QMF based filtering depends directly on the variations of the noise on the force signal, it is more reliable than the accelerometer aided filter, and thus recommended for this snowplow application.

REFERENCES

[1] I. L. Al-Qadi, A. Loulizi, et. al., “Feasibility of Using Friction Indicators to Improve Winter Maintenance Operations and Mobility”, NCHRP Web Document 53, November 2002

[2] J. Wang, P. Agrawal, L. Alexander, R. Rajamani, “An Experimental Study with Alternate Measurement Systems for Estimation of Tire-Road Friction Coefficient”, Proceedings of the 2003 American Control Conference, Denver, Colorado, June 2003

[3] R. Rajamani, “Vehicle Dynamics and Control”, Springer Verlag, ISBN: 978-0-387-26396-0, 2006

[4] I. Miller, J.E. Freund, “Probability and Statistics for Engineers”, ISBN: 978-0-131-43745-6, Aug 2004

[5] F. Gustafsson, “Slip-based tire-road friction estimation,” Automatica, vol. 33, no. 6, pp. 1087–1099, June 1997.

[6] James Lacombe, “Tire Model for Simulations of Vehicle Motion on High and Low Friction Road Surfaces”, Proceedings of the 2000 Winter Simulation Conference, 2000

[7] J. O. Hahn, R. Rajamani, A. Lee, “GPS-based real-time identification of tire-road friction coefficient”, IEEE Transactions on Control Systems Tech., v 10, n 3, May, 2002, p 331-343

[8] S. Muller, M. Uchanski, K. Hedrick, “Estimation of the Maximum Tire-Road Friction Coefficient”, ASME Journal of Dynamic Systems, Measurement and Control, v 125, n 4, December, 2003, p 607-617.