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Anti-Lock Brake System Acceleration Analysis with Wavelet Transforms

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Abstract

In Run-off-Roads scenarios, vehicles can encounter multiple road surfaces between the two sides of the axle while braking. The efficiency for braking depends entirely on the friction level which is a function of both road and tire parameters. Research on multiple friction surfaces is limited to simulations with minimum in situ testing. This document investigates vehicle performance in terms of acceleration, under full braking for different split-surface scenarios. To characterize friction profiles during braking, a Wavelet Transform Filter approach is proposed. Testing results show that split-road conditions offer better braking performance, and prevent significant vehicle instability. Similarly, data analysis shows that Wavelet Transform Filter offers a reliable tool for characterizing multiple friction surfaces from acceleration data.

Keywords: Acceleration Analysis, Signal Processing, Wavelet Transform, Anti-Lock Braking, Vehicle Performance, Vehicle Stability.

Introduction

Motivation

Anti-Lock Braking Systems (ABS) serve to prevent vehicle locking by maintaining a proportional decrease in wheel speed to forward vehicle speed during braking events. Electronic Stability Control (ESC) systems take advantage of ABS to maintain a constant yaw direction to prevent spin out scenarios through applying different braking pressures to compensate for uneven surfaces. Extensive research has been performed evaluating models of ABS and ESC with successful implementations in vehicles [][][]. The performance of these systems rely entirely on the tire-road interaction that occurs while braking. For this reason, extensive research has been performed on determining appropriate coefficients of friction (COF), for multiple tire-surface interactions [][][].

However, there is minimum research on scenarios where the vehicle encounters two surfaces simultaneously or changes in friction surfaces. High speed scenarios where the vehicle is deviated from the highway road can force a driver to either maintain a split surface path or switching to a different road surface altogether. This lead to a study of split road surfaces with Wavelet Transforms conducted at the University of Nebraska – Lincoln (UNL).

Conventional methods for determining COF involve a full braking test in which the average acceleration (in g’s) of the braking event determines the COF for the corresponding tire-surface pair []. In this paper, this method is expanded upon the introduction of wavelets decomposition for acceleration data. In signal analysis, decomposition methods are used to filter out noise and preserve the nature of the true signal that the system has. The most common technique for this is Fourier Signal Decomposition, in which the signal is modeled through sinusoids and filtered through Fast Fourier Transforms (FFT). During braking events, the ideal acceleration profile has a ramp-up function followed by a constant, and a ramp-down function. These profiles are harder to model through Fourier Decomposition because of the noise present in the signal and the desired ideal profile (i.e. non-periodic, non-smooth profiles). For this reason, a different approach was obtained through the use of Wavelet Decomposition. The results show a promising method for acceleration profile filtering through the use of Coiflet Wavelet Filtering.

The remainder of this paper explains the baseline parameters for ABS profiles, describes the Wavelet Formulation to filter the acceleration data. The results obtained from the experimentation on split-surfaces are discussed, and the effectiveness of Coiflet Wavelet Filtering thereof. A section of Recommendations and Conclusions are offered for further investigation on Split-Surfaces, and Coiflet Filtering.

ABS Acceleration Profiles

ABS exerts braking forces at different frequencies in order to prevent wheel lock, which can lead to skidding and tire burn out. The forces actuated by ABS maintain a quasi-linear deceleration rate which depends on the relationship between the forward vehicle velocity and forward wheel rotational velocity. This is quantified, through the slip ratio defined as:

Where:

S = Slip Ratio

v = Forward Velocity of Vehicle (m/s)

= Wheel Speed (rad/s)

r = Wheel Radius (m)

In practice, the slip ratio should be kept in a range close to 20 percent to prevent wheel lock while maintaining maximum friction developed at each tire simultaneously []. During these events, the ideal acceleration profile determined by physics resembles Figure ###.



In general, the profile is dependent on the tire-road interactions []. Such that different tires and different road surfaces interact differently, changing parameters such as rise time, height, and fall time of the profile. However, the COF of the road varies greatly higher compared to that of the rubber tires (i.e. assuming not high-performance tires). In braking scenarios, rise time, and fall time differ while the amplitude of the signal maintains a constant slope. Maximum COF’s are determined to be the highest amplitude obtained from the acceleration profile. In practical applications, COF is the average over the range in which the acceleration holds a constant value (with acceleration measured in G’s).

Wavelet Filtering Formulation

Wavelet Background

In data processing, signal waves are an oscillating function defined in time and space, such as sinusoids. These sinusoids are used as basis functions to construct any periodic signal. Such construction is known as a Fourier Series representation. This is done with a Fast Fourier Transform (FFT) to filter signals by finding the frequency content that represents the desired signal and removing all other frequencies that are categorized as noise. This method has limitations in terms of locating the time event of the frequencies captured. One primary disadvantage of sinusoids is that simple discontinuities (i.e. sharp edges), are subject to Gibbs phenomena in which the signal reconstructions create artificial cusps which can only be avoided by infinite summations (i.e. not practical computationally) []. For these reasons, wavelets were introduced to compensate for the limitations on representing signals with Fourier Series. Wavelets can be interpreted as a small wave with its energy concentrated in a position in time. These wavelets serve as the new basis functions that can decompose signals that are non-periodic while maintaining information about both frequency and time contents.

To exemplify a signal decomposition in wavelets, a Fourier series decomposition is shown in Figure ### for a direct comparison. Instead of sines and cosines, the wavelet decomposition is composed of two functions: The Scaling Function and the Wavelet Function. Similar to sines and cosines, both the scaling and wavelet functions are orthogonal functions that are linearly independent of each other.

Fourier Series Decomposition:

Wavelet Decomposition:

The coefficients c and d can be found through the principle of inner product for orthogonal functions. These coefficients receive the name of Discrete Wavelet Transform (DWT) Coefficients, which is analogous to the FFT Coefficients for signal decomposition. In general, the “d” coefficients serve to make a level of decomposition [1]. Instead of a basis function in the form of a sine or a cosine, wavelets have the advantage of an infinite range of Wavelet functions available for signal construction. In general, the scaling function has the following form below, where consists of scaling coefficients.

To define a Wavelet Function, the scaling function from before is used with a shift, along with some Wavelet Coefficients h\_1 (n) as shown below.

Wavelet Selection: Coiflet

The base function selected for the Wavelet Signal Decomposition is the Coiflet 2, which is shown in Figure ###. The selection was based upon having a function that can handle discontinuities, and the time series for this wavelet favors a non-equal rise time and fall time for the signal. This was taken into consideration to resemble the ideal acceleration profile under ABS braking.

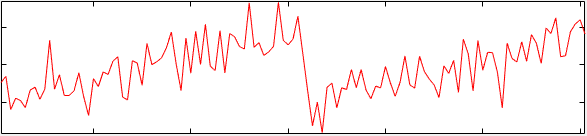


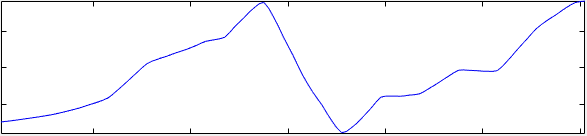
Figure – Coiflet 2

The formulation of this Wavelet Transform Filter utilized the MATLAB Wavelet Tool Analyzer, with it, the procedure can be summarized as follows:

* Obtain a Wavelet Decomposition using a Coiflet 2 Wavelet at a level 6 decomposition to obtain an approximation.
* Run a moving average filter with the Wavelet approximation that detects sudden brake changes with its average values.
* Detect changes by a user defined threshold
* Store data that surpasses threshold
* Repeat

A sample noisy signal is shown in Figure ### (top) that is subject to a Coiflet 2 Wavelet with a 3 level decomposition. Its DWT coefficients are then to approximate the reconstructed signal (bottom).





Raw Signal (top) and Reconstructed Signal Approximation with DWT Coefficients (bottom)

Experimental Setup

Testing was performed at Midwest Roadside Safety Facility testing grounds. The vehicle used was a 2007 Crown Victoria in which, friction testing parameters were evaluated in a previous study []. The testing equipment included a DTS and a VC4000 data recording systems. Vehicle and instrumentation are shown in Figures ####.

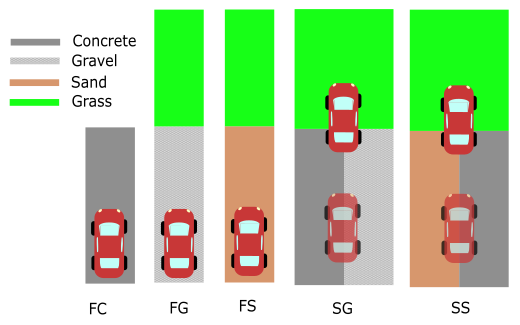


Figure 2007 Ford Crown Victoria



Figure DTS Data Recording (Left), and VC4000 Data Recording (Right)

To test ABS acceleration performance, 4 surface types were organized in 5 different braking scenarios. First, a full concrete (FC) baseline is used to measure standard ABS braking performance. The following two involves testing under full gravel (FG) and full sand (FS) surfaces. The last two were split gravel with concrete (SG), and split sand with concrete (SS). All test beds except for the concrete baseline, had a subsequent grass bed for the vehicle to keep braking. These tests are illustrated in Figure ###, and the testing bed is shown in Figure ####. Every test was repeated twice for reproducibility, which gives a total of 10 tests.

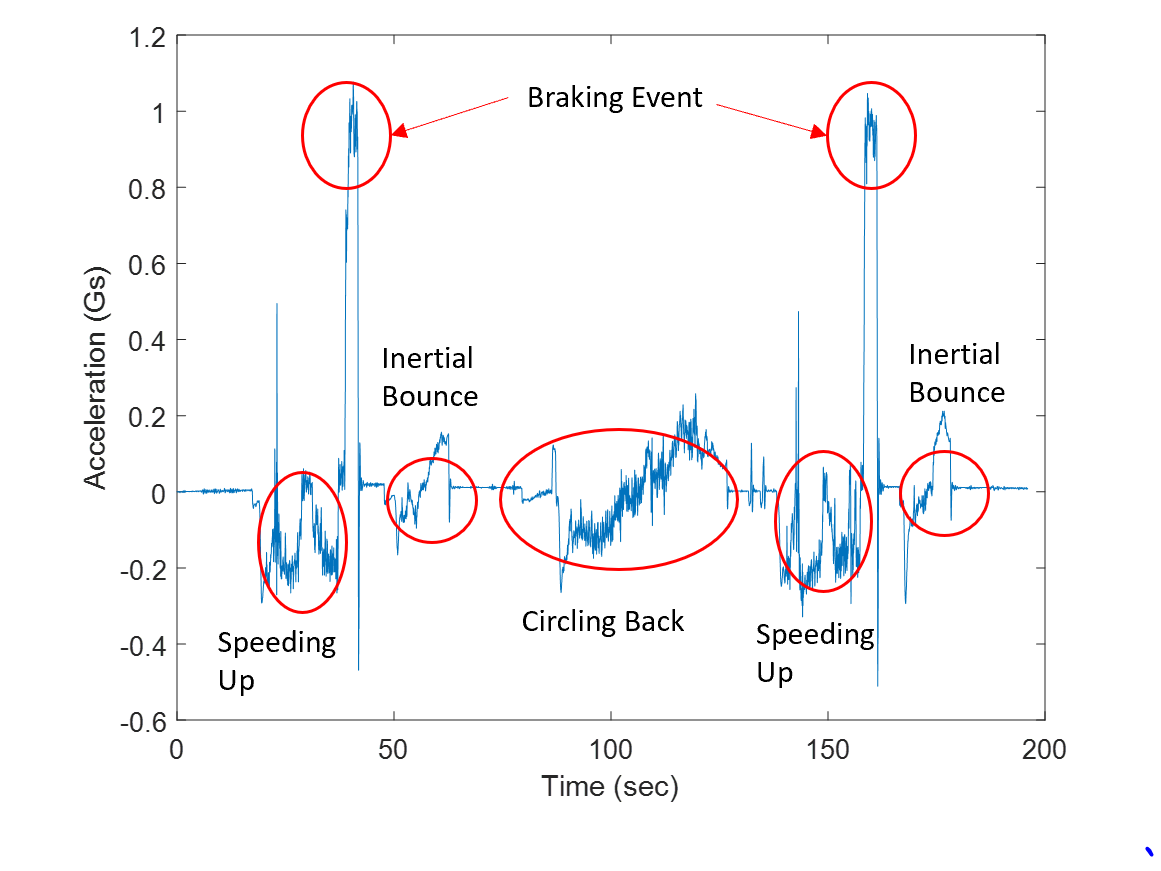




The data for each repeated test (i.e. 1-2, 3-4, etc.) was performed within the same run-trial to maintain a consistency with equipment calibration in between surface changes. Testing consisted of the following sections: speeding up to 55 mph, full brake to stop, idle stop, circle around to the starting position, and repeat. During all trials, the testing driver was instructed to maintain a firm steering to avoid and deviations of the vehicle.

Test Data Results/Post-Processing

All tests can be divided into consecutive sections that align with the experimental testing procedure as shown in Figure ###. The results of the 10 tests is shown in Figures ### in the Appendix for ease of organizational flow. It can be noted for all tests that noise is considerably reduced from the original signal. A sample from the FC test is shown in Figure #### below.



Full Concrete 1-2 Tests Signal Layout



Full Concrete 1-2 Tests Acceleration Raw and Filtered Signals

To verify that the acceleration did not lose any characteristic information after the Wavelet Decomposition, velocity profiles were numerically integrated for the raw data and the reconstructed approximation. Spline interpolation was utilized along with Simpson’s quadrature scheme to provide exact results which are shown in Figure ###. It is noticeable how the integrated Coiflet approximation matches the raw signal integrated profile.



Velocity Profile of FC1 Test (Top), and FC2 Test (Bottom)

After obtaining the Coiflet approximation and verifying the velocity profile consistency, the next step is two use the moving average with sudden rate change detection. A sample code is given below for determining braking accelerations. The code has a user defined threshold to vary the severity of the braking rate (i.e. high-speed vs low-speed braking). The detected braking rates during the FG Tests are given as an example in Figure ###.

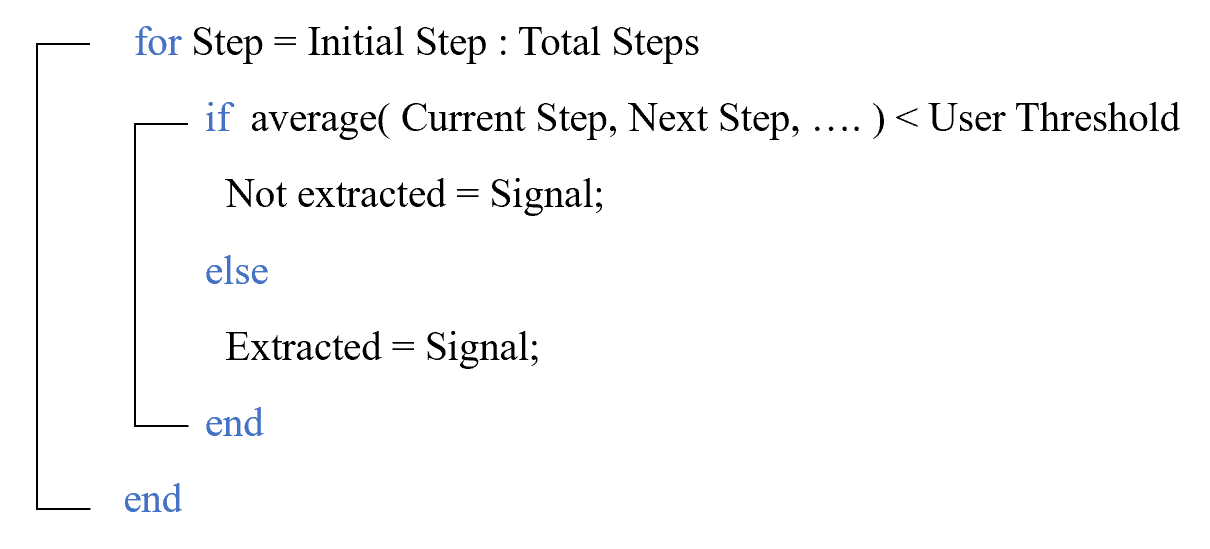


Figure Braking Detection Pseudo-Code



Full Gravel 3-4 Test Braking Acceleration Detection

Using the extracted braking rate section, it is possible to analyze the quality of the Coiflet to detect the COF. A tabulation of all results is shown in Table ###.

|  |  |  |  |
| --- | --- | --- | --- |
| Test Name | Average COF | Literature Value | Relative Error |
| FC1 | 0.9224 | 1 | 7.76% |
| FC2 | 0.9168 | 1 | 8.32% |
| FG1 | 0.5206 | 0.55 | 5.35% |
| FG2 | 0.4709 | 0.55 | 14.38% |
| FS1 | 0.4428 | 0.55 | 19.49% |
| FS2 | 0.5595 | 0.55 | 1.73% |
| SG1 | 0.6327 | 0.7 | 9.61% |
| SG2 | 0.6513 | 0.7 | 6.96% |
| SS1 | 0.5891 | 0.61 | 3.43% |
| SS2 | 0.6039 | 0.61 | 1.00% |

Discussion/Recommendations

Consider Maneuvering

Summary/Conclusions

In conclusion, a method was proposed to calculate trajectories based on discrete

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Appendix



Figure Tests FC1 and FC2 with Coiflet Approximations



Figure Tests FG1 and FG2 with Coiflet Approximations



Figure Tests FS1 and FS2 with Coiflet Approximations



Figure Tests SG1 and SG2 with Coiflet Approximations



Figure Tests SS1 and SS2 with Coiflet Approximations