

Leveraging Connected Vehicles to Provide Enhanced Roadway Condition Information

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1 INTRODUCTION

2 Winter road conditions are hazardous for drivers to navigate and are a challenge for agencies to
3 manage. According to the US Federal Highway Administration's Road Weather Management
4 Program (RWMP), out of approximately 5,748,000 vehicle crashes each year, about 22% of these
5 crashes are weather-related (1). From 2005 to 2014, an average of 445,303 persons were injured
6 and 5,897 persons were killed annually in weather-related crashes. Of these weather-related
7 crashes, 17% of occurred during snow or sleet, 13% occurred on icy pavement, and 14% occurred
8 on snowy or slushy pavement. The estimated annual cost of weather-related crashes ranges from
9 \$22 to \$51 billion (2). Additionally, it is estimated that weather-related delay costs the trucking
10 industry about \$8 to \$9 billion annually (3).

11 In 2015, the Road Weather Management Performance Measures report (4) evaluated a set
12 of 27 performance measures aimed to assess the status of the transportation system during
13 inclement winter weather conditions. The objectives identified in an updated report (5) included
14 "advancement of the state of the art for mobile sensing and integrating vehicle data into road
15 weather applications," and "improve integration of weather-related decision-support technologies
16 into traffic operations and maintenance procedures."

17 Before the advent of onboard vehicle communication electronics in the late 1980s (6, 7), it
18 was difficult to obtain any type of vehicle telematics data without dedicated instrumentation.
19 However, modern vehicles have come equipped with localized networks that facilitate
20 communication between the various onboard components (8), and report vehicle dynamics
21 information such as wheel speed, engine controls, drivetrain, and brake pressures at sub-second
22 frequencies. The data are typically used for controlling and coordinating vehicle features such as
23 traction control and anti-lock braking systems (9, 10). However, if the same data were to be
24 packaged and delivered via a system that can integrate with data-driven software interfaces to
25 generate weather-related performance measures using modern-day cellular networks, it can
26 provide tremendous value to stakeholders and agencies. Recent studies have shown that modern
27 production vehicles can be used to detect loss of friction conditions using signals from integrated
28 onboard components (11, 12) and, if the data can be harvested and calibrated, may have the
29 potential to achieve the objectives outlined by the 2015 RWMPM (4).

1 METHODOLOGY

2 This study developed methods to extract on-board vehicle data to assess whether current vehicle
 3 technologies can provide informative road condition data during winter storms. The experimental
 4 setup was comprised of a series production vehicle with built-in wireless internet access and a
 5 laptop. A web dashboard was developed to verify the uploaded vehicle signals in the database
 6 (Figure 1). The windshield wiper activation (callout i), anti-lock brake (ABS) activation, hazard
 7 lights on (callout ii), hazard lights off (callout iii), traction-control intervention (callout iv), wheel
 8 ticks, and brake pressure signals were forwarded from the various communication buses in the
 9 vehicle to the laptop. Once a notable status change of the identified signal was detected, the signal
 10 was uploaded with a time stamp, together with a GPS point where the change occurred, to a secure
 11 server via the onboard internet access point. Additionally, an on-board camera captured road
 12 condition images at once-per-second frequency for human classification. Friction data was also
 13 collected using a MARWIS mobile road weather sensor and data collector system to correlate
 14 vehicle status events.

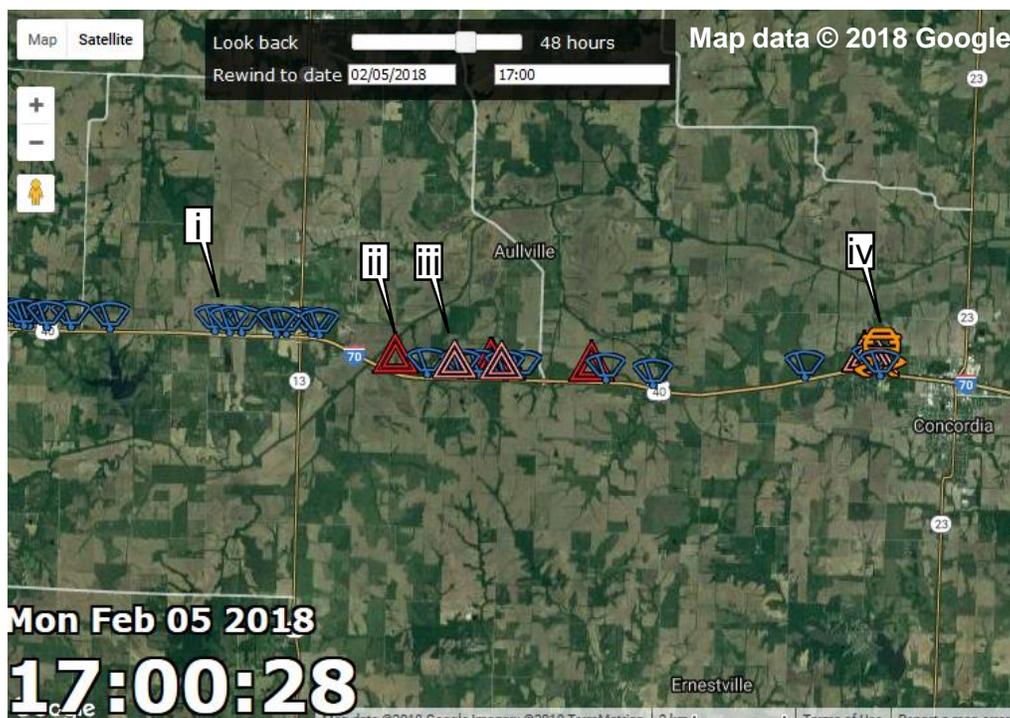


Figure 1. Web dashboard showing real-time sensor data information.

15 The test vehicle was driven in a pre-determined loop of 7 miles in the area around West
 16 Lafayette, IN. The experiment was repeated on four different days with different conditions in
 17 2018:

- 18 • February 11 (icy),
- 19 • March 24 (dry to snowy),
- 20 • July 4 and July 9 (both dry and sunny).

21
 22 The drivers were aware and consented to the data collection, and were told to drive normally as
 23 they would under each weather condition. The experiments collected measurements from multiple

1 in-vehicle bus signals, and were repeated along the same road links in the test loop. This was to
2 essentially emulate fleet data as time progressed in each day.

3 Wheel tick data were used to estimate the angular velocities of each of the four wheels over
4 a predefined time interval of 100 ms. Any large discrepancies between the wheels were noted as
5 potential slip event occurring. The amount of braking applied was measured using static brake line
6 pressures sampled in bar units from the vehicle bus at 200 ms intervals. In addition to static
7 pressure, the change in pressure (Δ Bar/sec.) can also be calculated over two consecutive data
8 samples to measure the rate at which the driver applies or releases braking force. Both the braking
9 and the wheel slip data was compared to the MARWIS friction data.

10 Braking behavior during winter (icy and snowy) and non-winter (dry) conditions was
11 analyzed using cumulative frequency diagrams (CFD) and the significant difference between the
12 two conditions were tested using the Kolmogorov-Smirnov (KS) test. Braking data was then
13 grouped by the corresponding friction values collected using the MARWIS sensor and statistical
14 significance was tested among groups using the Brown-Forsythe test.

15 FINDINGS

16 The MARWIS estimates provide reasonable overall segment characterization of friction ranges,
17 but do not have the fidelity to identify localized very short segments with low friction as performed
18 with on-board vehicle bus data. Wheel slip data provided high-fidelity information at locations
19 where low friction levels result in vehicle wheels sliding. However, it was found that under
20 unfavorable road conditions the driver was less inclined to perform aggressive maneuvers as she
21 would in dry conditions to intentionally prevent wheel slip. Therefore, it is impractical to assume
22 that as conditions deteriorate, drivers would proportionally increase the vehicle slip, and thus
23 wheel slip alone may serve as an inconclusive proxy for actual road conditions. Therefore, static
24 brake pressure (bar) and change in brake pressure (Δ bar/sec.) were recorded in each experiment
25 to determine if a driver changed his braking behavior based on actual road conditions.

26 Data from the study determined that for all speed categories, the brake pressure applied as
27 well as the rate of braking were greater during the dry condition than in the icy condition. Using a
28 2-sample Kolmogorov-Smirnov (KS) test, there was found to be high significance (P-value <
29 0.001) disproving the null hypothesis between the braking samples of the two conditions at all
30 speed categories. To see if there was any correlation between the braking rate and the different
31 friction levels experienced on the roadway, the samples were joined spatially and temporally and
32 plotted against each other in Figure 2. The scatter plot of brake pressure rates follows a tapering
33 conical shape – as the friction values decrease, the extremities of the rate of braking also appeared
34 to be curtailed. This may be due to the driver adjusting his braking behavior as the conditions
35 deteriorated throughout the day. To verify whether the trends were significant, the Brown-Forsythe
36 test (13) for the equality of group variances was used to compare the rates of braking in each
37 friction group. The test determined that at 95% confidence level, the variance of braking rates was
38 found to be statistically significant between most friction groups except for (0.5 μ , 0.6 μ), and (0.7

- 1 $\mu, 0.8 \mu$). This suggests as road conditions deteriorated, the change in variance in the rate of braking
- 2 deviated from normal braking conditions.

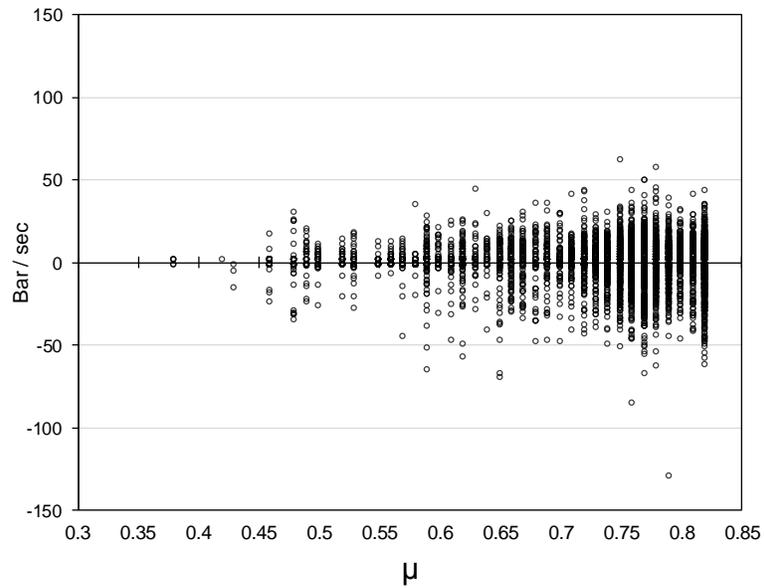


Figure 2. Brake rates during deterioration from dry to snowy conditions.

1 CONCLUSION

2 The experiments conducted in this study demonstrated the application of high-frequency vehicle
3 CAN data for observing winter weather road conditions. A system was deployed to collect wheel
4 tick and brake pressure data at 100 to 200 ms time resolution. A web application was developed
5 to display windshield wipers, hazard lights, traction control and ABS activations for both real-time
6 and historic events during an ice storm. Additionally, two separate winter events with independent
7 road friction validation were used as test cases to demonstrate the applicability of using on-board
8 vehicle data to monitor changing road conditions.

9 Key findings in this study suggested that:

- 10 1) a driver may reduce his or her applied braking pressure in deteriorating road
11 conditions up to 60% at the median intensity;
- 12 2) the braking pressures applied during wintry conditions were most different
13 compared to dry conditions at speeds between 20 mph and 39 mph where the
14 heaviest braking was performed;
- 15 3) the variance of the rate of braking was found to be significantly different at
16 different friction levels only when the conditions start deteriorating, not when the
17 road conditions were already slippery;
- 18 4) wheel slip data alone may not account for adjustments to driving behavior that
19 would mask actual slippery road conditions;
- 20 5) extreme vehicle intervention events such as traction control and ABS were
21 typically rare, even at locations where very low friction values were measured;
- 22 6) speed data alone may not be sufficient to characterize changing road conditions on
23 arterials.

24 Finding 3 is particularly interesting. The driver anticipated deteriorating conditions at least
25 15 minutes before the road was actually slippery. This has potential for predicting deteriorating
26 conditions ahead of time. Furthermore, it shows that images labeled by humans do not represent
27 the ground truth friction. There is tremendous opportunity in the area of winter road research to
28 leverage the in-vehicle data collection, processing and analysis methods presented in this study
29 over a large fleet and a larger driver pool. For instance, different vehicles with front or rear-wheel
30 drivetrains and type of tires equipped may reveal slip conditions even more effectively. Having
31 data over different equipment and demographic groups would validate or disprove using the data
32 elements currently employed in this study.

33 Further tests may also suggest incorporating new data elements such as gas pedal usage,
34 lateral acceleration, and air temperature sensors for determining road conditions. Moreover,
35 applying these and similar methods in a real-time system with an informative interface, given
36 enough protections to encrypt and secure anonymized user data, can be leveraged by agencies to
37 operate and maintain their roads during winter events without costly infrastructure. These
38 technologies can be further synergized with existing networks of Automatic Vehicle Location
39 (AVL) fleets such as snowplows.

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