MARITIME TRANSPORTATION RESEARCH AND EDUCATION CENTER
TIER 1 UNIVERSITY TRANSPORTATION CENTER
U.S. DEPARTMENT OF TRANSPORTATION

MarTREC
Maritime Transportation Research & Education Center

Identifying High-Risk Roadways for Infrastructure Investment Using Naturalistic Driving Data
10/01/2013 – 06/31/2015

Brian Wolshon, Ph.D., P.E., PTOE
Director and Professor
Gulf Coast Center for Evacuation and Transportation Resiliency
Department of Civil & Environmental Engineering
Louisiana State University
Baton Rouge, LA 70803
Phone: +1(225) 578-5247
Email: Brian@rsip.lsu.edu

Scott A. Parr, Ph.D., E.I.T.
Assistant Professor
California State University, Fullerton
Department of Civil and Environmental Engineering
Fullerton, CA 608621
Phone: +1(954) 937-8610
Email: sparr2@lsu.edu

Seyedeh Maryam Mousavi
Masters Student
Research Assistant
Louisiana State University

August 2015
FINAL RESEARCH REPORT
Prepared for:
Maritime Transportation Research and Education Center
University of Arkansas
4190 Bell Engineering Center
Fayetteville, AR 72701
479-575-6021

ACKNOWLEDGEMENT
This material is based upon work supported by the U.S. Department of Transportation under Grant Award Number DTRT13-G-UTC50. The work was conducted through the Maritime Transportation Research and Education Center at the University of Arkansas.

Executive Summary

The state-of-the-practice for most municipal traffic agencies seeking to identify high-risk road segments has been to use prior crash history. While historic traffic crash data is recognized to be valuable in improving roadway safety, it relies on prior observation rather than future crash likelihood. Recently, however, researchers are developing predictive crash methods based on "abnormal driving events." These include abrupt and atypical vehicle movements thought to be indicative of crash avoidance maneuvers and/or near-crashes. Because these types of near-crash events occur far more frequent than actual crashes, it is hypothesized that they can be used as an indicator of high-risk locations and, even more valuably, to identify where crashes are likely to occur in the future. This paper describes the results of research that used naturalistic driving data collected from global positioning system (GPS) sensors to locate high concentrations of abrupt and atypical vehicle movements in Baton Rouge, Louisiana based on vehicle acceleration and vehicle rate of change of acceleration (jerk). Statistical analyses revealed that clusters of high magnitude jerk events while decelerating were significantly correlated to long-term crash rates at these same locations. These significant and consistent relationships between jerks and crashes suggest that these events can be used as surrogate measures of safety and as a way of predicting safety problems before even a single crash has occurred.

1. Introduction

The state-of-the-practice for most transportation agencies in identifying high-risk road segments has been the use of long-term historic traffic crash data. Traffic engineers analyze this data to quantify crash frequency, rate, severity, and economic loss; and locations with higher levels of these metrics are typically classified to be "less safe" compared to other locations. And since crashes are used as the primary measure to assess the need for and potential benefit of highway safety investments, these "less-safe" locations usually receive more attention in the form of funding for safety improvements (Hauer, 1996; Tarko and Kanodia, 2004; Persaud et al., 1999).

While analysis of historic traffic crash data has proven to be a valuable tool in improving roadway safety, it is a *retroactive* measure. In effect, it can only be used *after* damage, injury, and loss of life have occurred; in some cases for many years. To address this problem, recent research has sought to develop measures to *proactively* identify high-risk roadway segments (Gettman et al., 2008; Dixit et al., 2011; AASTO, 2010). If created, these techniques could be used to identify safety problem *before* any crashes, injuries or fatalities, have occurred.

These new avenues of research have focused on quantifying parameters that are correlated with roadway safety, including measures such as conflicts and time-to-collision. Such variables, referred to as "surrogate safety measures," are observable, non-crash, events that have a relationship to crashes (Tarko et al., 2009). The advantages of surrogate safety measures are that they can be observed long before crashes have occurred and they often happen far more frequently than actual crashes; in some cases, 10 and 15 times more frequently (Guo et al. 2010), enabling more powerful statistical analyses to be applied. Surrogate safety measures developed from the analysis of human factors identify the characteristics of "risky" or "unsafe "drivers. These are drivers that self-report being involved in an unusually high number of crashes. Bagdadi and Varhelyi (2011) found that unsafe drivers experienced an unusually large number of high magnitude negative jerks. The jerk characteristic of a drive is the rate of change of acceleration and is measured in feet per second cubed (ft/s^3). Drivers who showed a pattern of high negative jerk values were also statistically more likely to have a higher number of traffic crashes.

This method of identifying high-risk road users by analyzing their jerk patterns has promise in the field of human factors and insurance pricing. However, previous research has not yet been able to leverage this emerging avenue of safety research into a method to identify unsafe roadway segments. In this research, it is hypothesized that locating high concentrations of abnormal negative jerk values (i.e., jerk-clusters) would enable high-risk locations to be identified in advance and potentially with greater accuracy. By examining jerk-clusters instead of individual drivers, this analysis can also be used to illustrate a general trend of safety for a roadway segment.

This paper describes the results of recent and ongoing research that uses naturalistic driving data collected with global positioning system (GPS) sensors. The research applies geographic information systems (GIS) analysis and other quantitative methods to GPS data to use jerks-clusters for future crash prediction. From this dataset, jerks were geo-located to a roadway network and graphed in combination with historic traffic crashes. This combined dataset was analyzed to determine if a statistical relationship existed between jerk-clusters and traffic crashes. Such information would, in effect, give safety analysts a "crystal ball" to see into the future and predict locations that are likely to have a higher numbers of crashes in the future. With this knowledge, safety improvements could be planned and implemented to *prevent* damage, injury, and death well *before* any significant number of crashes had even occurred.

1.1 Literature Review

Due to the rare occurrence of traffic crashes and deficiency of adequate data, transportation professionals have sought to develop surrogate safety measures to better understand, analysis, and prevent vehicle crashes. Various techniques have been used to develop surrogate safety measure but the most prominent has involved the use of traffic conflicts (Chin et al., 1992; Chin and Quek, 1997; Glauz and Migletz, 1980; Parker and Zegeer, 1989) and time-to-crash (Hyden, 1987; Hyden, 1996; Svensson, 1998; Svensson and

Hyden, 2006). These studies share the common goal of identifying where or when traffic crashes may occur and the factors that increase the likelihood of occurrence.

The Highway Safety Manual (HSM) is a reference tool for traffic professionals to facilitate improved decision-making based on safety performance. The HSM allows for a quantitative analysis of safety for highway planning, programing, project development, construction, operations, and maintenance. The goal of the HSM is assemble the most current methodologies and information for measuring, estimating, and evaluating roadway safety in terms of crash frequency and severity. Published in 2010, the HSM includes Safety Performance Functions (SPF) that permit expected future numbers of crashes to be forecast on specific segments of roadway given a particular set of traffic, design, and operational conditions.

The advent of geographic information systems (GIS) and global position systems (GPS) has allowed driving data to be collected and processed with ever increasing levels of detail and accuracy. This technology has been applied extensively in the traffic engineering field in areas ranging from fleet management and dashboard navigation to travel time estimation and traffic simulation. It has been suggested that this technology has potentially significant applications in the area of quantifying traffic safety (Pande et al., 2014) and has the potential to replace traditional methods of measuring safety (e.g., Hauer, 1996). Studies that have adapted in-vehicle GIS and GPS technology to analyze driving behavior are classified as “naturalistic driving studies” because they use driver information collected during their natural driving routines (Dingus et al., 2006). Naturalistic driving data has many applications but traffic safety has received the most attention in recent years. The “100-Car Study” used 100 vehicles instrumented with video recording devices and advanced GPS sensors to collect naturalistic driving behavior from 241 drivers. The advanced instrumentation was used to document 8,295 critical incidents (Dinjus et al., 2006). The 100-car study led to significant advances towards crash-avoidance systems used in modern vehicles (McLaughlin et al., 2008).

Bagdadi and Varhelyi (2011) used GPS data to analyze braking characteristics and jerks (the rate of change of acceleration) from 166 private vehicles. Using a critical jerk threshold of -32.4 ft/ s^3 (-9.9 m/s^3), the research found drivers that showed a pattern of jerk values above this threshold were more likely to have history of self-reported crashes. More recent studies have used critical jerk values to differentiate between controlled powerful braking and "critical braking" for crash avoidance in naturalistic driving data (Bagdadi, 2013; Bagdadi and Varhelyi, 2013). These previous works have examined individual drivers and their jerk characteristics to identify unsafe driving behavior. However, an analysis of jerks has not yet been applied to multiple drivers over same road to examine the relationship jerk-clusters and roadway safety.

2. METHODOLOGY

This research estimates roadway safety by analyzing clusters of high magnitude negative jerks from multiple driver observations. The research methodology consisted for five analytical tasks. The first task was the collection and processing naturalistic driving data using advanced GPS devices. The second task used linear referencing to match the data collection points to roadway maps. This task also included referencing the historic vehicle crash data to the same map. The third task was to quantify the jerks of the research participants. The fourth task was a sensitivity analysis to identify the optimum roadway segment length and critical jerk-value threshold that best match the historic traffic crash data. The fifth and final task was to develop a crash-frequency model, establishing a quantitative relationship between jerk-clusters and historic crashes. Each of these tasks and their results are described in the following sections of this paper.

2.1 Data Collection and Processing

The naturalistic driving data used in this research was collected from 31 staff members and their household members at Louisiana State University. The goal of the participant selection was to recruit drivers with similar driving patterns. This was necessary to ensure that the participants in the study would consistently travel over the same routes to develop jerk-clusters. Participants were selected using a questionnaire that screened drivers based on personal characteristics and driving patterns. Participants were then segregated based on age, commuting route, and driving frequency. To maintain confidentiality, a unique random identifier was assigned to each participant that was later assigned to the GPS data collection unit. All participants were between the ages of 20 and 65 and included 12 female and 19 male drivers. The data collection period spanned from July 2012 to January 2013 with each driver contributing around 10 days of data.

The GPS data was collected by a GPS Data Logger V3.15 (data logger), able to record daily travel patterns for up to two weeks. The data loggers were charged by a 3.7 volt rechargeable battery and recorded data in a comma-separated format, adhering to the National Marine Electronics Association standards. The data logger recorded position information in World Geodetic System 84 standard, collecting latitude, longitude, altitude, heading, speed, number of satellites utilized, position dilution of precision, horizontal dilution of precision, and vertical dilution of precision as well as universal time code and date. Readings from the device were recorded at a rate of three hertz (i.e., three readings per second) and was programmed with a “sleep” mode which would stop data recording if the position information did not change after 300 seconds. This was done primarily to preserve battery life.

The data loggers were housed in a waterproof, crush-proof, airtight case to protect the unit and hard drive from damage. Drivers were asked to place the unit in their center console or glove box. Extensive testing prior to the data collection period showed that neither location affected the accuracy of the data obtained from the device. Participants were also asked to refrain from allowing anyone else to use their vehicle during the 2-week experiment period.

The GPS data collected from each participant was processed by combining multiple data files into a single file, labeled with each participant’s unique identifier. This data file was then linked to the initial questionnaire filled out by the participant. The dataset was divided into individual trips which were delineated by 30-minute intervals of inactivity. These were then assigned a trip number. The trip information was imported into ESRI ArcMap and plotted over a base-map of the Baton Rouge, Louisiana road network file. The data was then visually inspected to identify the streets the participants were driving on and for errors.

Three error types were found in the data: a) GPS noise at intersections, b) GPS wandering and c) gaps in the GPS data. These errors were consistent with those observed in the San Louis Obispo, CA (Pande et al., 2014). GPS noise was the most common of the three errors. It occurred when the GPS position changed but speed and heading did not match. This error was typically associated with vehicles being stopped or moving at slow speeds and was characterized by a “cluster” of data points observed in the vicinity of the stopping location. GPS wandering occurred when the GPS data points did not correspond to the actual vehicle location. This phenomenon was characterized by data points appearing in areas where no road exists and appeared to be random in nature. The third error, the presence of gaps in the data, was identified by segments of roadways, which were void of data collection points. This error was likely caused by a temporary loss in GPS satellite availability resulting from impedance or a communication error.

2.2 GIS Linear Referencing

Linear referencing was used to link the data collection points to the road network of Baton Rouge, LA. Linear referencing links geographic locations (x, y) to a measured linear feature. The road network used for this study was provided by the Louisiana Department of Transportation and Development (LDOTD, 2014). The roadways evaluated in this study were: (1) a 7.5 mile long stretch of LA 42, known locally as Burbank Drive, a four-lane divided highway with posted speeds varying from 45 to 55 mph. (2) a 5.15 mile long stretch of LA 1248, known as Bluebonnet, a four lane divided highway with posted speeds varying from 30 to 45 mph.

By linearly referencing each data point to the road network, linear distances between each point could be calculated. This linear referencing procedure was repeated for each individual participant. Data points were linearly referenced to the nearest road within a radius of 300 ft. This large radius value was selected to bypass any possible GPS noise or wandering errors. However, this required the GPS data points to be further filtered to remove any erroneous location information that may have resulted from referencing the data to an incorrect road. Furthermore, data points with incorrect heading information as well as data points that reported communication with fewer than five satellites were removed from consideration. The removed data constituted about one percent of the overall data collected. This filtering process ensured that only accurate data with reliable position information was included in the analysis.

To identify the roads segments of LA 42 and LA 1248 which were deemed “safe” or “hazardous,” 5-year vehicle crash data, from 2009 to 2013, were used. This is a commonly accepted measure for determining relative safety (Hauer, 1996). The historic crash data were also linearly referenced to the same road network as the GPS data. The crash rate was calculated for each segment in accordance with the United States Department of Transportation (USDOT) defined method, Equation 3 (FHWA, 2014). This was used to normalize the total number of crashes by the amount of ADT, a measure of exposure.

$$R = \frac{C \times 100{,}000{,}000}{V \times 365 \times N \times L} \tag{1}$$

Where:

R: Road segment crash rate expressed for 100 million vehicle-miles traveled

C: Total number of crash on the roadway segment

V: Traffic volume (ADT)

N: Number of years of crash data

L: Length of the road segment

2.3 Jerk Analysis

The road network was partitioned into equal length analysis segments. The segments varied with regard to the curvature of the road and average daily traffic (ADT); these two variables were added to the dataset for analysis. Calculated from the driving data was each participants acceleration(a) and jerks (j) between consecutive data point. The equation for acceleration (a) and jerk (j) are given in equation 2 and equation 3, respectively.

$$a = \frac{dv}{dt} \tag{2}$$

$$j = \frac{da}{dt} \tag{3}$$

Where:

a: Acceleration (ft/s²)

dv: Change in velocity between successive observations (ft/s)

j: Jerks (ft/s³)

da: Change in acceleration between successive observations (ft/s²)

A histogram of acceleration (a) and jerk (j) was analyzed for quarter-mile segment lengths to understand the distribution of these variables. This analysis indicated that the jerk variable (j) warranted further evaluation. This was logical since low magnitude negative jerk values are likely associated with gradual braking maneuvers, as opposed to high magnitude negative jerk values, indicating sudden braking. As seen in Pande et al. (2014), drivers traveling on freeway segments characterized by high long-term crash rates had to make more sudden braking maneuvers resulting in an above average rate of high jerk values on those segments.

2.4 Sensitivity Analysis

The jerk (j) value was a continuous variable without an intuitive method to identify which threshold value of jerk distinguished between gradual braking maneuvers and sudden braking maneuvers. Bagdadi and Varhelyi (2011) used a constant jerk threshold of -32.4 ft/s³ (-9.9 m/s³). The threshold value used for this research was determined using a data driven sensitivity analysis. Twenty-one jerk value thresholds were evaluated in the sensitivity analysis from -0.5 (ft/s³) to -10.5 (ft/s³) at an increment of 0.5 (ft/s³). A jerk event was defined as any negative jerk value with a magnitude that exceeded a predefined threshold value. The number of jerk events exceeding the threshold value within a road segment was counted. The count for each segment was normalized by the total number of data points observed in that segment to yield a jerk-rate or percentage of the high jerks events, observed in each segment. The jerk-rate was then compared to the crash rate *R*, for each segment using a Pearson Correlation analysis. Also because it was unknown how the segment length would affect the analysis, three different segment lengths were selected: eighth-mile (0.125), quarter-mile (0.25), and half-mile (0.5). The results of the sensitivity analysis are shown in Figure 1.

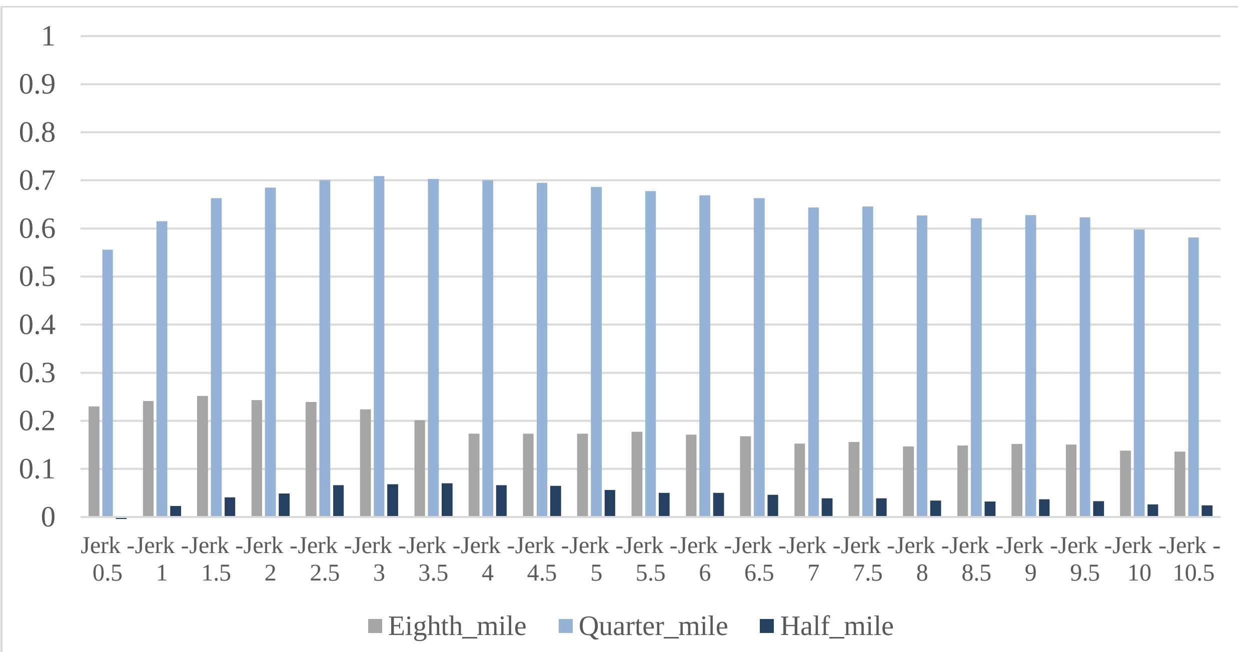

Figure 1: Sensitivity Analysis Results

The figure indicates that a jerk threshold value of -3 ft/s³ resulted in the highest Pearson Correlation Coefficient for all segment lengths. Compared to other studies, this jerk threshold value is much smaller and is likely too low to be indicative of an evasive driving maneuver. However, since this research examines combined jerk-clusters from multiple drivers, the value may indicate a general trend of atypical braking behavior (not necessarily evasive). On the overhand, the benefit of a reduced threshold value increases the number of jerk events, enabling high-risk segments to be identified earlier and with greater statistical certitude.

Additionally, the results of the sensitivity analysis indicated that the quarter-mile segment length (highest correlation coefficient) was the best choice. This suggested that the smaller, more homogenous eighth-mile segments may have been smaller than the precision of the crash location data, resulting in crashes being incorrectly assigned to the adjacent segments by linear referencing. The half-mile segments appeared to be too large and insensitive to generate the high Pearson Coefficients seen in the quarter-mile segments.

To illustrate the strength of the correlation, Figure 2 and 3 present heat maps of the jerk-rate percentage (with the threshold value is set to -3 ft/s³) and historic crash rates. The images show the strength of the relationship between high relative jerk-rates and crash-rates.

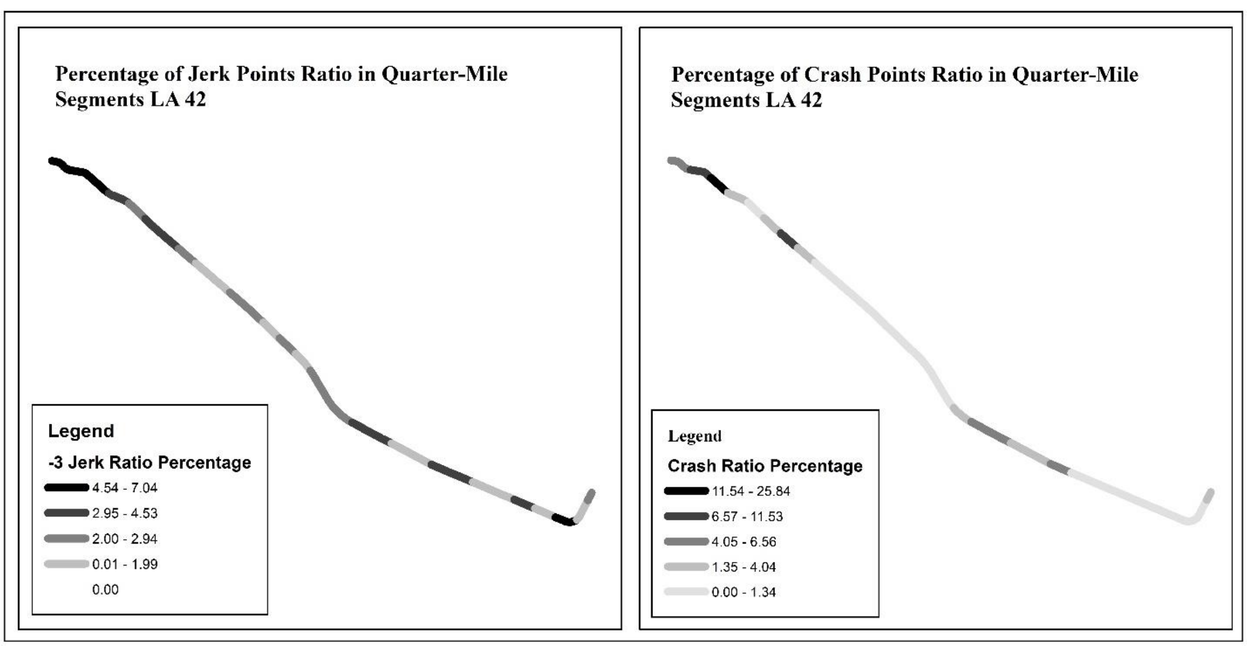

Figure 2: Quarter-Mile Segments with Crash Locations on LA 42

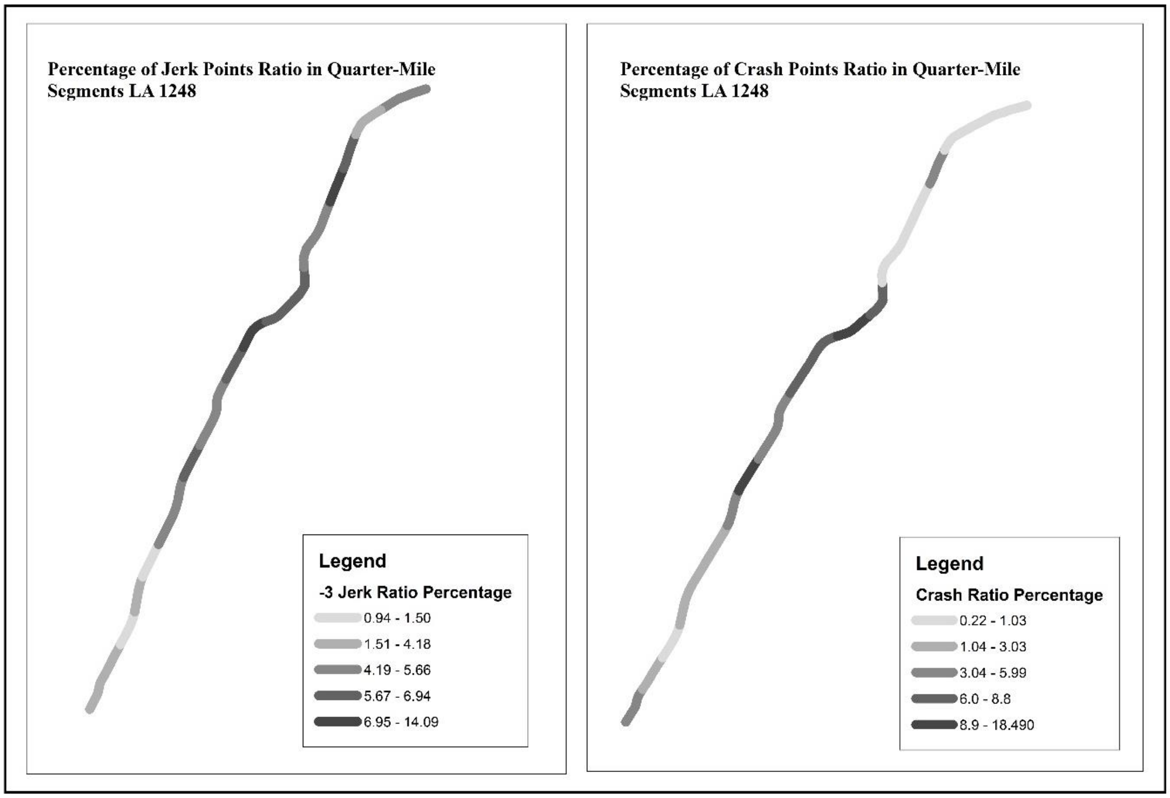

Figure 3: Quarter-Mile Segments with Crash Locations on LA 1248

3. CRASH-FREQUENCY MODELING RESULTS

Long-term crash frequency was estimated for each quarter-mile segment using a negative binomial model. In practice, negative binomial models are often used in crash frequency analysis (Shankar et al., 1995; Abdel-Aty and Radwan, 2000).Two independent models were estimated for LA 42 and LA 1248. Results are shown in Table 1 and 2 and include ADT, curvature and jerk-rate. The jerk-rate was the only variable to be significantly related to the long-term crash-frequency in both models. The model developed for LA 1248 also showed a correlation between ADT and crash-frequency. The results of the analysis suggest that the crash-frequency experienced on LA 42 and LA 1248 in Baton Rouge, LA are significantly related to high magnitude negative jerk-clusters than variables traditionally used in crash-frequency estimation.

Table 1: Crash Frequency Estimation Model of LA 42

Parameter	DF	Coef.	S.E.	95% C.L.		Chi-Square	Pr > ChiSq
Intercept	1	0.6879	1.69	-2.624	4	0.17	0.684
Jerk-Rate	1	0.5068	0.099	0.3119	0.702	25.99	<.0001
ADT	1	0.0001	1E-04	-1E-04	2E-04	0.61	0.4336
Curve	1	-0.506	0.301	-1.096	0.084	2.82	0.093
Dispersion	1	0.6441	0.162	0.394	1.053		

Table 2: Crash Frequency Estimation Model of LA 1248

Parameter	DF	Coef.	S.E.	95% C.L.		Chi-Square	Pr > ChiSq
Intercept	1	-0.022	1.627	-3.211	3.167	0	0.9892
Jerk-Rate	1	0.1374	0.062	0.0165	0.258	4.96	0.0259
ADT	1	0.0001	0	0	2E-04	4.28	0.0386
Curve	1	0.1361	0.238	-0.33	0.602	0.33	0.5672
Dispersion	1	0.6265	0.186	0.3497	1.122		

CONCLUSIONS

This research has demonstrated a relationship between the location of jerk-cluster and vehicle crashes on two major arterials. While more research is required to generalize the relationship to all cases, findings suggest that a clustering of high magnitude negative jerks may precede vehicle crashes. Compared to traditional measures used to estimate crash frequency (ADT and the presence of geometric curves), jerk-clusters provided a much stronger indicator of safety for the study segments. This finding may allow analysis to identify crash prone locations in a proactive manner before the crash data (along with the losses and suffering that accompanies these crashes) is allowed to accumulate.

A secondary goal of this research was to examine the effects of segment length on the relationship between jerk events and crash rates. Segments that were too short (less than or equal to 1/8 mile) or too larger (greater than or equal to 1/2 mile) reduced the ability to correlate jerks and crashes. The results suggest there is an ideal segment length for analysis that yields the highest correlation. Future research should examine this finding and explore spatial analysis tools capable of identify the optimal segment length, as this may lead to more accurate crash prediction models.

Information technology advances are opening up new opportunities for traffic agencies to be able to identify locations with relatively high jerk events. With the number of GPS enabled devices, such as “smartphones” and “tablets” increasing, future research may have the ability to access this information to analyze jerk events through “crowd sourcing”. This would result in identifying unsafe roadways significantly earlier because traffic engineers would not have to wait for sufficient crash data to accumulate. Identification of unsafe roadways prior to any crashes occurring would be a lifesaving measure. The results of this research could have a profound impact on the way highway safety is quantified and capital investment on roadway projects is allocated in the not-too-distant future.

REFERENCES

Abdel-Aty, M.A. and A. E. Radwan, “Modeling traffic accident occurrence and involvement,” *Accident Analysis and Prevention,* vol. 32, no. 5, pp. 633–642, 2000.

American Association of State Transportation Officials, *Highway safety manual*, 1st ed., vol. 1, 3 vols. American Association of State Highway and Transportation Officials, 2010.

Bagdadi, O. “Assessing safety critical braking events in naturalistic driving studies,” *Transp. Res. Part F Traffic Psychology and Behavior,* vol. 16, pp. 117–126, 2013.

Bagdadi, O. and A. Várhelyi (2011). “Jerky driving an indicator of accident proneness”. *Accident Analysis and Prevention* 43 (4), 1359-1363

Bagdadi, O. and A. Várhelyi, (2013) “Development of a method for detecting jerks in safety critical events,” *Accident Analysis and Prevention*, vol. 50, pp. 83–91.

Chin, H. and S. Quek (1997). “Measurement of traffic conflicts”, *Safety Science.* ***26*** *(3)*, pp. 169–185.

Chin, H., Quek, S., and Cheu, R. (1992). “Quantitative examination of traffic conflicts”. *Transportation Research Record,* Journal of Transportation Research Board, *1376*, 67-74.

Dingus, T. A. Klauer, S. G. Neale, V. L. Petersen, A. Lee, S. E. Sudweeks, J. D. Perez, M. A. Hankey, J. Ramsey, D. J. Gupta, S. and others, “The 100-car naturalistic driving study, Phase II-results of the 100-car field experiment,” DOT HS 810 593, 2006.

Dixit, V., Pande, A. Abdel-Aty M., Das, A. and E. Radwan, “Quality of traffic flow on urban arterial streets and its relationship with safety,” *Accident Analysis and Prevention*, vol. 43, no. 5, pp. 1610–1616, 2011.

Gettman, L. Pu, T. Sayed, and S. G. Shelby, “Surrogate safety assessment model and validation: Final report,” 2008.

Glauz, W.D., Migletz, D.J. (1980). “Application of Traffic Conflict Analysis at Intersections”. *NCHRP Report 219*, Transportation Research Board, National Research Council, Washington, DC.

Guo, F., S. Klauer, M. McGill, and T. Dingus (2010), “Task 3-Evaluating the Relationship Between Near-Crashes and Crashes: Can Near-Crashes Serve as a Surrogate Safety Metric for Crashes?” U.S. Department of Transportation, National Highway Traffic Safety Administration Report DOT-HS-811-3826, Washington D.C.

Hauer, E. “Identification of sites with promise,” *Transportation Research Record, Journal of the Transportation Research Board*, vol. 1542, no. 1, pp. 54–60, 1996.

Hydén, C. (1987). “The Development Of A Method For Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique”. Department of Traffic Planning and Engineering, Lund University, Lund, Sweden.

Hyden, C. (1996). Traffic conflicts technique: state of the art. In: Topp, H.H. (Ed.), *Traffic safety work with video processing* (pp. 3–14). University Kaiserslautern, Transportation Department, Green Series No. 37.

McLaughlin, S. B., Hankey, J. M. and T. A. Dingus, “A method for evaluating collision avoidance systems using naturalistic driving data,” *Accident Analysis and Prevention,* vol. 40, no. 1, pp. 8–16, 2008.

Pande, J. Loy, V. Dixit, K. Spansel, B. Wolshon, and J. D. Kent, “Exploration of Naturalistic Driving Data for Identifying High Crash Risk Highway Locations,” in *Transportation Research Board 93rd Annual Meeting Compendium of Papers, #14-5291*, Washington D.C., 2014.

Parker, M.R., Zegeer, C.V. (1989). “Traffic Conflict Technique for Safety and Operation: Engineers Guide”. *Report FHWA-IP-88-026*, FHWA, U.S. Department of Transportation.

Persaud, C. Lyon, and T. Nguyen, “Empirical Bayes procedure for ranking sites for safety investigation by potential for safety improvement,” *Transportation Research Record, Journal of the Transportation Research Board*, vol. 1665, no. 1, pp. 7–12, 1999.

“Roadway Departure Safety: A Manual for Local Rural Road Owners - FHWA Safety Program,” *FHWA, US Department of Transportation*. [Online]. Available: http://safety.fhwa.dot.gov/local_rural/training/fhwasa1109/app_c.cfm. [Accessed: 31-Jul-2014].

Shankar, V. Mannering, F. and W. Barfield, “Effect of roadway geometrics and environmental factors on rural freeway accident frequencies,” *Accident Analysis and Prevention.*, vol. 27, no. 3, pp. 371–389, 1995.

Svensson, Å. (1998). “A Method For Analyzing The Traffic Process In A Safety Perspective”. Department of Traffic Planning and Engineering, Lund University, Lund, Sweden. *& Prevention*, 38:379-385.

Svensson, Å. and Hyden, C. (2006). “Estimating the severity of safety related behavior,” *Accident Analysis and Prevention,* 38: 379-385

Tarko, P. and M. Kanodia. (2004). “Effectiv and fair identification of hazardous locations,” *Traffic safety work with video processing* (pp. 3-14) University Kaiserlautern, Transportation Department, Green Serires No. 37.

Required MarTREC Final Research Report Content and Format

1. Project Description
2. Methodological Approach

3. Results/Findings
4. Impacts/Benefits of Implementation (actual, not anticipated)
5. Recommendations and Conclusions