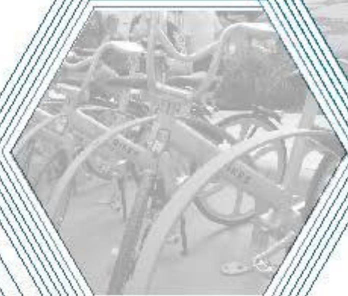

DEVELOPMENT OF A REAL-TIME ROADWAY DEBRIS HAZARD SPOTTING TOOL USING CONNECTED VEHICLE DATA TO ENHANCE ROADWAY SAFETY AND SYSTEM EFFICIENCY

SISINNIO CONCAS
MOHSEN KAMRANI

FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

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FINAL DRAFT PROJECT REPORT

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16. Abstract

Using the information residing in connected vehicle Basic Safety Message (BSM) data, this project develops an algorithm that is capable of identifying the location of unwanted objects, i.e. debris on road segments. Vehicles' lateral accelerations are used to detect lane changing and swerving behaviors to create density maps that pinpoint the locations with high frequency of swerving behavior and thus debris locations. Two vehicles were used to collect the required data on a selected US DOT Tampa CV Pilot road segment. A portion of the data was used to fine-tune the algorithm parameters and the rest was used to test its ability to locate the object on the road. The overall accuracy of the algorithm to detect individual lane changes is estimated to be 96 percent. Coupling the algorithm with density diagrams, debris locations could be identified almost precisely. The algorithm has the potential of reducing time and money spent by state and local agencies to swipe and remove debris from the road, as well as reducing the risk of crashes caused by drivers' swerving behavior to avoid on-road debris.

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Table of Contents

List of Tables

List of Figures

Abstract

Using information residing in connected vehicle (CV) Basic Safety Message (BSM) data, this study develops an algorithm that is capable of identifying the location of unwanted objects, or debris, on road segments. Vehicles' lateral accelerations are used to detect lane changing and swerving behavior to create density maps pinpointing to the locations with high frequency of swerving behavior and thus debris locations. Two vehicles were used to collect the required data on a selected US DOT Tampa CV Pilot road segment. A portion of the data was used to fine-tune the algorithm parameters and the rest was used to test its ability to locate the object on the road. The overall accuracy of the algorithm to detect individual lane changes is 96 percent. Coupling the algorithm with density diagrams, debris locations can be identified almost precisely. The algorithm has the potential of reducing time and money spent by state and local agencies in patrolling to identify and remove debris from the road, as well as reducing the risk of crashes caused by drivers' swerving behavior in avoiding debris on the road.

Chapter I: Introduction

Roadway debris and other unexpected obstructions, such as surface damage can lead to significant traffic delays or worse, crashes. The presence of roadway debris is particularly concerning in high-traffic and high-speed roadways where dense traffic conditions reduce visibility and large volumes of vehicles are exposed to risk. According to the Florida Department of Highway Safety and Motor Vehicles (DHSMV), in 2018 there were 2,949 crashes resulting in 702 injuries and 17 fatalities, where the main contributing cause was an obstruction in the roadway or debris [1]. Although prevention of the various causes of obstructions and defensive driving can reduce these consequences, the problem cannot be eliminated entirely. Currently, unexpected roadway obstructions are handled by relying on drivers' self-reporting (e.g., the Waze app) or through local maintenance departments, which is either unsafe because it can lead to distracted driving or not cost effective. In addition, pinpointing the exact debris location can be challenging and adds to delays between notification and actual removal from the responsible transportation agency. This study takes advantage of information residing in Basic Safety Messages (BSM) generated by connectively-enhanced vehicles as part of the US DOT Connected Vehicle (CV) Pilot Deployment, Tampa, Florida, to develop algorithms for identifying the location of debris. As CV market penetration increases, the results become more accurate due to more data availability in a specific time and road segment. The debris location information can dispatched to local or state transportation, traffic, and maintenance agencies to improve the process of addressing road debris and other road hazards. In addition to providing the coordinates of possible hazards, the algorithm can provide a timelier and safer identification of road hazards compared to existing methods. For instance, currently in the State of Florida, the Traffic Incident Management Program addresses road debris and hazards. Drivers can call the Florida Highway Patrol (FHP) by phone. FHP then deploys the district's maintenance to the location to address congestion and safety issues for quick roadway clearance. The Florida Department of Transportation's Road Rangers also continuously patrol the roadways looking for debris and disabled vehicles. Utilizing real-time data generated from connected vehicles, this tool has the potential to provide a large benefit and cost-savings over the current methods for identifying road hazards.

An AAA Foundation research [2] estimated that road debris was one of the contributing factors in 202,631 police reported crashes from 2011 to 2014 that resulted in 501 deaths and 39,220 injuries. While no studies explicitly developed methods to detect debris on the roads for quick response and removal, the detection of foreign object debris (FOD) on airports runways is a topic of interest in the aviation industry [3]. As the region of interest in airports is much smaller when compared to roads, most of the developed detection methods rely on sensors such as imaging, millimeter-wave, Radar, and LiDAR [4-6]. A noise filtering algorithm along with a background subtraction technique were used to process and detect objects from images taken from objects on an airport surface [5]. In another study [6] LiDAR technology was used to detect objects on airport surface using an autonomous rover. Although technologies such as LiDAR and Radar are proposed and even used in vehicles for surrounding object detection and driving assists [7-14], the detections are beneficial and limited to vehicles having those technologies and they cannot be used at the aggregate level by agencies or highway patrols for removing unwanted objects and debris in a timely manner. Lehtomäki et al. [7] used vehicle based laser scanning to detect pole-like objects e.g., traffic lights, tree trunks with the accuracy of 81%. Kato et al. [9]

proposed a method that fuses information from Radar and a camera capable of detecting moving and stationary objects such as vehicle, pedestrian in host vehicle path. However, the experiments were done with vehicles and pedestrian as objects and with no debris and other foreign objects. Munawar and Creusot [11] proposed a method to detect anomalies on roads using a machine learning algorithm applied to images taken from a camera in front of the host vehicle. Similarly in another study [12], a system for detection and tracking of objects (i.e. Vehicles, pedestrians, cyclists) through processing of images coming from a mounted camera and applying Color Road Background Model and Entropy. Other studies [13, 14] added real-time detection features to their algorithms for on-road object detection. Therefore, there exists a gap in the literature: the detection of debris and foreign objects on roads at the aggregate level for the safety benefit of traffic system (as opposed to algorithms that detect objects for the benefit of individual vehicles).

One of the emerging sources of data to address the road debris problem more efficiently is connected vehicles. To effectively deploy vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) applications, connected vehicles exchange information via basic safety messages (BSM). BSM data contain detailed information on vehicles kinematics and locations broadcasted at high frequency (up to ten times per second). As BSM data become more available, their potential in providing useful information for traffic mobility and safety purposes becomes more relevant. Previous studies have used such data to address safety and mobility problems from new perspectives [15-18]. By using BSM data, the method proposed in this study provides an innovative, yet feasible and low-cost, approach to identify debris locations as such data become more common and available to agencies and highway patrols.

Chapter II: Methodology and Data Collection

The research focus is on detection of lane changes from vehicle kinematics. In particular, an initial analysis of the Tampa CV Pilot data revealed that among vehicle kinematics, lateral acceleration is the parameter to use because there is not relative variability in other parameters such as longitudinal acceleration and speed during the short period of a typical lane change. To develop the detection algorithm and fine-tune the parameters, this study used two test vehicles from the Tampa CV Pilot: one vehicle belonging to the principal investigator for this project and one fleet vehicle provided by the Tampa-Hillsborough Expressway Authority (THEA). THEA owns and operates the Selmon Expressway and the Reversible Express Lanes (REL), a reversible elevated express lane, an all-electronic toll (AET) facility that serves as a main commuter route, connecting the bedroom community of Brandon with downtown Tampa. The REL system is at the core of the Tampa CV Pilot deployment and served as the testbed for this project tests. The facility provides a contained environment in which to safely test and refine the road-debris-identifying algorithms. THEA has established three, elevated lanes known as the Reversible Expressway Lanes (REL) for westbound traffic during the morning commute and for eastbound traffic during the evening commute and weekends. In the interim, as the lanes are closed to all traffic before changing the direction of traffic flow, the REL provide a contained environment in which simulated road debris can provide the opportunity to observe, test, and refine the road debris identifying algorithms using real-time connected vehicle data from THEA's own connected vehicles. In addition to CV fleet, THEA provided support in ensuring REL availability and closure to the public during testing (Figure 1).

Figure 1 THEA Selmon Expressway System

Experimental Data Generation

Figure 2 shows the location of the experiment area within the REL system. A 28-inch orange traffic cone served as the “debris” for the experiment. Since avoiding an object on the road requires swerving or lane change behavior, multiple runs of these behaviors were experimented for the analysis. The data collection resulted in about 50,000 valid BSMs.

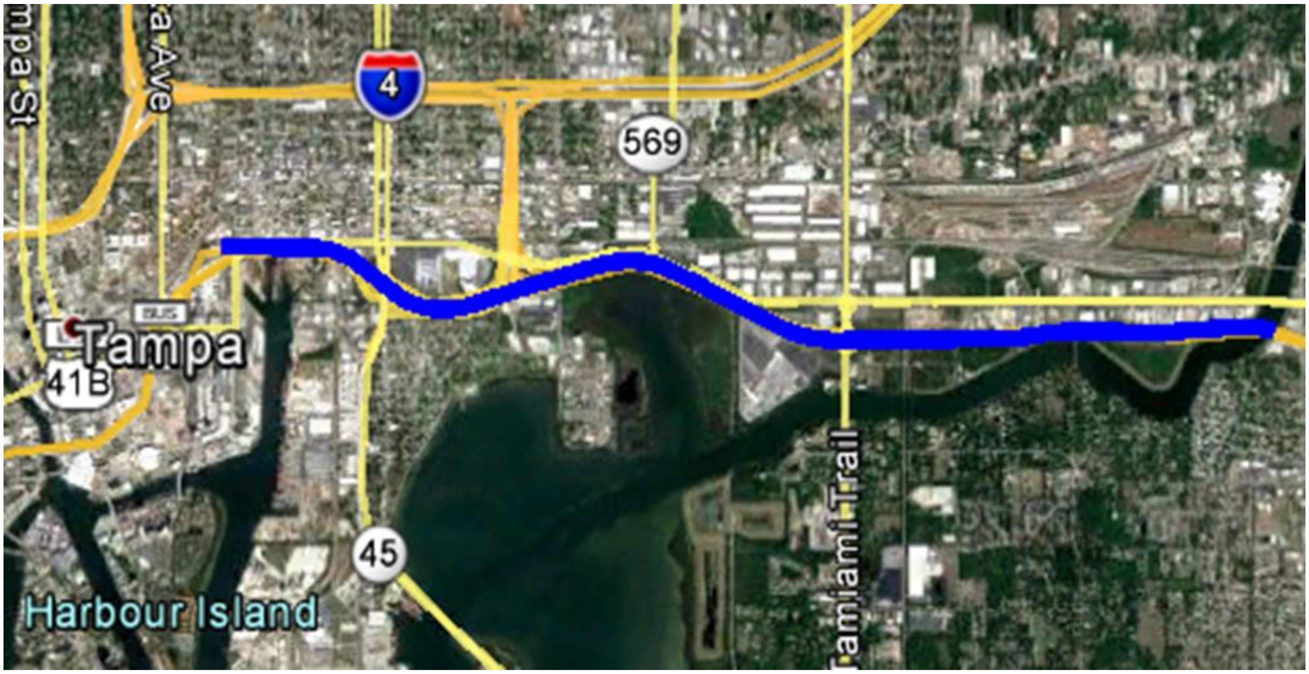

Figure 2 Experiment Location

Figure 3 reports the variation in vehicle speed, longitudinal and lateral acceleration for one of the lane changing runs where each vehicle broadcasts 1 BSM every tenth of a second. For comparison, the speed is in meters per second (m/s) and the y-axis has a limited the range of 3 m/s. The right side of the figure plots individual longitude and latitude observations on the road segment. The red boxes show the moments of lane change. The figure indicates that during a typical lane change, there exist significant fluctuations in lateral acceleration, while variations in the speed and longitudinal acceleration are not considerable.

Focusing on lateral acceleration, as shown in Figure 3 not all observations during the lane change can a priori be considered as extreme values. Therefore, to detect those observations within normal range, typical time series anomaly-detection methods, which mostly work on remainders (i.e. residuals of the time series after removal of other components) of time series, do not work. In our initial analysis, we tested the following approaches, which did not yield satisfactory results in detecting lane changes: Seasonal Decomposition of Time Series (STL) [19], Twitter Anomaly Detection [20], Inner Quartile Range (IQR) and Generalized Extreme Studentized Deviate Test (GESD) [21].

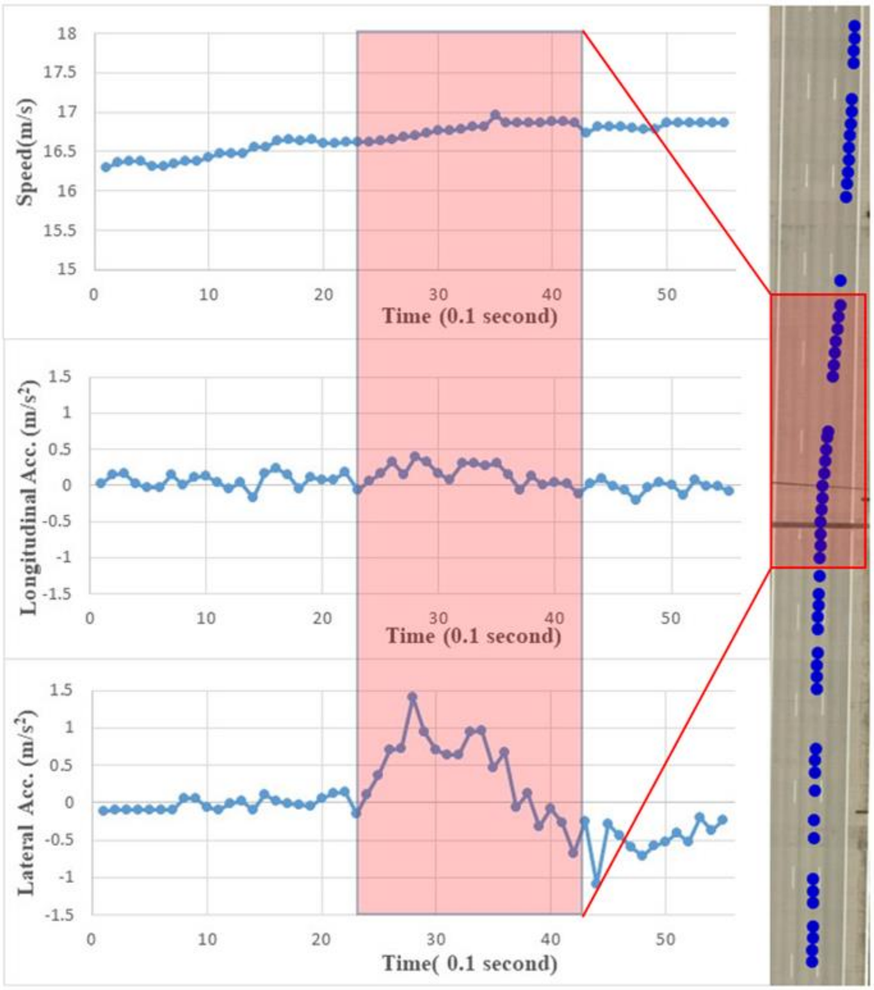

Figure 3 Vehicle speed and acceleration profiles during a lane change

Proposed Algorithm

To address the limits of the currently available anomaly-detection methods, the proposed algorithm relies on five tunable parameters:

1. **Absolute threshold**: observations beyond this value are flagged as initial anomalous values.
2. **Relative threshold**: this helps the algorithm detect those observations that are considerably higher than the mean of the sample. Particularly at curves, lateral acceleration values increase. Solely relying on the absolute value for flagging leads to mistakenly including observations at curves as part of the lane changing. To avoid this, the algorithm calculates the absolute deviation of individual observations and compares it with the relative threshold. This is also helpful in flagging observations belonging to a lane change that precedes or follows the local minimums and maximums e.g., points 25 to 27 and 29 to 32 in lateral acceleration plot (where point 28 is the maximum) in **Figure 3**.
3. **Number of bridging points**: this parameter is used to consider the observations connecting local maximum to local minimum points as part of a lane change.

Commonly, as per analysis on collected data, there exist a local maximum and local minimum, which are detected via the absolute threshold. The sequence of their appearance in the data depends on the direction of the lane change i.e. right to left and left to right because of the positive and negative lateral acceleration definition per Society of Automotive Engineers (SAE) J2735 standard on BSM data structure [22]. There are also observations in between, some of which are flagged through the absolute and relative thresholds. However, those lateral acceleration values around zero that are part of a lane change remain undetected due to their within-normal-range values. Not considering them as a part of lane change will cause an overestimated number of lane changes. Therefore, by setting the number of bridging points, the algorithm is able address this issue.

4. **Minimum number of consecutive points**: having detected lane change observations through the above three parameters, the algorithm also checks if the number of flagged observations meets a minimum number of consecutive points. This parameter is beneficial in working with high resolution data (i.e., BSM data generation rate). For instance, if the data are generated at a rate of one observation per second, observing three or more consecutive flagged observations is enough to be considered as a lane change while in 0.1-second data, this parameter should be set to at least 10. If the number of flagged observations is below this parameter, they will be dropped.
5. **Moving average parameter**: high-resolution data can be smoothed and used instead of using raw data. If this parameter is set to 1, raw data are used.

The steps of the algorithm are as follows:

1. **INPUT** parameters 1 to 5 (explained above and shown below in red).
2. **READ** lateral acceleration vector from BSM dataset.
3. **REPLACE** it with calculated moving average values using *movingAveragePar*, call it "x".
4. **FOR** all $x_i \in x$ **IF**:
    - **i.** ($x_i \geq$ *absThreshold* **OR** $x_i \leq$ *absThreshold*)**AND**
    - **ii.** ($|x_i$ – mean $(x)|) \geq$ *relThreshold*)
    - iii. **THEN:** Flag x_i as an initial member of a lane change.
5. **IF** number of observations between two consecutive flagged x_i's $\leq$ *numBridgPoint*
    - i. **THEN:** flag those observations in between as initial member of the lane change.
6. **FOR** each series of lane change (LC_j) **IF:** length $LC_j \leq$ *minNumConsPoint*

    THEN: keep LC_j as finalized lane change
    ELSE: drop LC_j
7. **RETURN** longitudes and latitudes of finalized lane changes.

Per the algorithm steps, the process identifies the moments of lane changes and their locations can be obtained for purpose of pinpointing debris on the road. Note that as debris might cause more drastic lane changes, the absolute and relative threshold parameters can be fine-tuned to exclude regular or smoother lane changes from the ones that occurred due to debris presence.

Input Data

The final dataset consists of 17 lane change runs on the REL. Of these, 13 have one-lane changes (to avoid the cone), three have two-lane changes, one three-lane changes, for a total of 22 lane changes. To test false positives, four lane-keeping driving runs were also generated. After downloading from the vehicle, the data were error checked, cleaned and the 17 individual lane-change profiles were labeled (i.e., individual lane change, no lane change, and swerve) for subsequent testing of algorithm performance. The data contain BSM Part I core elements, including vehicle longitude, latitude, speed, lateral and longitudinal acceleration, and heading. As discussed in the methodology section, the lateral acceleration was used for the development of the algorithm.

Chapter III: Results

Lane Change Detection

The algorithm was applied to the data to investigate its ability to detect lane changes. The confusion matrix of **Table 1** summarizes the results of the algorithm's accuracy. The algorithm was able to correctly detect 12 out of 13 one-lane changes and all multiple-lane (two-lane and three-lane) changes. Then the algorithm was tested to detect no-lane changes over the four no-lane change runs. In all four cases, the algorithm correctly classified the runs as no-lane change runs. Figure 4 shows lateral acceleration value of driving profiles characterizing multiple lane changing behavior. For better illustration, the correct and incorrect lane change detections are indicated using green (correct) and red (incorrect) polygons overlaid on the figure.

Table 1 Algorithm Accuracy Confusion Matrix

		Algorithm Classified as		
		Lane Change	Not Lane Change	Accuracy
Ground Truth	Lane Change	21	1	95%
	Not Lane Change	0	4	100%
		Total		96%

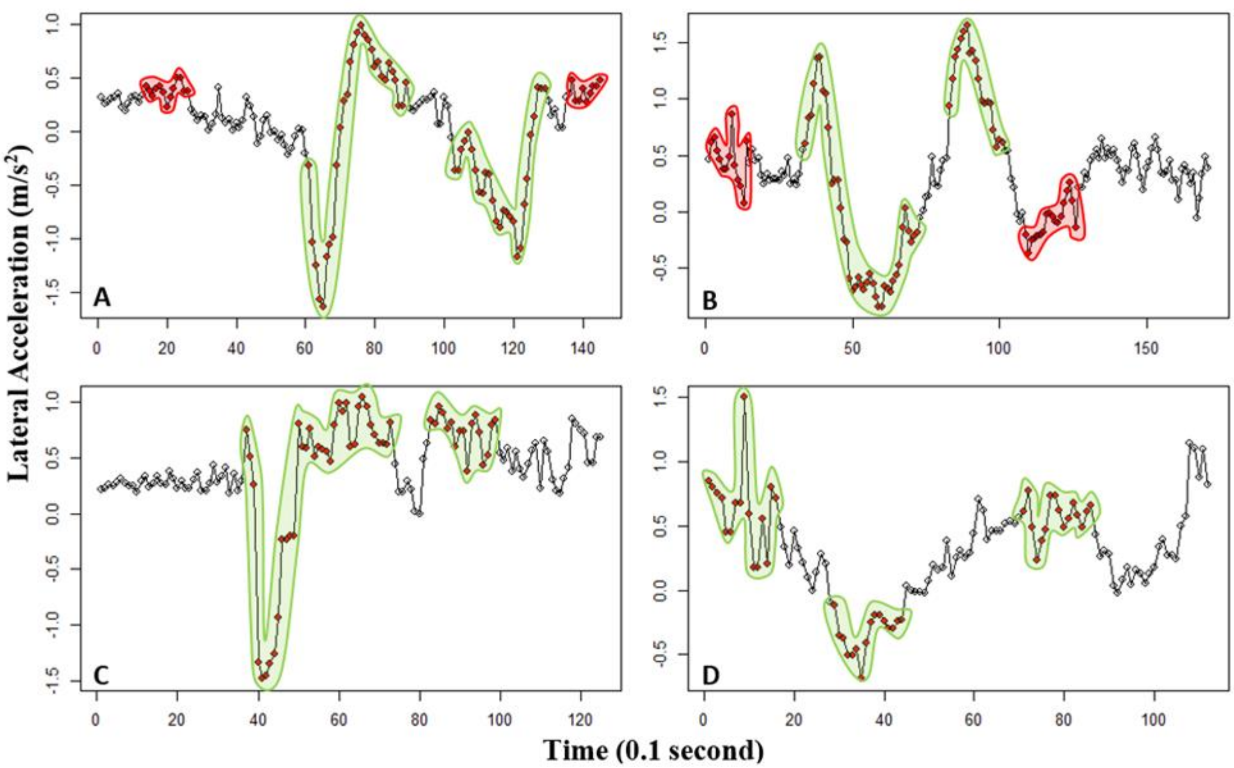

Figure 4 Lateral acceleration of driving profiles with multiple-lane changes

When testing over multiple lane changes, the algorithm identified four lane changes that were not explicitly generated as part of the vehicle runs. The four misclassifications are shown in Figure 4.A and Figure 4.B, two of which are indeed the continuation of previously detected lane changes. As the figure shows, there are less than a second apart. It is interesting to note that both A and B driving profiles are at a curved part of the road making it a more difficult for the algorithm to avoid false positives. The algorithm performed well in driving profiles C and D. As noted in the methodology section, increasing the number of bridging points can solve this issue. However, the parameters were left unchanged for consistency and to assess the performance of the algorithm under different conditions. Different parameters can be tuned for straight and curved road segments to increase lane-detection accuracy. When it comes to identifying the locations of debris, false positives will not affect the results as we discuss next.

Debris Location Identification

In this step, the algorithm was applied to the object avoidance experimental data. During the two experiments with two different vehicles and drivers, 13 cone-avoidance runs were attempted. To further challenge the algorithm, instead of introducing separate object avoidance profiles, the entire experiment dataset was used. Therefore, the dataset contains all lanes changes, including regular lane changes and U-turns that were taken to repeat the experiment along the REL. Figure 5 shows the moments where the algorithm detected the lane changes in red colored points. However, lane changes due to object avoidance are clustered in space but not necessarily so in time, reflecting traffic density and travel behavior as drivers approach to specific debris fixed in space at different times.

Once the algorithm detects the lane change moments, their geocoded locations are obtained and a density heat-map is created to spatially identify the location of the debris (i.e., the cone in our experiment), as shown in Figure 6**.** The density graph is in fact a two-dimensional kernel density estimation with an axis-aligned bivariate normal kernel, evaluated on a square grid [23]. Regular lane changes, U-turns, as well as false positives will be less dense in space compared to the lane changes due to debris. Conversely, the density will be higher around the debris locations because more lane changes are observed from different drivers. In the case of real-world data, the probability that the algorithm generates false positives in the same location for different drivers is low and thus it does not affect the results. Those moments are spread across time and space and depicted as ellipses in the heat map showing the area(s) on which the lane changes happened. The ellipse shown in the left quadrant of Figure 6 has as semi-minor axis length of 200 ft., which indicates the approximate average length of lane changes to avoid the cone. The plus sign indicates that the location of the cone as detected by the algorithm (27.9555197, -82.4442500), which is 3.68 ft. (82 cm) from the location of the actual location of the cone (27.9555198, -82.4442406).

The algorithm was also able to estimate the location of the cone for the second experiment, as shown in the right quadrant of Figure 6. In this instance, the estimated location is 180 ft. from the actual location of the cone. This is because the centers of the ellipses correspond to the highest density areas of the heat maps, which are created based on the density of seconds flagged as part of lane changes. As noted earlier, lane changes show themselves as event durations in the data rather than exact moments and account for the heterogeneous response of drivers to the debris presence. Indeed, different drivers might initiate lane changes at different distances to objects on the road. Therefore, the center of ellipses is considered as a proxy for the location of objects rather than exact locations.

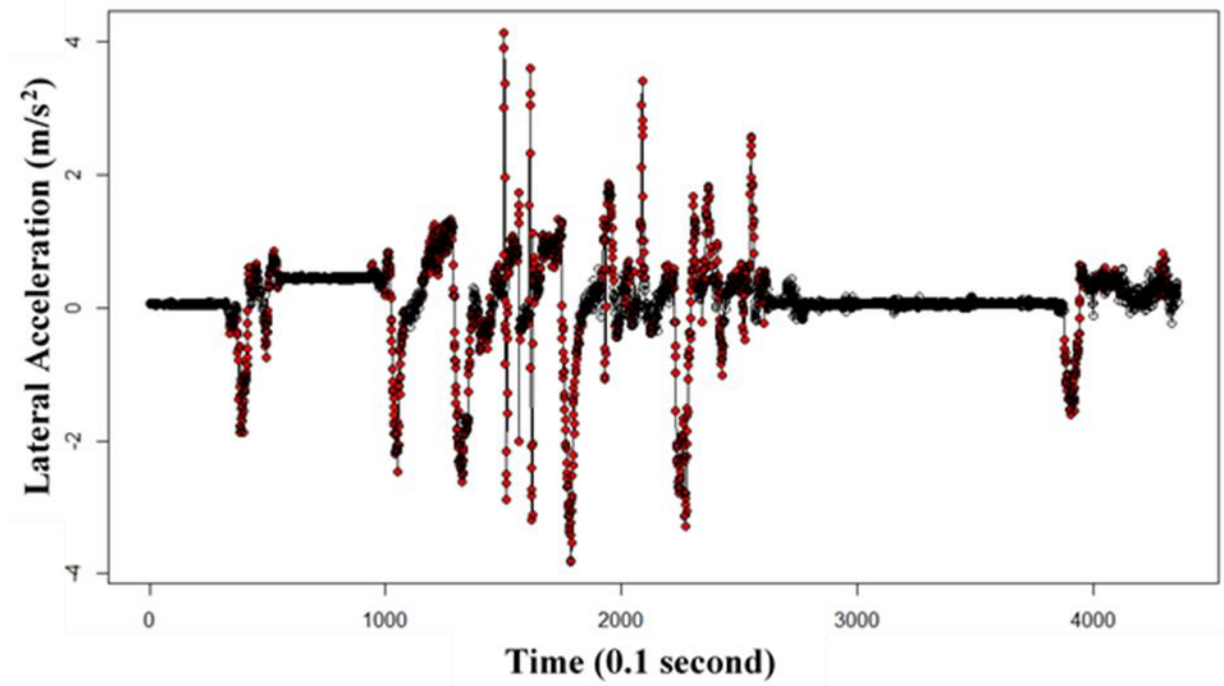

Figure 5 Lane-change moments detected by the algorithm (shown in red)

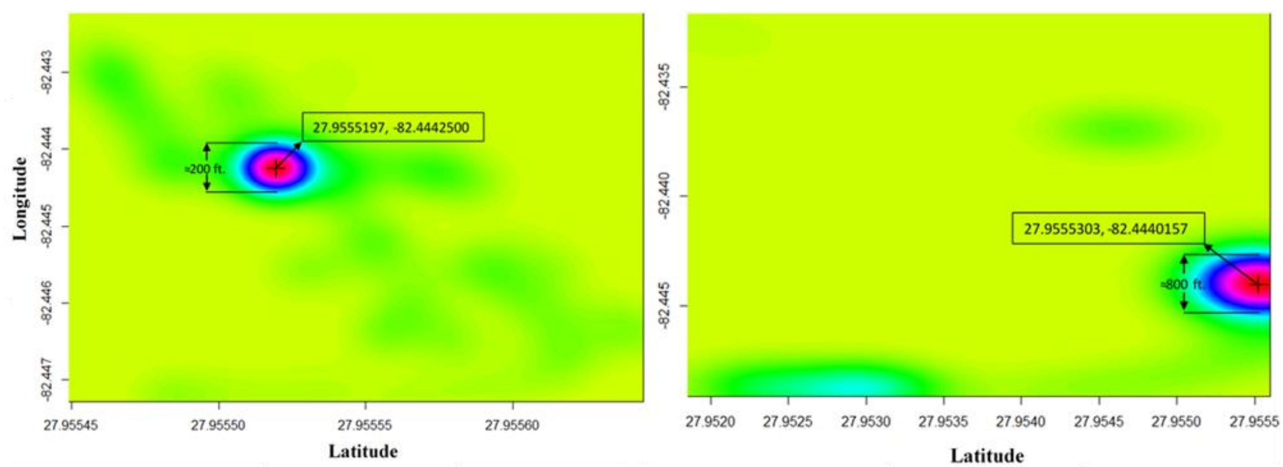

Figure 6 Density heat map showing the test cone (i.e., debris) location (Left: experiment 1, Right: experiment 2)

Conclusion

Roadway debris, potholes, or other unexpected obstructions can lead to significant traffic delays or worse, crashes. These roadway obstructions are particularly concerning in high-traffic and high-speed roadways where dense traffic conditions reduce visibility and large volumes of vehicles are exposed to risk. Although prevention of the various causes of these obstructions and defensive driving can reduce these consequences, the problem cannot be eliminated entirely. The existing manner in which unexpected roadway obstructions are handled is by driver reporting, which is inefficient because the act of reporting while driving can lead to distracted driving Using self-reported information can result in the untimely removal of the debris or in excessive resources deployed to swipe a high risk corridor to remove unexpected objects.

The objective of this project was to create a tool that can be used by local or state transportation, traffic, and maintenance agencies to improve the process of addressing road debris and other road hazards. This research developed a debris spotting algorithm the relies on high-frequency connected vehicle data. The algorithm is able accurately pinpoint obstruction objects by identifying lane change moments of individual drivers by monitoring their vehicles' lateral acceleration values. In the case of road hazard and debris, drivers' exhibit swerving and lane changing behaviors when they approach objects on the road. Thus, the algorithm is able to identify road debris locations by identifying repeated swerving and lane changes by different drivers. The algorithm parameters were fine-tuned using experimental data from two vehicles from the USDOT Tampa CV pilot sending their BSM data to road side units (RSUs), and ultimately to the local Traffic Monitoring Center (TMC). The overall accuracy of the algorithm in lane changing and swerving detection is about 96 percent. Finally, the algorithm's output generated a series of spatial heat maps reporting the approximate coordinates of the debris. With the increased installation of RSUs to cover the entire traffic network of major urban areas, TMCs can inject the algorithm's output in their monitoring platforms and utilize the heat maps for fast and efficient debris-removal dispatching. Since the current state of practice to address road debris rely on drivers' reports or continuous roaming of state patrols or city agencies, this tool can provide large benefits in identifying road hazards in terms of response time, accuracy and cost savings.

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