Using DSRC Road-Side Unit Data to Derive Braking Behavior

Rahul Sengupta, Tania Banerjee, Yashaswi Karnati, Sanjay Ranka and Anand Rangarajan
University of Florida, U.S.A.

Keywords: Connected Vehicle, DSRC, CV2X, Road-Side Unit, Braking, Traffic Safety.

Abstract: With the increasing deployment of Connected Vehicle Technology (via DSRC/CV2X), public traffic authorities are presented with a potential treasure trove of valuable data for analysis. However, several practical limitations exist that pose unique challenges in this publicly-collected data such as lack of vehicle re-identification due to privacy measures, sparsity of data, limited range of transmission, noise in recorded trajectories etc. In this paper, we analyze trajectories for braking behaviors of Connected Vehicle Road-side Unit (RSU) data. The dataset consists of trajectories collected from a dense urban grid consisting of 25 intersections along 4 high-volume arterials, for a period of 1 year. We begin by providing a brief description of the data collection and processing modalities. We then present a tool to perform exploratory analytics on the data with a focus on anomalous trajectories with hard-braking events. We show the benefits of such a tool for public traffic authorities to gain insights into the performance and safety aspects of urban arterials, and to guide policy decisions.

1 INTRODUCTION

The recent advancements in the Intelligent Transportation System (ITS) have led to the extensive deployment of various real-time sensing and data collection systems. Public traffic agencies collect various types of data, including loop detector data (Haas et al., 2001; Lamas et al., 2015), GPS, video, BlueTooth, CV2X (Cellular Vehicle-to-Everything), DSRC (Dedicated Short Range Communications) (Kenney, 2011), (Wolf et al., 2014). Such publicly-collected data has the potential for use in gaining insights into the state of corridors and real-time adaptive arterial traffic signal optimization (Wang et al., 2022; Zhao et al., 2012). However, it is resource-intensive to collect, collate, store several terabytes of data, and then perform analytics to gain insights.

To address this challenge, this paper[1] describes a tool that uses the data broadcast by V2X (Vehicle-to-everything) enabled vehicles to analyze anomalous trajectory events, specifically unexpected braking. The V2X communication systems, like DSRC (Dedicated Short Range Communications) and CV2X (Cellular Vehicle-to-Everything), are becoming increasingly widespread in urban traffic networks. These communication systems usually consist of two types of components: On-board Units (OBUs), which are installed and interfaced with vehicles, and Road-side Units (RSUs) which are usually installed at intersections. OBUs and RSUs communicate with each other via a series of predefined messages (Kenney, 2011). Importantly, OBUs transmit their host vehicles' data including location, speed, heading to RSUs.

While there is significant work (Liu et al., 2022) that uses trip-level probe vehicle data via GPS (Global Positioning Satellite), such data is usually available in real-time to auto guidance platforms (such as Android Auto[2], Apple CarPlay[3], HERE Technologies[4], WEJO[5] etc.) and ride-sharing companies (such as Uber[6], Lyft[7] etc.). This proprietary data is not publicly accessible. However, public traffic authorities may have access to GPS trajectory traces transmitted by OBUs to RSUs, when the vehicles are within a couple of hundred meters of the RSUs near intersections.

Interactions of vehicle trajectories within a signal-

[1]The work was supported in part by NSF CNS 1922782 and by the Florida Department of Transportation (FDOT). The opinions, findings and conclusions expressed in this publication are those of the authors and not necessarily those of NSF or FDOT.

[2]www.android.com/auto/
[3]www.apple.com/ios/carplay/
[4]www.here.com/
[5]www.wejo.com/
[6]www.uber.com/
[7]www.lyft.com/

Sengupta, R., Banerjee, T., Karnati, Y., Ranka, S. and Rangarajan, A.
Using DSRC Road-Side Unit Data to Derive Braking Behavior.
DOI: 10.5220/0012025300003479
In *Proceedings of the 9th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2023)*, pages 420-427
ISBN: 978-989-758-652-1; ISSN: 2184-495X

ized intersection is a complex phenomenon(Banerjee et al., 2022), influenced by factors such as signal timing plan, road geometry, surrounding driver behaviors, pedestrian behaviors etc. Intersections are also critical points of conflict along the roadways and account for one-quarter of all traffic fatalities as well as one-half of all traffic injuries (FHWA, ; FDOT,).

Vehicle trajectories near intersections (including anomalous braking behavior) can be detected by video data with automated object segmentation and tracking algorithms (Huang et al., 2020; Banerjee et al., 2022). These algorithms detect and track the trajectories of various road users. Based on these, dangerous braking can be detected. However, these algorithms are greatly limited by the deployed video camera instrumentation and have a very limited field of view: fish-eye lens cameras can only capture the inner intersection region and regular cameras can generally capture only one approach of the intersection.

GPS-based trajectories have been used to detect dangerous interactions. For example, in (Li et al., 2021), important bus-driving events (using GPS trajectory data) were extracted and used for surrogate safety measures for pedestrians and bicycles.

In this paper, we focus on utilizing the anonymized GPS data from the Connected Vehicles infrastructure to develop algorithms to detect braking incidents which are often representative of the dangerous events that happen near intersections. The GPS data was collected at the RSUs for the Connected Vehicles such as transit buses and official University vehicles that broadcast their coordinates, in terms of latitude and longitude, to the RSUs. An added advantage with this data over video is the larger tracking region over which vehicles can be tracked.

The contributions in this paper may be summarized as follows:

1. We created a system for collecting and storing data in real-time from 25 intersections in the vicinity of University of Florida, by connecting to the RSUs. The collected data was then stored on the cloud in data buckets.
2. We developed a novel system to analyze and visualize location coordinate data transmitted by OBUs to the RSUs, to determine braking behavior which is an important marker for traffic intersection safety.
3. In this work, we lay the groundwork for effectively using DSRC (and in future, CV2X) data for analyzing braking behaviors by local traffic authorities based on the RSU data likely available to them. This is despite the practical challenges associated with such data including the lack of vehicle re-identification (due to privacy concerns), limited range restricted to the proximity of the RSU and low OBU penetration rates.

This work is intended to serve as a foundation for future applications, particularly as the number of Connected Vehicles grows and their presence at intersections becomes more widespread. The paper is organized as follows: Section 2 describes our data collection framework and methodology for determining the braking behavior. Section 3 presents our results of analyzing data collected for over a year for braking behavior at an intersection-level as well as at the network-wide system-level. Finally, we conclude in Section 4.

2 DATA COLLECTION AND PROCESSING

In this section, we describe the data source, the data location, and the data collection and storage pipeline, the data processing, and our methodology for detecting braking behavior.

2.1 Data Source

The data source comprises of the RSUs at various intersections. The collected data is composed of incoming and outgoing data with respect to an RSU. The incoming data are DSRC messages sent by the OBUs, and by neighboring RSUs. On the other hand, the outgoing DSRC messages are sent by the RSU to the neighboring RSUs, and all OBUs in its range.

DSRC, or Dedicated Short-Range Communications (Biddlestone et al., 2012), is a radio communication technology that follows the IEEE 802.11 ”Wi-Fi” standards and enables secure one-way and two-way communication between vehicles and the road traffic infrastructure. The range of DSRC communication can vary from 100-1000m based on the topography and line-of-sight. This technology enables vehicles to share information with other Connected Vehicles and to send messages about road conditions and safety issues. In addition to relaying information between vehicles and road traffic infrastructure, DSRC technology also enables vehicles to communicate with RSUs installed at traffic intersections. This communication capability can be utilized for signal timing management and optimization (Hsu and Shih, 2015; Mandava et al., 2009). For the purpose of this work, we gather the messages sent from vehicles to the RSUs. These messages are formatted in a specific way and include various fields. Our main focus is on the GPS coordinates fields within these messages.

GPS, or Global Positioning System (Hofmann-Wellenhof et al., 2012), is a radio navigation system that uses satellites to send low-energy radio signals to Earth, which can be picked up by GPS receivers commonly found in smartphones, for example. When GPS receivers are installed on vehicles, these sensors provide an estimate of the vehicle's location, heading, and speed. It should be noted that GPS signals can become inaccurate in areas with tall buildings due to scattering effects, in which case we would need to post-process the information to dampen the noise.

GPS data has been widely utilized in traffic flow analysis, particularly for congestion analysis (Yongchuan et al., 2011; D'Andrea and Marcelloni, 2017; Kan et al., 2019; Wang et al., 2016; Sun et al., 2019). Connected vehicles have GPS systems built into the OBUs which broadcast their GPS trajectory at a 10Hz resolution to RSUs via Onboard Units (OBUs) by embedding the latitude and longitude within a Basic Safety Message (BSM). Figure 1 shows the structure of a DSRC BSM message.

ASN.1 Representation:

```
BSMcoreData ::= SEQUENCE {
    msgCnt         MsgCount,
    id             TemporaryID,
    secMark        DSecond,
    lat            Latitude,
    long           Longitude,
    elev           Elevation,
    accuracy       PositionalAccuracy,
    transmission   TransmissionState,
    speed          Speed,
    heading        Heading,
    angle          SteeringWheelAngle,
    accelSet       AccelerationSet4Way,
    brakes         BrakeSystemStatus,
    size           VehicleSize
    }
```

Figure 1: Fields in a Basic Safety Message (BSM) from SAE J2935.

This study focuses on the structure of Basic Safety Messages (BSMs) registered by OBUs as they pass near intersections equipped with RSUs. The BSM format, described in J2935 (DSRC, 2020), allows the RSU to capture various properties of the vehicle, including its location, speed, and more. However, to maintain privacy, the vehicle is assigned a temporary ID that changes every few minutes, so the count of such IDs does not reflect the actual number of unique vehicles.

The type of data that can be captured by the OBU depends on its capability to connect to the vehicle. If the OBU is directly interfaced with the vehicle, it can record fields such as transmission, heading, angle, acceleration and braking. However, for this study, the vehicles were fitted with external portable OBUs. Hence, only the vehicle's ID, time stamp, latitude and longitude, and speed (*id, secMark, lat, long, speed* fields in the BSM message structure) were captured.

Thus, the data of interest was obtained from RSUs. Although the collected data included incoming messages from OBUs and neighboring RSUs, this paper focuses on the messages received from OBUs in the form of BSMs. The OBUs generally transmit BSMs at a rate of 10 messages per second. The BSMs gathered include GPS coordinates of the vehicles in terms of latitude and longitude, and they are extensively utilized in this study.

2.2 Data Location

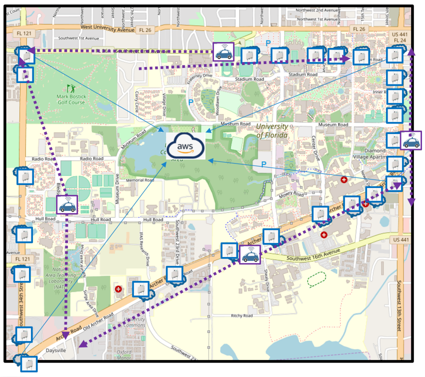

Figure 2: Intersections fitted with RSUs are shown here. The intersections surround the vast campus of the University of Florida. The four roads forming a Trapezium have 25 intersections that are fitted with RSUs.

In this section, we provide an overview of the region from which the data is collected. The region is the Trapezium surrounding the University of Florida in Gainesville, as shown in the Figure 2. The Trapezium is formed by four major roads: 34th Street, West University Avenue, 13th Street, and Archer Road, forming its Western, Northern, Eastern, and Southern boundaries, respectively. These roads are among the busiest in Gainesville, with high levels of pedestrian traffic.

The data for this study was collected from 25 signalized intersections, primarily from vehicles owned by the City of Gainesville and the University of Florida, including transit buses and service vehicles. The data collection took place from April 2021 to July 2022 and involved 50-60 vehicles. Although the limited deployment of OBUs at the time of the study resulted in sparse data, the methodology developed in this paper provides a foundation for future connected vehicle applications as their deployment increases.

The distribution of unique identifiers in our message logs is depicted in Figure 3. Our logs contained approximately 200,000 unique identifiers for Connected Vehicles. It's noteworthy that while a single physical vehicle may have multiple identifiers for privacy purposes, the relative number of unique identifiers is indicative of the relative number of actual ve-

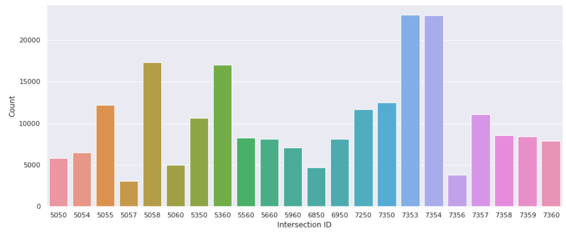

Figure 3: Counts of unique identifiers of Connected Vehicles tracked between the months of April 2021 to July 2022, across various intersections.

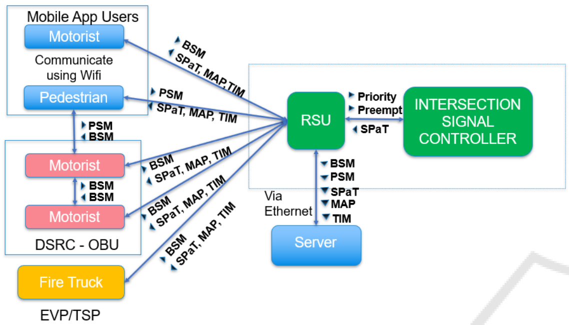

Figure 4: Various messages exchanged between the users and the RSUs. The data collection software resides in the server, which in our case is housed at the City of Gainesville Laboratory.

hicles at the intersection, especially considering that the speed limits at these intersections are similar. As such, we can conclude, for example, that intersections 7353 and 7354 have a higher presence of OBUs compared to intersection 5057.

2.3 Data Collection

This section details the data collection process used in our study. The data was collected from Road Side Units (RSUs) in the region surrounding the University of Florida, Gainesville. There are two methods for connecting to the RSUs: through the RSU web application (provided by the Original Equipment Manufacturer) or using Java WebSocket APIs. We chose the latter method for data collection.

To receive messages from the RSUs, a Java application was written to subscribe to the messages using websocket. In the process of collecting data from the RSUs, the Java application sent the subscription command and executed the "!wait" command to keep the websocket connection alive and receive messages from the RSUs.

Once a message was received, it was written to the standard output and forwarded to a Python (version 3.7) interpreter through the Python subprocess PIPE. In addition, the control message was also written to the standard output for the Python interpreter to monitor the connection status.

The Python interpreter, upon receiving the messages, first extracted the byte-encoded XML message from the raw message wave and decoded it. The syntax and semantics of the XML message can be found in the SAE J2735 standard (Kenney, 2011). In addition to the BSM, we received other types of messages from the RSUs such as PSM (Personal Safety Message), SPAT (Signal Phase And Timing Message), TIM (Traveler Information Message), MAP (Map Data Message), SSM (Signal Status Message), and SRM (Signal Request Message). Figure 4 shows the various DSRC message senders and recipients in a CV2X infrastructure. The data collector and processor codes reside in the Server.

Finally, the messages received from the RSUs were stored in an Amazon Web Services (AWS) S3 bucket [8]. AWS S3 provides high data durability and availability, close to 100%, and the data was organized by city, year, month, day, and intersection properties for quick access. All data stored in AWS S3 is encrypted by default, and the S3 API endpoints support Secure Sockets Layer/Transport Layer Security for encrypting data in transit.

2.4 Data Processing

The initial stage of the data processing pipeline involves downloading the RSU logs from AWS S3 bucket and using the data parsing module to read the logs and establish a spatio-temporal trajectory database. This is achieved by using Python XML-parsing library LXML 4.9.0[9] and Pandas 1.4 [10], to parse the BSM messages. A trajectory database is built including all available tracks, which is stored as dictionaries indexed by vehicle IDs and containing time-stamped latitude and longitude of the vehicles' paths.

However, the stored trajectories often contain noise due to factors such as surrounding buildings and atmospheric conditions. To address this, trajectory smoothening algorithms are developed using vehicle motion data, based on windowed moving averages and interpolation techniques to fill any gaps in the data. The goal of these algorithms is to provide a smoother representation of the raw, noisy trajectories. The original data is obtained at one decisecond resolution. We smoothen the data by using a moving average with a window of five deciseconds.

[8] aws.amazon.com/
[9] www.lxml.de
[10] pandas.pydata.org/

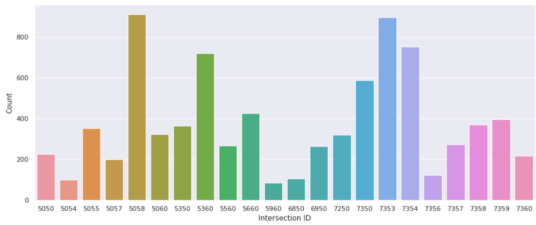

Figure 5: Counts of unique identifiers of Connected Vehicles tracked showing braking behavior of concern (MILD/HARD/EXTREME) between the months of April 2021 to July 2022, across various intersections. Compared to Figure 3, we can see that there is a correlation between the intersections with most vehicle identifier detections, and the intersections having more braking events of concern.

2.5 Methodology for Detecting Braking Behavior

A near-miss traffic event can be described as an event where a significantly higher risk is involved in the interactions between road users than in an ordinary case. One of the key indicators of a near-miss is unexpected sudden braking by a vehicle. The sudden braking may be in response to another road user (such as another vehicle or pedestrian) coming too close. It could also be in response to a static hazard such as a pothole. While both cases are undesirable, they can be distinguished by their frequency of occurrence. Suppose multiple vehicles show a similar braking pattern in the same region, around the same time, which is sustained for at least several minutes. In that case, it can be reasonably inferred that the braking is in response to a persistent static hazard. However, if such braking only occurs sparsely and irregularly, it may be of concern. In this analysis, we focus on detecting braking behavior that may be of concern.

We obtain braking behavior from GPS (Global Positioning System) trajectory data from Basic Safety Messages (BSMs), by looking at the deceleration profiles. Deceleration is found by taking the second difference of the smoothened trajectory, as the vehicles were not digitally interfaced with the OBU and were thus not able to capture actual braking. Numpy 1.23.0[11] Python library is used to compute the second difference (i.e. second derivative). Haversine formula[12] is used to convert the latitude/longitude coordinates to meters.

We characterize braking behavior based on deceleration thresholds (Baldanzini et al., 2016; Staputis and Žuraulis, 2023). In this analysis, we use the acceleration due to gravity "g" (9.8 m/s^2) as a unit, and mark:

- 0g to -0.35g as SAFE Braking
- -0.35g to -0.47g as MILD Braking
- -0.47g to -0.62g as HARD Braking
- Beyond –0.62g is EXTREME Braking

We only present results for MILD, HARD, and EXTREME braking in this paper. SAFE braking is not of concern.

3 EXPERIMENTS

In this section, we present the outcomes of implementing our approach on a per-intersection basis and also take a comprehensive view that encompasses all the intersections.

3.1 Intersection Braking Behavior

Figure 5 shows all MILD/HARD/EXTREME combined events per intersection. We break up this information based on braking severity per instance in Figure 6. Note that it is possible that a single identifier may contain multiple braking instances. An instance here lasts for 1 decisecond, which is the time resolution of Basic Safety Messages. Thus, this plot also captures the duration (in deciseconds) of the class of braking behavior seen. Also, in the plots shown, blank rectangles indicate that exactly zero such braking instances were found in the given time bucket.

3.1.1 Temporal Behavior

Our study on braking events includes an analysis of the occurrences based on the time of the day and the day of the week. This analysis is represented in the form of three plots, each one for a specific level of severity - mild, hard, and extreme braking events.

The plots in Figures 7, 8, 9 and 10 depict that the majority of the braking events of concern occur during the weekdays and during the mid-day hours. This could be due to several reasons such as the presence of a higher number of pedestrians during the lunch hour, but also the increased presence of Connected Vehicles on the road at that time.

3.1.2 Spatial Behavior

In order to better understand the braking behavior of vehicles, we segment the data based on the distance from the intersection where the braking event occurred. To do this, we divide the distance into three categories: 0-20 meters, 20-40 meters, and 40 meters

[11] www.numpy.org

[12] rosettacode.org/wiki/Haversine_formula

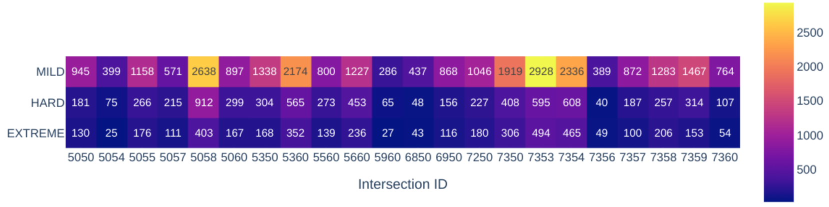

Figure 6: Counts of unique identifiers of Connected Vehicles tracked showing braking behavior of concern (MILD/HARD/EXTREME) between the months of April 2021 to July 2022, across various intersections. Compared to Figure 3, we can see that the intersections with most vehicle identifier detections, also have more braking events of concern. .

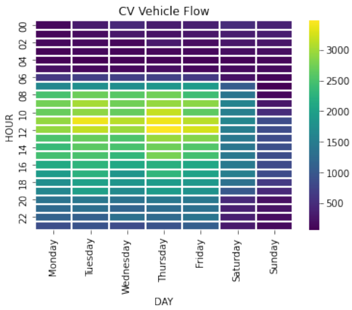

Figure 7: Heatmap showing the flow of all Connected Vehicles across the week, system-wide.

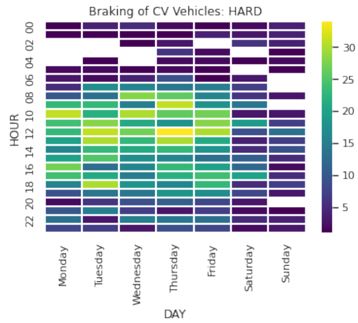

Figure 9: Heatmap showing HARD braking events of all Connected Vehicles across the week, system-wide.

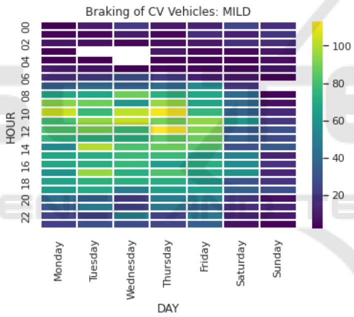

Figure 8: Heatmap showing MILD braking events of all Connected Vehicles across the week, system-wide.

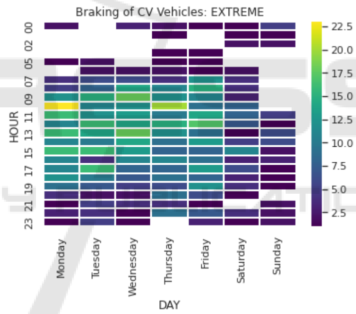

Figure 10: Heatmap showing EXTREME braking events of all Connected Vehicles across the week, system-wide.

and above. The first category, 0-20 meters, is particularly important as it captures the braking events that occur near the intersection. This is likely to indicate braking in response to pedestrian crossings, which are common near intersections. On the other hand, the next category of 20-40 meters likely indicates braking due to a vehicle's response to last-minute lane changes, as vehicles prepare to make a turn at the intersection.

As an illustration of the analysis, Figure 11 shows the different levels of braking behavior against the distance from the intersection for intersection 5050. From the plot, it can be observed that most of the braking events of concern occurred beyond 40 meters from the intersection, which is likely due to a variety of factors such as road conditions, vehicle speed, and driver behavior.

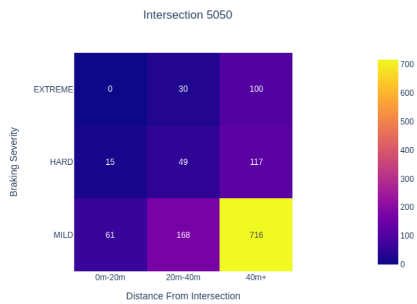

Figure 11: Plots showing the severity of braking against the distance from the center of the nearest intersection.

3.1.3 Speed Characteristics

Our next analysis involves examining the relationship between braking behavior and vehicle speed. To do

Figure 12: Plots showing the severity of braking against the speed at which the braking took place.

this, we plot the braking events against the speed of the vehicle at the time of the event. We divide the vehicle speeds into three segments: 0-20 mph (0-32.2 kmph), 20-40 mph (32.2-64.4 kmph), and 40 mph (64.4+ kmph) and above.

As shown in Figure 12, for intersection 5050, we observe that a significant number of hard and extreme braking events occur at relatively low speeds. This information is useful in understanding the severity of braking behavior and its relationship with the speed of the vehicle. It could indicate that drivers are more likely to brake harshly when they are traveling at lower speeds, which could be due to a variety of factors, such as sudden traffic changes, road conditions, or distractions. This observation also may be due to the fact that most vehicles approach the intersection at lower speeds. The future development of the dashboard will allow for combined derived metrics such as such as events normalized by vehicle flow (based on nearby loop detector data) to explore such insights. These findings can help inform future studies on braking behavior and road safety.

3.2 System-Wide Braking Behavior

We also developed an interactive visualization tool to provide a more in-depth analysis of braking behavior. This tool, which runs in a web browser, presents the braking events of concern (i.e., MILD, HARD, and EXTREME events) on a map in the form of a heatmap, providing a bird's-eye view of the distribution of such events. The user can interact with the tool to view specific regions and zoom in to inspect particular intersections or stretches of roads.

This tool makes it easier to identify hotspots where braking events of concern are more prevalent. As an example, Figures 13 and 14 show the overall view of the braking behavior and a zoomed-in view of an intersection approach, respectively. From the visualization, one can see that some stretches of West University Avenue and Archer Road have fewer braking events of concern compared to other areas.

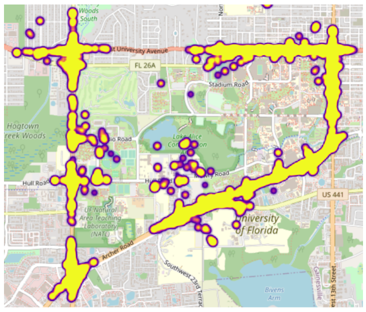

Figure 13: Interactive web browser-based application containing a plot of all braking events of concern.

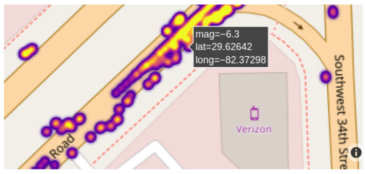

Figure 14: Zoomed-in view of an intersection approach in the interactive application. It allows the user to inspect intersection approaches. Here the East-bound approach of the intersection of Archer Road and 34th Street is shown.

4 CONCLUSION AND FUTURE WORK

The recent advancements in ITS have led to the extensive deployment of various real-time sensing and data collection systems for public traffic agencies. Our work focuses on using the Connected Vehicle (CV) data available through V2X (Vehicle-to-everything) communication systems like DSRC and CV2X. The data collected by these technologies is useful for studying the braking dynamics of vehicles as they approach, enter, and exit intersections.

We presented a methodology for analyzing braking behavior in connected vehicle data. The study utilized a spatio-temporal trajectory database created from RSU logs and BSM messages, which were parsed using XML-parsing libraries and Python. The trajectories were smoothened using windowed moving averages and interpolation.

We presented a study, for which we collected data in real-time from 25 intersections surrounding the University of Florida and stored the data on the cloud. The data was processed offline and braking behavior was analyzed on a per-intersection basis as well as from an overall perspective, taking into account the time-of-day and day-of-week, distance from the intersection, and speed at which the vehicle was traveling. The results of the analysis were presented in various plots and an interactive visualization tool was developed to allow the user to get a better understanding of braking behavior in the network. Overall, the methodology provides a valuable tool for analyzing braking behavior and identifying potential hotspots for safety concerns.

During our investigation into the real-world dynamics and potential of data analytics in an urban traffic grid, we encountered the challenge of sparse data caused by the limited deployment of Connected Vehicle (V2X) technology. Nevertheless, this research sheds light on the enormous potential of utilizing Connected Vehicle data to optimize traffic flow and improve road safety, opening up a promising future for transportation and traffic management.

REFERENCES

Baldanzini, N., Huertas Leyva, P., Savino, G., and Pierini, M. (2016). Rider behavioral patterns in braking manoeuvres. *Transportation Research Procedia*, 14:4374–4383.

Banerjee, T., Chen, K., Almaraz, A., Sengupta, R., Karnati, Y., Grame, B., Posadas, E., Poddar, S., Schenck, R., Dilmore, J., Srinivasan, S., Rangarajan, A., and Ranka, S. (2022). A modern intersection data analytics system for pedestrian and vehicular safety. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 3117–3124.

Biddlestone, S., Redmill, K., Miucic, R., and Ozguner, Ü. (2012). An integrated 802.11p wave dsrc and vehicle traffic simulator with experimentally validated urban (los and nlos) propagation models. *IEEE Transactions on Intelligent Transportation Systems*, 13(4):1792–1802.

D'Andrea, E. and Marcelloni, F. (2017). Detection of traffic congestion and incidents from gps trace analysis. *Expert Systems with Applications*, 73:43–56.

DSRC (2020). *DSRC Technical Committee On-Board System Requirements for V2V Safety Communications*.

FDOT. Intersection operations and safety, https://www.fdot.gov/traffic/trafficservices/intersection-operations.shtm.

FHWA. Intersection safety, https://highways.dot.gov/safety/intersection-safety.

Haas, C., Mahmassani, H., Khoury, J., Haynes, M., Rioux, T., and Logman, H. (2001). Evaluation of automatic vehicle identification for san antonio's transguide for incident detection and advanced traveler information systems.

Hofmann-Wellenhof, B., Lichtenegger, H., and Collins, J. (2012). *Global positioning system: theory and practice*. Springer Science & Business Media.

Hsu, M. and Shih, A. (2015). A traffic signal control mechanism in a connected vehicle environment. In *2015 IEEE International Conference on Consumer Electronics - Taiwan*, pages 256–257.

Huang, X., He, P., Rangarajan, A., and Ranka, S. (2020). Intelligent intersection: Two-stream convolutional networks for real-time near-accident detection in traffic video. *ACM Transactions on Spatial Algorithms and Systems (TSAS)*, 6(2):1–28.

Kan, Z., Tang, L., Kwan, M.-P., Ren, C., Liu, D., and Li, Q. (2019). Traffic congestion analysis at the turn level using taxis' gps trajectory data. *Computers, Environment and Urban Systems*, 74:229–243.

Kenney, J. B. (2011). Dedicated short-range communications (dsrc) standards in the united states. *Proceedings of the IEEE*, 99(7):1162–1182.

Lamas, J., Castro-Castro, P.-M., Dapena, A., and Vazquez-Araujo, F. (2015). Vehicle classification using the discrete fourier transform with traffic inductive sensors. *Sensors*, 15.

Li, P., Abdel-Aty, M., and Yuan, J. (2021). Using bus critical driving events as surrogate safety measures for pedestrian and bicycle crashes based on gps trajectory data. *Accident Analysis & Prevention*, 150:105924.

Liu, Y., Jia, R., Ye, J., and Qu, X. (2022). How machine learning informs ride-hailing services: A survey. *Communications in Transportation Research*, 2:100075.

Mandava, S., Boriboonsomsin, K., and Barth, M. (2009). Arterial velocity planning based on traffic signal information under light traffic conditions. In *2009 12th International IEEE Conference on Intelligent Transportation Systems*, pages 1–6.

Staputis, A. and Žuraulis, V. (2023). Research of efficiency of anti-lock braking system during emergency cornering manoeuver. In *TRANSBALTICA XIII: Transportation Science and Technology: Proceedings of the 13th International Conference TRANSBALTICA, September 15-16, 2022, Vilnius, Lithuania*, pages 224–235. Springer.

Sun, S., Chen, J., and Sun, J. (2019). Traffic congestion prediction based on gps trajectory data. *International Journal of Distributed Sensor Networks*, 15(5):1550147719847440.

Wang, X., Sanner, S., and Abdulhai, B. (2022). A critical review of traffic signal control and a novel unified view of reinforcement learning and model predictive control approaches for adaptive traffic signal control. *arXiv preprint arXiv:2211.14426*.

Wang, Y., Cao, J., Li, W., and Gu, T. (2016). Mining traffic congestion correlation between road segments on gps trajectories. In *2016 IEEE International Conference on Smart Computing (SMARTCOMP)*, pages 1–8. IEEE.

Wolf, J., Bachman, W., Oliveira, M., Auld, J., Mohammadian, A. K., Vovsha, P., and Zmud, J. (2014). Applying gps data to understand travel behavior, volume ii: guidelines. Technical report.

Yong-chuan, Z., Xiao-qing, Z., Zhen-ting, C., et al. (2011). Traffic congestion detection based on gps floating-car data. *Procedia Engineering*, 15:5541–5546.

Zhao, D., Dai, Y., and Zhang, Z. (2012). Computational Intelligence in Urban Traffic Signal Control: A Survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(4):485–494.