Centre for Accident Research & Road Safety - Queensland

USING CROWD SOURCED DATA TO IMPROVE ROAD MANAGEMENT

Final Report

October 2024

Mohamed Elhenawy
Evan Nadhim
Sebastien Demmel
Andry Rakotonirainy
Sebastien Glaser

research.qut.edu.au/carrsq

TEQSA PRV12079 | CRICOS 00213J

INTENTIONALLY BLANK

TABLE OF CONTENTS

Acknowledgements

This research is jointly funded by the Department of Transport and Main Roads (TMR), Queensland University of Technology, iMOVE Australia and supported by the Cooperative Research Centres program, an Australian Government initiative.

1. Introduction and objectives

The iMOVE “Using crowd sourced data to improve road management” (iMOVE project 1-048) project has investigated the use of crowd-sourced and edge-computed data to support efficient road management. It has also delivered a local expertise to analyse and interpret such data source.

This report summarises findings of this project and focuses on the development of scoped applications and validation of data quality.

Detailed methodologies and associated studies for the project are outlined in a series of unpublished reports prepared for the Department of Transport and Main Roads, including:

- Report (MIL-02) – Literature and Data Review, M. Elhenawy, S. Glaser, December 2022
- Report (MIL-03) – Integration Report, M. Elhenawy, S. Glaser, March 2023
- Tech Report (MIL-04) – Qualitative and Quantitative Road Attributes Accuracy evaluation, E. Nadhim, S. Glaser, A. Rakotonirainy, S. Demmel, M. Elhenawy, E. Nadhim, October 2024
- Presentation (MIL-05) – Using Crowdsourced data to generate MAPEM, M. Elhenawy, E. Nadhim, Nov 2023
- Presentation (MIL-06) – Processing tools, M. Elhenawy, E. Nadhim, March 2024
- Report (MIL-07) – Tools and guidelines, M. Elhenawy, E. Nadhim, S. Glaser, May 2024

Traditional methods of collecting road asset information, such as annual drives using cameras and sensors, have provided valuable insights, but these methods are limited by the time lag in data collection and manual data extraction processes. While machine learning tools have been developed to automate the extraction of attributes from these data, their reliability has remained questionable, and the information they generate is often outdated by the time it is used.

Recent advancements in automated vehicle technology and edge computing now enable near real-time mapping of the road network. These high-definition (HD) maps, also known as automated vehicle (AV) maps, are critical for achieving high levels of automation. With the rapid deployment of 4G/5G communication technologies, automotive manufacturers and equipment suppliers are collecting massive volumes of data, including vehicle dynamics and environmental information, to create more accurate and dynamic representations of the road environment. The increasing number of sensors in modern vehicles has resulted in a surge of crowd-sourced road network data.

This project primarily developed two tools, focused on improving road safety, that use commercially available crowd-sourced data. Additionally, the project also verified the accuracy and currency of the crowd-sourced data as well as how road asset can be assessed utilising Large Language Models.

2. Scope

The use of crowd-sourcing in transportation systems, particularly in road management and safety applications, is a growing area of interest. Traditional methods of collecting traffic data and road safety information, such as manual surveys, camera-based systems, and fixed sensors, often suffer from high costs, limited coverage, and slower data refresh rates. In contrast, crowdsourcing provides a more scalable and near real-time approach to gathering such data by leveraging the power of widespread participation through mobile devices, connected vehicles, and advanced sensor technologies.

This project, which focuses on utilising crowd-sourced data for generating road safety insights, aims to understand the capabilities of such data by developing two prototype applications for road infrastructure manager. The first application develops an automated process to produce MAPEM messages in an intersection. MAPEM is a Cooperative Intelligent Transport System (C-ITS) message with detailed road topology information used by the Road and Lane Topology (RLT) service. The second application endeavours to produce as many parameters as possible from the International Road Assessment Program (iRAP). The project also assessed the data quality through the application development process and in conjunction with dedicated data collection.

A third application was initially proposed. This application was targeted at the road asset management and identifying degradation over time. Given the modification in the scope of data provided by the third parties, this application was no longer feasible, and thus not pursued.

3. Literature Review

3.1 MAPEM

MAPEM (MAP Extended Message) describes the topology of intersections, including lane geometries and the allowed movements at each lane. The general message structure is standardised by ISO/TS 19091:2017 "Intelligent transport systems – Cooperative ITS – Using V2I and I2V communications for applications related to signalized intersections", and SAE J2735 protocols.

MAPEM attributes

The **reference point**, typically the centre of an intersection's conflict area, is calculated by analysing the centroid of GPS data points within the conflict zone.

Lane is part of an approach. Approaches are classified as an ingress approach and an egress approach. If direction information is not available or unreliable, the timestamp of the GPS point that belongs to the same trajectory could be used to identify the approach type (i.e., ingress vs egress).

Nodes are lists/sequences of nodes describing each lane's centre line. Each node's sequence starts at the conflict area. In other terms, the first node of the ingress lane starts from the stop bar, whereas the egress lane's first node starts at the end of the conflict area. The node identification depends on the identification of the reference point, which is considered the local x-coordinate and y-coordinate origin at the intersection.

Intersection lane connections are essential information provided by the MAPEM. Connections define the allowed movements/manoeuvres starting from an ingress lane and all reachable egress lanes.

MAPEM Generation

The MAPEM generation using crowd-sourced Vehicle data is not straightforward. The literature shows that different data modalities can be used to infer the road infrastructure as GPS trajectories [1,2,4], aerial images [2,3], or mobile laser scanning [5,6], but the specific use of crowd-sourced data is limited to specific criteria such as GPS trajectories and speed profiles [7,8]. Moreover, these methods often rely on many threshold definitions or manual processing.

Several authors transform the trajectory into an image before using Machine Learning (ML) approaches to extract the relevant information [9]. However, the image transformation may generate a loss in the process, as distance loss (using Convolutional Neural Network (CNN) requires having the same image dimensions, and when applied to multiple intersections, the relative distances between the nodes may be lost) and temporal information loss (the image is no longer processes as sequential information).

3.2 Safety risk assessment tool of the road infrastructure

iRAP developed five protocols based on various Road Assessment Programs. These protocols include Crash Risk Mapping, Star Ratings, Fatalities and Serious Injuries estimation mapping, Safer Road Investment Plans, and Performance tracking. This project focuses on the coding of road attribute data, which is part of the process of producing Star Ratings and Safer Roads Investment Plans (SRIP).

According to the iRAP coding manual (see https://irap.org/specifications/), the coding includes more than 70 attributes. The evaluated road is segmented into 100-meter sections and the attributes are recorded for each road segment. In some cases, the value of the attribute changes with the evaluated segment, so the worst value safety-wise will be assigned to this section.

Some of them require expert analysis to decide on the outputs (as "upgrade cost") or information unavailable through the crowd-sourced data (as "skid resistance"). Therefore, the existing applications cover a limited subset of attributes. The satellite-based extraction of attributes [10] shows promising results, allowing a large network cover. The results are, however, limited because of the level of detail and the obstruction that can happen. Using in-vehicle cameras [11] informs several attributes of the iRAP. They managed to identify 33 attributes with different levels of quality. However, their method relies on ML/CNN and requires an extensive annotated database to train their process efficiently.

4. Crowd-sourced data

The project integrates data from two primary sources relying on various in-vehicle sensors. Data were acquired for 100km of varied road's sections in South East Queensland. The first one is designed to aggregate information from the vehicle dynamic and the road infrastructure attributes (line markings, traffic signs, identified obstacles…). This type of information is being collected by vehicles to build the foundation for HD-Maps to be used in the future automated vehicle driving systems. The second only integrates data from the vehicle dynamic (GPS location and speed). For future reference, we will call the first ADAS data and the second Vehicle data. This section provides an overview of how data was collected, processed, and analysed to achieve the project's objectives.

4.1 Data Collection

ADAS Data

"ADAS Data" provides high-resolution data collected from vehicle-mounted cameras that capture detailed road infrastructure attributes. The system collects images and sensor data from vehicles driving in diverse conditions. These images are processed to detect key road infrastructure attributes, such as lane markings, stop lines, intersections, and road signs (Figure 1). ADAS data is crucial for generating detailed road maps and identifying specific road safety attributes like pedestrian crossings and traffic signs. These data set is claimed to have high relative positioning accuracy which is dependent on number of vehicles traversing through the road section, however its absolute positioning accuracy is not known.

The data collected for this project spans a broad geographical area, covering various types of roads and intersections. The system collects data, capturing frequent and detailed snapshots of road conditions. The collected images and data points are geotagged, enabling precise mapping of the features detected by the system.

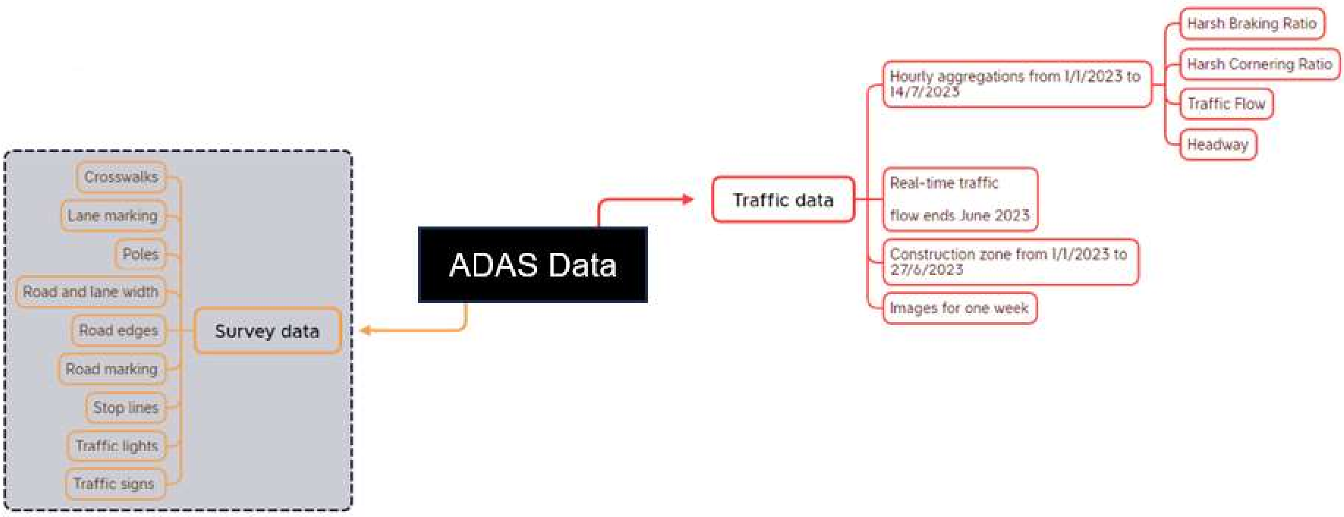

Figure 1 ADAS Data Structure

Vehicle Data

This type of data is often collected via vehicle telematics systems and includes real-time traffic and vehicle trajectory data. The system provides (Figure 2) detailed data on vehicle movements, including position, speed, and acceleration, which is critical for analysing traffic flow, identifying ingress and egress lanes, and determining road safety features. These data set is aggregated from several vehicle brands and therefore their positioning accuracy is not known.

Both data were integrated to enhance the overall dataset's granularity and to allow for cross-validation of key elements like lane geometry and intersection characteristics. This integration is particularly useful in verifying road safety features and ensuring data accuracy across different sources.

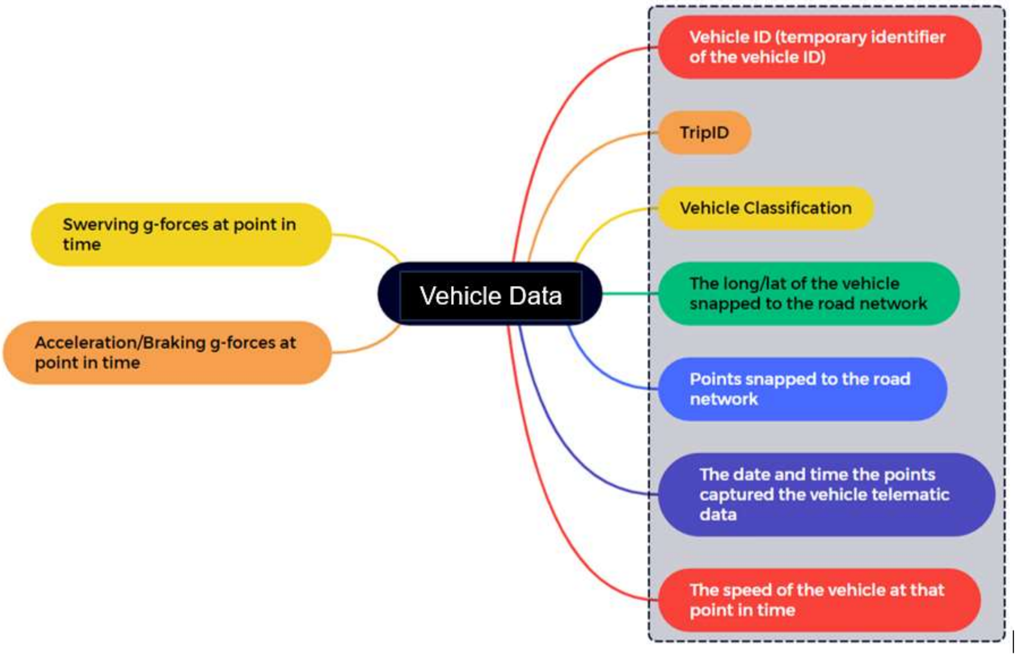

Figure 2 Vehicle data

4.2 Accuracy and Validation

The accuracy of the crowd-sourced data was a key focus of this project. Given the variability in quality that is often seen in crowd-sourced data, multiple validation techniques were employed to ensure the reliability of the findings.

Direct data validation

When feasible, the datasets were compared with ground truth at qualitative and quantitative levels using data from the ZOE2 vehicle (with an RTK-GPS and a FoG IMU) and land surveyed data from the Queensland's department of Transport and Main Roads.

The ADAS data was used to automatically identify critical road features, such as lane markings, stop lines, and pedestrian crossings. This information was then mapped and analysed to ensure that the physical infrastructure on the roads matched the behaviours observed in the Vehicle data. Discrepancies between these datasets indicated ADAS data has potentially not detected certain road features or signs.

MAPEM Validation

One of the core validation techniques used in this project was the generation and validation of MAPEM data against the MAPEM data from the Ipswich Connected Vehicle Pilot (ICVP). MAPEM messages are commonly used in Cooperative Intelligent Transport Systems (C-ITS) to provide accurate, real-time information about road layouts, intersections, and lane configurations. The process of generating MAPEM data involved integrating both datasets to create detailed maps of intersections, including lane geometries, stop lines, and other critical road features.

iRAP validation

iRAP attributes are derived from the road infrastructure geometry. The ground truth for these attributes were derived from visual confirmation from the recent imagery of the infrastructure or from the road geometry. Further information is available in Section 5.1.

5. Key Findings

This section outlines the key insights from analysing the crowd-sourced ADAS data and Vehicle data. The findings focus on data accuracy, the MAPEM validation process, and the application of this data to support iRAP assessment.

The crowd-sourced nature of the data allowed for large-scale, near real-time coverage across diverse road environments. This was particularly useful in assessing road infrastructure and safety features over a wide geographic area.

5.1 Accuracy and Validity of Crowd-sourced Data

The integration of ADAS data, Vehicle data and ground truth data provided ability to employ various validation methods to assess the accuracy of the datasets both qualitatively and quantitatively.

ADAS Data

The comparison was conducted using collected detailed imagery of lane markings, stop lines, vertical roadside infrastructure, and traffic lights, projected on Google Earth and Google Street View. In several places (Brisbane, Ipswich, Cornubia), the data was found to be reliable. The visual inspection of the database showed only few missing elements. It was not possible to determine whether these missing elements were because of a limitation in the contracted geographic boundaries with the data supplier, or because of a lack of its detection. For example, the ADAS data was sought for the Ipswich Road; intersections on the Ipswich Road had accurate stop lines however that was not the case for the interesting roads.

Moreover, there was one traffic sign (Figure 3) that was not detected which could be attributed to it not being part of the Vienna Convention signs.

Figure 3 Watch for wildlife sign

Detailed evaluation between the two datasets demonstrated:
Absolute positioning error of:

- Up to 5 metres for the traffic signs
- below 1 metre (average) for the line markings.

Considering the limitation of the crowd-sourced data at Mt Cotton test track (where the ground truth data set was available for comparison), these errors should be considered as the worst-case scenario, as not many vehicles with suitable ADAS technology traverse over the Mt Cotton test track compared to public roads.

The image data demonstrated high reliability in terms of capturing key road-related information, especially in well-lit conditions and when the camera was properly positioned in the vehicle. While the images are in low definition and all elements outside the road are blurred to ensure privacy, the critical details needed for analysis were still captured effectively.

Vehicle Data

Vehicle data were not evaluated for accuracy as the ADAS data. However, the application of these data, through the MAPEM application demonstrated a high variability and limited accuracy.

5.2 MAPEM Generation

The MAPEM (MAP Extended Message) generation process using both ADAS data and Vehicle data is feasible. The process involved generating precise maps of intersections, including lane geometries and stop lines, and validating these maps against actual vehicle trajectories. The process still requires human intervention in the selection of the best-fitting method and some visual inspection of the results.

Using Vehicle data to check the accuracy of the generated MAPEM is found to be the most labour-intensive as the Vehicle data itself does not have sufficient level of accuracy. However, the Stop line definition validation benefits from the knowledge of the speed profile provided by the Vehicle data.

5.3 iRAP Applications

The tools development for the iRAP application included information from the ADAS data and detailed trips information from the Vehicle data. The feasibility was demonstrated on multiple attributes using Matlab functions and visual interface. The attributes associated with the road geometry, road structure, lane width, speed limit, pedestrian crossing and school zone were visually compared with the ground truth using Google Earth. Roadside objects like poles and traffic lights appeared to be consistent. Several attributes needed for iRAP assessment were not available in the ADAS attributes dataset, such as roadside slope and structure on the side of the road, or the high-level understanding of the environment. To overcome these limitations, the images from the ADAS dataset were processed using Multi-Modal Large Language Model (M-LLM). However, the quality of results was impaired by the low definition (see Section 5.1) of images. Higher definition images, such as google street view, enables broader contextual understanding for extracting some iRAP attributes such as Pedestrian fencing detection, Traffic Calming, Vehicle Parking or School Zone identification. It's worth noting the quality of the outputs depends on the used LLM.

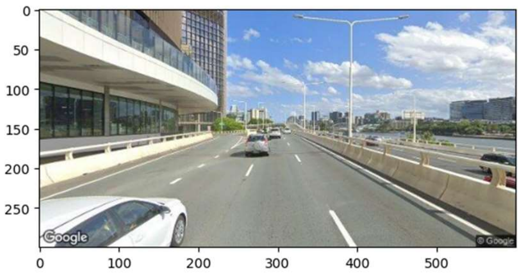

Figure 4 Image from Google Street View, used for M-LLM processing

Here is an example of an automatically extracted attributes from the image using M-LLM:

Attribute	M-LLM extracted output
Roads that Cars Can Read	Yes
Roadworks present	No
Pedestrian Fencing	Present
Carriageway type	Divided
Quality of curve	No curve detected

6. Challenges and Lessons Learned

In conclusion, this project has shown the potential of crowd-sourced data, particularly from ADAS data and Vehicle data, in improving road infrastructure safety assessments and infrastructure layout mapping. The integration of these data sources with advanced computational tools allows for more efficient attributes extraction and analysis, reducing the need for traditional labour-intensive methods. However, significant challenges remain, such as ensuring data quality and reducing operator intervention. The primary challenge is that ADAS data are produced using relative positioning methods, while infrastructure managers need absolute positioning. As a result, the accurate absolute positioning of some attributes could be off by several meters, requiring human intervention.

Recommendations for future work include:

- Improving Data Quality and Validation: Invest in mechanisms that allow for the cross-verification of crowd-sourced data with more accurate, professionally collected absolute positioning datasets to ensure reliability.
- Addressing Regional Biases: Develop strategies to encourage data collection from underrepresented areas, such as rural zones, or minor roads to enhance the comprehensiveness of safety assessments.
- Standardising Link Definitions and IDs for Enhanced Crowd-sourced Data Integration: The various sources of crowd-sourced data often use different IDs or even inconsistent link definitions for the same road segment. To enhance future data integration, it's essential to establish a standardised link definition and ID system that can be universally adopted by all crowd-sourced data providers. This would ensure consistency and improve the accuracy and usability of the collected data.
- Expanded Data Layers: To improve the effectiveness and accuracy of applications like iRAP assessments, adding more data layers that cover additional attributes would be highly beneficial. For example, incorporating data regarding parked cars and weather conditions on either side or both sides of the road would address specific iRAP requirements. Additionally, another crucial iRAP attribute is the presence of pedestrian fences, which also should be considered for further data layer integration.
- Pedestrian trajectory data: It's vital to emphasise the need for incorporating pedestrian trajectory data to refine the accuracy of crosswalk location estimates. This inclusion would not only complement the existing vehicle trajectory data but also provide a more holistic view of traffic and pedestrian dynamics at sidewalks and intersections. The integration of such data should be prioritised to mitigate the current limitations posed by relying solely on vehicle-focused datasets.
- Tool Development: Continue to refine the toolbox created in this project, ensuring that it can be commercially viable and scalable for broader applications across various regions.
- Use of Large Language Models: Large Language Models provide additional possibility to identify iRAP attributes, using either Google Street view images or digital images taken by infrastructure managers. Further research needs to be conducted to validate this process.

Bibliography

1. Li, Y., et al., Fusing taxi trajectories and RS images to build road map via DCNN. IEEE Access, 2019. 7: p. 161487-161498.
2. Yuan, J. and A.M. Cheriyadat, Image feature based GPS trace filtering for road network generation and road segmentation. Machine Vision and Applications, 2016. 27(1): p. 1-12.
3. Zhou, L., C. Zhang, and M. Wu. D-LinkNet: LinkNet with pretrained encoder and dilated convolution for high resolution satellite imagery road extraction. in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2018.
4. Ruan, S., et al. Learning to generate maps from trajectories. in Proceedings of the AAAI conference on artificial intelligence. 2020.
5. Ma, L., et al., Boundarynet: extraction and completion of road boundaries with deep learning using mobile laser scanning point clouds and satellite imagery. IEEE Transactions on Intelligent Transportation Systems, 2021.
6. Wen, C., et al., Recovery of urban 3D road boundary via multi-source data. ISPRS Journal of Photogrammetry and Remote Sensing, 2019. 156: p. 184-201.
7. Méneroux, Y., et al., Traffic signal detection from in-vehicle GPS speed profiles using functional data analysis and machine learning. International Journal of Data Science and Analytics, 2020. 10(1): p. 101-119.
8. Yang, X., et al., Generating lane-based intersection maps from crowdsourcing big trace data. Transportation Research Part C: Emerging Technologies, 2018. 89: p. 168-187.
9. Guo, Y., et al., A novel method for road network mining from floating car data. Geo-spatial Information Science, 2021: p. 1-15.
10. Brkić, I. et al., Utilizing High Resolution Satellite Imagery for Automated Road Infrastructure Safety Assessments, Sensors 2023, 23, 4405. https://doi.org/10.3390/s23094405
11. Kačan, M. et al., Multi-Task Learning for iRAP Attribute Classification and Road Safety Assessment, 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), Rhodes