Mobile IoT-RoadBot: An AI-powered Mobile IoT Solution for Real-Time Roadside Asset Management

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ABSTRACT

Timely detection of roadside assets that require maintenance is essential for improving citizen satisfaction. Currently, the process of identifying such maintenance issues is typically performed manually, which is time consuming, expensive, and slow to respond. In this paper, we present Mobile IoT-RoadBot, a mobile 5G-based Internet of Things (IoT) solution, powered by Artificial Intelligence (AI) techniques to enable opportunistic real-time identification and detection of maintenance issues with roadside assets. The Mobile IoT-RoadBot solution has been deployed on 11 bin service (waste collection) trucks in the western suburbs of Melbourne, Australia, performing real-time assessments of road-side assets as they service areas within the local government. We present the architecture of Mobile IoT-RoadBot and demonstrate its capability via an online 'points of maintenance' (PoMs) map.

KEYWORDS

Mobile 5G, IoT, Roadside Asset Management, Smart City

1 INTRODUCTION

Effective monitoring of roadside infrastructure is of high priority for city councils and residents. Timely identification of maintenance issues with roadside assets (e.g., damaged road signs, rubbish dumped on the roadside) helps to address them proactively while significantly contributing to improvements towards appearance of a local government areas (LGAs). Currently, roadside asset maintenance requests are logged using manual methods (e.g., citizens reporting issues to the local government). These methods are reactive in nature and incur major operational and financial burden for local governments. To automate roadside asset monitoring, citizen reports were often used to collect the city's asset data[4]. However, requests received via crowd-sourced reports are often unclear and inaccurate [3]. Furthermore, this approach is not feasible in larger areas as it only covers very small geographical areas and is reliant on the number of citizens participating, making it unscalable and impractical. Thus, there still remains increasing needs for an automated, real-time solution for better maintaining roadside assets [1].

Advancement of mobile computing along with high speed wireless networks (including 5G), IoT and AI (in particular deep learning (DL)) aids the collection, analysis and reporting of roadside asset maintenance issues in real-time. Smart phones and wearable cameras along with Google's street view have recently been explored for collecting large-scale road scene data [2, 5]. However, such devices require active human involvements to operate and manage. It is also challenging to develop data-driven DL models that can detect issues in roadside assets automatically due to insufficient real-world data for training machine learning models.

To address these challenges, this paper presents an innovative mobile AI-powered 5G IoT solution, *Mobile IoT-RoadBot*. It comprises of IoT devices, depth-sensing stereo-vision cameras, 5G routers, and GNSS sensors deployed on bin service trucks to capture and transmit high-resolution data of roadside assets. Such a deployment not only enables high quality capture of roadside asset data, but owing to the natural mobility of the trucks, allows data collection to span a large geographical area, without needing the extensive deployment of roadside infrastructure. Mobile IoT-RoadBot transmits captured data by bin service trucks via 5G to the cloud for processing, and uses DL models that automatically monitor and detect roadside asset maintenance issues. We term such roadside asset that require maintenance as *Points of Maintenance* (*PoMs*) in the paper. Mobile IoT-RoadBot also includes a map-based dashboard to present PoMs (along with a short video clip for verification). To the best of our knowledge, Mobile IoT-RoadBot is the first research solution that combines advanced technologies such as IoT, 5G, and AI to automate PoMs management in real-time in a real-world setting.

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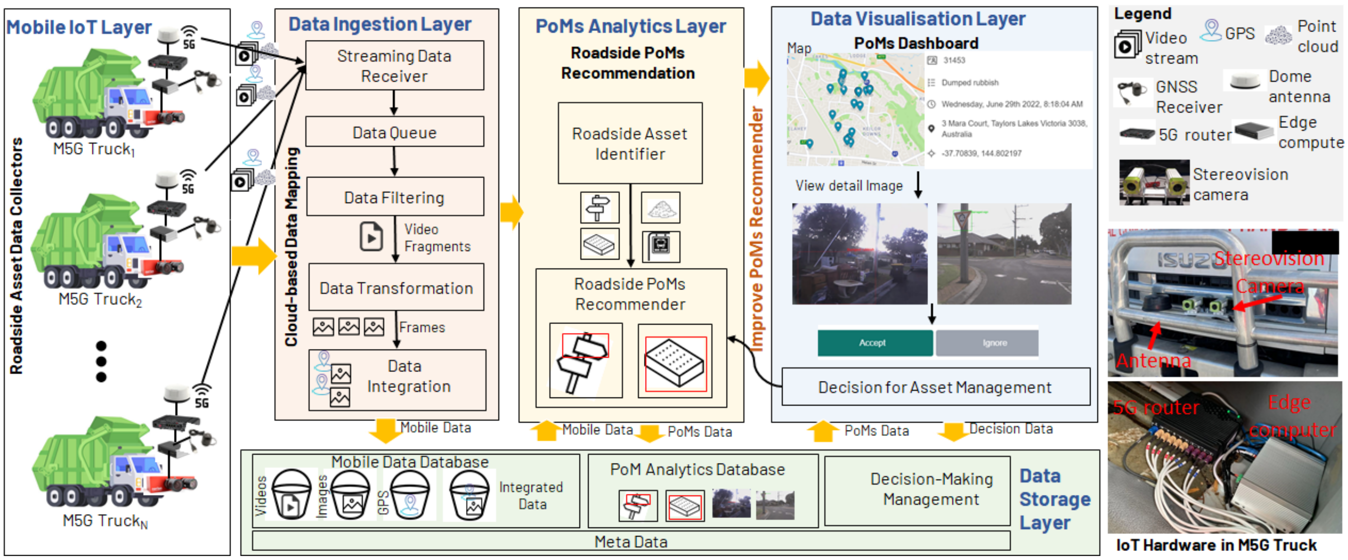
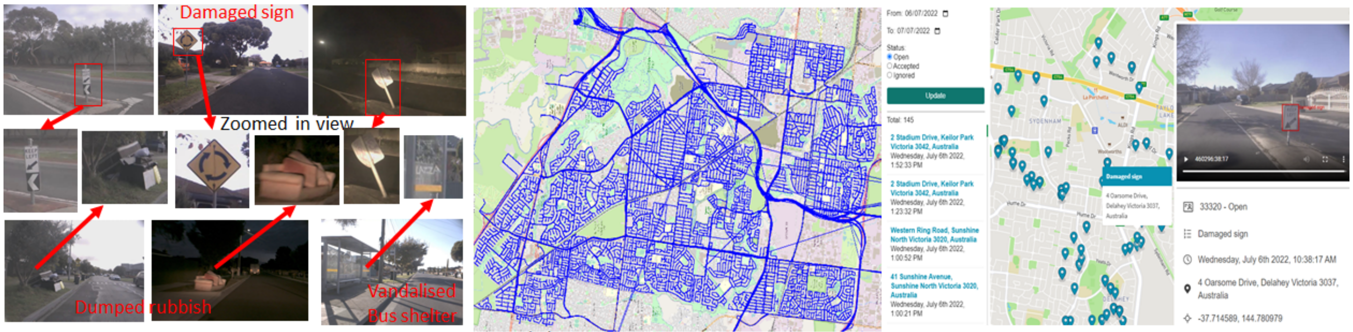


Figure 1: The overview of our developed Mobile IoT-RoadBot solution

2 Mobile IoT-RoadBot OVERVIEW

Figure 1 provides the architecture of Mobile IoT-RoadBot. Its core five layers are described as follows. **Mobile IoT Layer** is our roadside data producer. During waste collection rounds, multiple bin service trucks collect roadside asset data using IoT hardware and transmit the data to a cloud server via 5G. We refer to them as Mobile 5G trucks (M5G trucks). As shown in Figure reffig:system each M5G truck is equipped with a stereo vision camera and a 5G dome antenna mounted on the front bullbar. Inside the cabin, each truck has an on board edge computer, a Global Navigation Satellite System (GNSS) receiver and a 5G router. The camera produces RGB images at 32 frames/sec as well as 3D point clouds. Image frames are compressed, and partitioned into consecutive ~3 sec video segments with each segment containing 50 frames. The ~3 sec length is chosen to fit the segment into a smaller size (~1 MB) to achieve fast transmission and to avoid high data loss. Then, these segments are transmitted to the cloud with the corresponding GNSS coordinates and timestamp. **Data Ingestion Layer** is responsible for receiving streaming data from M5G trucks on the cloud. A streaming data receiver gets video segments including metadata (e.g., GNSS location, time) from M5G trucks. M5G truck data is queued in order to process every segment. A data filtering process removes irrelevant data based on GNSS location, truck speed, and time. That is, when a M5G truck is moving at very high speed on a highway, or is located in an area of no interest (e.g., a depot, landfill), or turned on outside service time hours for repair works (e.g, weekends), then those data are discarded. After that, the data transformation process is initiated to extract and choose frames (i.e., images) from a video segment. Specifically, we randomly choose 1 frame/sec from each video segment. We chose 1 frame/sec because scenes in a video segment tend to stay the same within a second due to the slow movement of the bin trucks. In the final step, the frames are integrated with location and time. All processed videos, frames, and metadata are stored in **Data Storage Layer**. **PoMs Analytics Layer** utilises our developed DL models to identify PoMs from new incoming frames stored in the data storage layer. This layer is responsible for two major tasks. First, we identify the target objects of interest (road side asset) using our object detection model, *Roadside Asset Identifier*. After that, we identify whether they require maintenance, i.e., identifying PoMs (*Roadside PoMs Recommender*). As the target objects of interest, we selected *damaged road signs*, *dumped rubbish*, and *vandalised bush shelters* according to prioritised assets of our local government partner. Our second task is to build our DL models, in order to identify PoMs. Rather than using pre-trained DL models, we train our models on real-life roadside asset data collected from M5G trucks. We collected data for a period of two weeks from M5G trucks and manually annotated the data using human annotators. After target PoMs are identified, they are stored in the data storage layer, which is then used by the data visualisation layer. **Data visualisation Layer** provides an interactive web-based dashboard with maps (PoMs Dashboard). This dashboard is designed to communicate interactively with maintenance crews about identified PoMs and allows the crew to verify them. This helps collect on-going data about the performance of Mobile IoT-RoadBot.



(a) Identified PoMs with zoomed in view (b) GNSS Coverage by trucks (c) Points of Maintenance (PoMs) dashboard

Figure 2: Mobile IoT-RoadBot's demonstration and deployment

3 Mobile IoT-RoadBot DEPLOYMENT

Mobile IoT-RoadBot is deployed on 11 bin service trucks in Brimbank City council (covering an area of 123 km^2 of western suburbs in Melbourne). As IoT hardware, we used Nerian's Stereo-vision camera, Sierra Wireless's 5G router and Optus's 5G antenna. Amazon Web Service (AWS) is used as a backbone for developing the cloud-based pipeline: Greengrass is used for the cloud-based edge device management, Rekognition is utilised to develop DL algorithms for Roadside Asset Identifier and Roadside PoM Recommender. Each M5G truck is normally in service for 7 hours (5AM and 2 PM). Figure 2(b) shows travel routes of 11 trucks over 2 weeks captured using the installed GNSS receiver and demonstrates that overall 95% of entire Brimbank area can be covered to find issues in that period using the natural mobility of the M5G trucks. Each truck streams approximately 5GB data/ day with an average of 2.5 MBps (max: 4.24MBps) transmission rate. Depending on weather condition, network coverage and truck speed varied that 10-20% data loss per day on average was observed. The PoMs Analytics Layer processes around 35,000 frames/day on average. Figure 2(a) shows some examples of PoMs (with zoom views) that were identified by our DL models. As seen, Mobile IoT-RoadBot can detect damaged road signs (e.g., bent, cracked), dumped rubbish on the street, and graffiti on bus shelters. Further as presented in Figure 2(a), our models are also capable of detecting PoMs when trucks are on the road in dark, cloudy or rainy conditions. Figure 2(c) shows our PoMs Dashboard, where maintenance crews can filter pins on the map based on a date range, a location, and a resolution status - open (newly recommended PoMs), accepted (as correct PoMs), ignored (as incorrect PoMs). More details of the identified PoMs such as the PoM type and location can be viewed as a popup by clicking a pin on the map. The user can also view the evidenced image/video, address (using reverse lookup), GNSS coordinates, and status of the job in the right frame. The user can also accept or ignore the identified issue, and the colour of the pin on the map changes accordingly. Currently, there is no such UI tool that facilitates local council users for visualising PoMs in real-time. A demonstration video of Mobile IoT-RoadBot is available at https://youtu.be/2nRBqxWbu6k.

4 CONCLUSION

We presented Mobile IoT-RoadBot, an innovative first of its kind mobile 5G-based IoT solution deployed on bin service trucks and uses DL models to automatically detect and report issues with road assets in LGAs. Mobile IoT-RoadBot incorporates IoT devices, a cloud-based pipeline for video/GNSS data collection, AI models for automatic identification of roadside asset issues, and a PoM dashboard for presentation of of identified issues. Optimisation and enhancement of our pipeline and the AI models will be explored in the future to increase accuracy when detecting issues with roadside assets automatically as well as deploying the models in the edge computer. We are confident the proposed solution can contribute significantly toward advancing further research in real-world and large-scale 5G and IoT experimentation.

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REFERENCES

[1] Maged Gouda, Bruno Arantes de Achilles Mello, and Karim El-Basyouny. 2021. Automated object detection, mapping, and assessment of roadside clear zones using LiDAR data. *Transportation research record* 2675, 12 (2021), 432–448.

[2] Gerhard Neuhold, Tobias Ollmann, Samuel Rota Bulo, and Peter Kontschieder. 2017. The mapillary vistas dataset for semantic understanding of street scenes. In *Proceedings of the IEEE international conference on computer vision*. 4990–4999.

[3] Edwin Salcedo, Mona Jaber, and Jesús Requena Carrión. 2022. A Novel Road Maintenance Prioritisation System Based on Computer Vision and Crowdsourced Reporting. *Journal of Sensor and Actuator Networks* 11, 1 (2022), 15.

[4] Maarten Sukel, Stevan Rudinac, and Marcel Worring. 2019. Multimodal classification of urban micro-events. In *Proceedings of the 27th ACM International Conference on Multimedia*. 1455–1463.

[5] M. Sukel, S. Rudinac, and M. Worring. 2020. Urban Object Detection Kit: A System for Collection and Analysis of Street-Level Imagery. In *2020 International Conference on Multimedia Retrieval*. 509–516.