COMBINING RFID AND IMAGE-BASED VEHICLE IDENTIFICATION DATA TO DETECT ILLEGAL VEHICLES

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ABSTRACT

Effective road law enforcement is a vital part of transportation systems. Escalating traffic congestion and widespread illegal road usage pose fresh hurdles for law enforcement systems. An intelligent law enforcement system that aims to reduce illegal road use must enable immediate intervention on a tactical level without disrupting the flow of legal vehicles. To achieve a fast tactical response, strategic level information, such as location and identity, is required to ensure law enforcement officials are in the right place at the right time. This paper presents a system that equips authorities with the right information to act against illegal road users while maintaining normal flow of traffic. The proposed system improves upon existing solutions by combining Radio Frequency Identification (RFID) and Computer Vision (CV) data to detect and identify illegal vehicles. The authorities can leverage this information to identify and remove such vehicles from the road without affecting the legal road user's experience. This paper will investigate the performance criteria for such a system within a real-world environment and will determine which combination of data fields can enable accurate vehicle identification within a practical setup. Practical measurements were performed to verify that theoretical requirements can be achieved in practice.

1. INTRODUCTION

Road transport systems support sustainable growth across society and the economy. However, increasingly congested traffic conditions and the illegal use of roads pose challenges to optimally managing road networks (Pretorius, Hoffman, and Wang, 2015). Intelligent Transportation Systems (ITS) aim to improve the user experience by increasing traffic safety and reducing congestion and illegal road use (Marais, Grobler and Holm, 2013). To achieve this, ITS systems must focus on effective law enforcement that can be reconciled with streamlined traffic flows within a traffic management system.

1.1 Aim of Paper

This paper investigates a new system for traffic law enforcement that combines two different technologies to overcome some of the challenges that existing approaches face. By embedding RFID tags in vehicle license plates, a unique identifier can be assigned to each vehicle, creating a "fingerprint" for the vehicle. This information can be used to uniquely identify vehicles and track them as they move. Computer Vision is used to extract vehicle identification information from traffic surveillance data.

Combining these technologies will enable multi-factor verification of the true identities of suspicious vehicles. It will also provide a means of detecting vehicles that do not conform to the regulatory marking requirements. The system will equip authorities with strategic-

ISBN: 978-0-7961-8245-6
Pretoria, South Africa
Produced by: www.betaproducts.co.za
Conference Proceedings

level information to achieve immediate intervention on a tactical level.
Previous research (Hoffman and Pretorius, 2015), (Pretorius, Hoffman, and Wang, 2015) described an intelligent vehicle monitoring system based on in-road RFID readers. It defines the technical requirements for such readers to successfully detect RFID-enabled license plates mounted on in-traffic vehicles. This paper extends that research by practically investigating the performance criteria of the proposed system.

1.2 Problem Statement

Currently the primary means of identifying suspicious vehicles is through static checkpoints. Ad Hoc static checks on a selected number of vehicles through roadblocks provide offenders with a chance to escape law enforcement by leaving vehicle queues approaching road blocks. The variability of human nature also exposes this approach to bribery and dishonest behaviour from law enforcement officials (Hoffman, Geldenhuys, and Pretorius, 2013). Most law enforcement actions require legal vehicles to be identified by a license plate. However, the license plates used in most countries are relatively easy to clone, and criminals buy these illegal plates from dealers or re-use scrapped legal plates (Hoffman and Pretorius, 2015).

Traffic cameras present an effective way to monitor traffic flow and enforce speed laws without disrupting traffic flow. Traffic cameras use license plates to identify vehicles; however, these systems cannot distinguish between legal and illegal license plates. Road users can also remove, obscure, and falsify plates to evade camera detection (Hoffman, Geldenhuys, and Pretorius, 2013).

It is therefore clear that current approaches to traffic law enforcement are not effectively combatting illegal road use. Consequently, there is a pressing need for a fool-proof system that can accurately detect and respond to illegal road use without compromising the experience of legal road users.

1.3 Scope of Paper

The aim of this study is not to develop a system that automatically detects and deters criminal activity by issuing tactical and strategic interventions to law enforcement, but rather to identify the critical technical components and investigate their potential within such a system. Therefore, the scope of the project includes the development of a combined RFID and camera-based system to uniquely identify vehicles. This entails the extraction of vehicle features from traffic cameras to serve as a digital fingerprint, storing this data on an RFID tag embedded in the license plate of a vehicle, and encrypting the data for security purposes. Furthermore, it includes deploying an operational RFID/camera system using in-road RFID readers and tagged number plates and testing the system to evaluate its potential in a traffic environment.

2. ELECTRONIC VEHICLE IDENTIFICATION (EVI)

The previous section provided evidence that reliable positive vehicle identification is required to allow law enforcement officials to act against perpetrators. This section will evaluate two existing technologies that may contribute to an improved vehicle identification system. EVI (Electronic vehicle identification) is a sub-system of ITS that uniquely identifies a vehicle electronically and stores identification information digitally. In this paper, we will focus on combining two distinct methods for EVI, namely RFID and Computer Vision.

2.1 RFID

Radio frequency identification (RFID) is an automatic wireless data collection technology used to identify objects (Ho and Li, 2023). RFID systems are composed of RFID readers and tags. There are two types of RFID systems, namely active and passive. Active RFID uses batteries to power tags, whereas passive RFID tags are powered by the reader's energy field. Active RFID supports longer read ranges than passive RFID, which may not be suitable for reliable identity verification. A longer read range means many objects outside the detection zone will be visible to the reading device, which affects the reliability of identifying a specific tagged object. Active tags are also more expensive and bulkier, making it difficult to integrate with existing regulated vehicle identifiers, e.g., license plates. UHF (ultra-high frequency) passive RFID supports read ranges of up to 10m, which makes it ideal for identifying vehicles moving in traffic.

RFID systems can accurately identify a vehicle but cannot automatically verify that the tag belongs to the vehicle. RFID should therefore be combined with imaged-based techniques to link the true identity with the detected identity. It must furthermore use cryptography to ensure that tag data can be authenticated (Hoffman, Geldenhuys & Pretorius, 2013).

2.2 Computer Vision

Video surveillance cameras are widely used in traffic scenarios to monitor traffic conditions, implement electronic tolling, or monitor criminal activities. Surveillance data can accurately depict reality; however, analysing this large amount of data can be nearly impossible on a human level. Visual processing techniques can easily be used to recognize and analyse patterns in data for more advanced tasks such as vehicle classification and ANPR (Automatic License plate Recognition) (Albini, Gutoski & Lopes, 2020).

License plate recognition has become an important part of ITS and has gained a lot of interest with the improvement of digital cameras and the increase in data processing capacity (Besbes, 2021). ANPR systems aim to uniquely identify vehicles through their license plates. These systems are composed of cameras that can detect and recognize license plates in a real-view scene. Claimed accuracies of ANPR systems are as high as 98%; however, in a real-world setting, this may be different. Weather, lighting conditions, and viewing angles all affect the accuracy of these systems (Dilek & Dener, 2023).

Furthermore, undesirable and illegal vehicle behaviour (e.g., obscuring the license plate) makes it nearly impossible for the ANPR system to accurately identify vehicles. Considering these factors, ANPR accuracies can decrease to less than 70%. A low ANPR accuracy reduces the proportion of correctly detected offenders and results in a high rate of false positive detections that must be manually filtered. Even if license plates are detected with 100% accuracy, the ANPR system cannot detect cloned or migrated license plates.

It is therefore clear that ANPR on its own may not provide the required reliability to identify vehicles' presence and legal status. ANPR data must be combined with other vehicle identification features to increase the system's reliability. Although ANPR may have low accuracy, it can detect anomalous vehicle behaviour, e.g., obscuring license plates. A vehicle with a failed detection can be flagged, and information such as colour, make, and model can be reported. This information can then be combined with RFID vehicle identification data to alert law enforcement officials of a suspicious vehicle.

In addition to ANPR, a Computer Vision system can be used to detect the make and model of a vehicle. Vehicle Make, and Model Recognition (VMMR) can be used to complement ANPR, especially in the case of intentional detection avoidance. A neural network can be trained to accurately detect vehicle make and model. A challenge with make and model recognition is that the variations between different models from the same manufacturer are so subtle that a normal feature extractor struggles to differentiate between them. Vehicle make and model recognition requires both fine-grained and coarse-grained classification (Besbes, 2021).

3. PERFORMANCE REQUIREMENTS

The previous section discussed the set of technologies that can provide the required functions of a vehicle identification system; however, because the system will be deployed in an inherently challenging environment, we need to carefully consider the technical challenges of each technology building block. This section discusses some of the performance requirements for successfully deploying the proposed vehicle identification system.

3.1 Reader Antenna Radiation Pattern

To provide sufficient tag illumination and counteract the blinding effect caused by a vehicle, it is necessary to have a directional pattern that maximizes radiation towards the travel path of the license plate tag, in contrast to the standard upward radiation of a patch antenna (Pretorius, Hoffman & Wang, 2015). Figure 1 depicts the ideal radiation pattern and contrasts it with the radiation pattern of an inroad patch antenna, which is the conventional antenna type for RFID readers. Additionally, according to (Pretorius, Hoffman & Wang, 2015), it has been observed that there are a maximum of five legally positioned license plate tags within the reading zone at any given moment, and it takes approximately 80 milliseconds to read all five UHF RFID tags. This means that tags travelling at 180 km/h require around 4m of illumination to complete the reading cycle. Our measurements will verify if this can be achieved in practice.

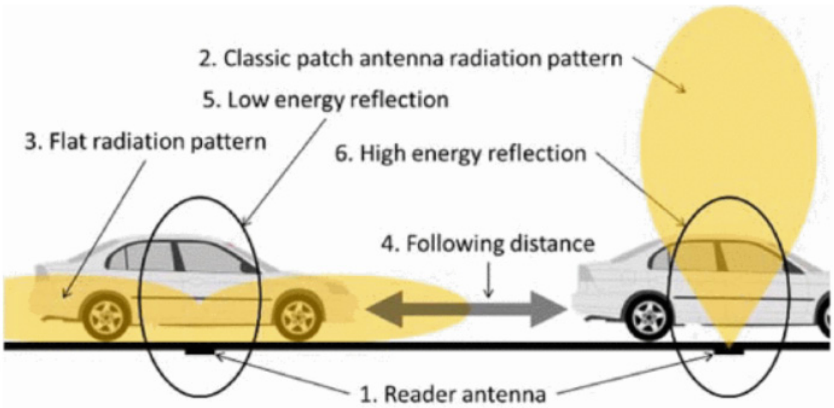

Figure 1: Desired radiation pattern

3.2 Computer Vision Model

Usually, CV models are trained naively with datasets representing controlled environments. This will result in an apparently high recognition accuracy but will be of no practical value. Instead, the model must be exposed to all possibilities within the real traffic environment to achieve accurate and repeatable results.

Confidence threshold - ANPR and VMMR each have their own confidence levels. A confidence threshold is used to determine whether an identification action was successful. An overly sensitive threshold will result in many false positives and unnecessary interventions; this will cause an inefficient allocation of law enforcement resources and traffic disruptions. Conversely, if the threshold is too insensitive, it can result in false negatives, i.e., some illegal vehicles will go undetected.

Vehicle data - Training a computer vision model for vehicle identification requires a dataset of historical observations that represents all vehicle makes, models, and license plates. Vehicle and license plate manufacturers each year release new or updated versions of previous models. This implies that the computer vision model may encounter new types of vehicles and license plates that it has not encountered before. Therefore, regularly updating the training dataset with currently available data is necessary.

External factors - In a real-world scenario, factors such as weather and lighting conditions cannot always be controlled. For example, rain or sunlight can create 'noise' in a camera system, making it challenging to perform feature extraction (Rio-Alvarez et al., 2019). Camera positioning must ensure vehicles are visible within the field of view long enough to capture and successfully read the vehicle attributes. The human factor is also important, as some drivers often go to great lengths to avoid detection, especially when involved in criminal activities. Drivers intentionally obscure the identities of their vehicles and very often mask themselves as legal vehicles.

4. VEHICLE MONITORING POINT

With the requirements known, we can design a system that meets the requirements for reliable vehicle identification. Vehicles are fitted with RFID tags in a typical in-motion identification system, which carries information linked to vehicle identification features. As vehicles pass an RFID monitoring point, tag data is read wirelessly. This allows for high-reliability vehicle identification. In addition to RFID stations, intelligent traffic cameras will monitor the traffic scene to extract useful identification features from real-time traffic footage. The three prominent features that will be extracted are the vehicle's make, model, and registration number. These potential features will provide three outputs, each with a specific reliability factor, that can be compared against the corresponding information read from the RFID tag.

4.1 RFID System Overview

4.1.1 Vehicle Tags
An RFID tag acts as a unique vehicle identifier, and its placement plays a vital role in the reliability and feasibility of the system. Passive RFID tags can be integrated into currently regulated vehicle identifiers in license discs (windshield) and license plates; however, this study will exclusively focus on the latter. RFID tags embedded in license plates provide a long lifecycle and can be easily managed through regulatory license plate life cycle processes. These tags can also easily be adapted to comply with country-specific requirements and registration systems. An example of an RFID-enabled license plate tag is the IDePLATE produced by TÖNNJES (Tönnjes International Group).

4.1.2 RFID Reader and Antenna
By scanning their designated RFID tags, RFID reader units can detect moving vehicles and determine their identities. There are three options for reader placement: overhead,

roadside, and in-road. Overhead gantry readers can detect tags on vehicle windshields but struggle to read tags on number plates. Roadside readers can detect both tags, but their coverage is limited to a single lane due to distance limitations and vehicles obscuring tags in distant lanes. Conversely, in-road readers can be deployed in each lane, giving a clear line of sight to numberplate tags.

Moreover, in-road deployments incur only a fraction of the expenses associated with overhead deployments (LicenSys). Therefore, in-road placement of readers can overcome most of the challenges related to overhead and roadside placements.

The RFID system used for this work includes a small form factor RFID reader (ThingMagic M6E Micro) and a custom-designed RFID antenna by LicenSys (LicenSys, 2018), which can be embedded in the road and used to read tagged license plates. When used in combination with a 2m diameter ground plane, the radiation pattern of the antenna conforms to the desired pattern shown in Figure 1. The ground plane bends the radiation pattern upwards to increase the field strength around the level of the license plate (LicenSys, 2018).

4.2 Intelligent Camera Monitoring Point

Computer Vision enabled traffic cameras will include firmware that can detect and recognize vehicle license plates and classify vehicles based on their make and model.

4.2.1 License Plate Recognition

The first step in license plate recognition is detecting the plate from the input image. The detection step involves localizing the bounding box containing the license plate from the input image. In Masood et al. (2017), the researchers use a deep CNN pipeline for license plate detection under different lighting conditions and with a variety of license plates using traffic camera image data. License plate recognition occurs after the plate has been extracted from the input image. In Besbes (2021), an end-to-end approach is proposed for detecting and recognizing license plates. The system is composed of two stages: the plate detection stage and the plate recognition stage. For the detection stage, a YOLOv2 network detects the license plate from the whole raw input image and then outputs the cropped plate image to the second stage. A CNN and RNN (Recurrent Neural Network) is used for the recognition stage and does not require character segmentation.

The system proposed in this paper utilizes cutting-edge open-source techniques to develop a robust ANPR pipeline consisting of multiple stages. Specifically, the first stage uses YOLOv7 for efficient and accurate detection, while the second stage employs Paddle OCR (optical character recognition) for reliable recognition.

4.2.2 Vehicle Make and Model Classification

As previously mentioned, accurately recognizing vehicle make and model entails detecting subtle inter-class variations. One approach is to extract features from individual vehicle parts. The researchers in Besbes (2021) proposed a robust methodology to extract local (parts-based) and global feature representations for make and model recognition. The system uses YOLO (Redmon et al., 2016) to detect vehicle parts, while a VVG16 model is used to extract both local and global feature representations in a multi-stream approach. Finally, a dynamic fusion layer combines the outcomes to form a final prediction.

Manually annotating vehicle parts is very challenging and labour-intensive. Therefore, another approach will be used. BCNNs (Bilinear Convolutional Neural Networks) consist of two CNNs whose outputs are combined using a bilinear pooling layer. The bilinear pooling layer multiplies the outputs using the outer product at each location and pools them across the locations to arrive at an image descriptor (Lin, RoyChowdhury & Maji, 2015). Bilinear pooling considers the combination of features between the channels. For example, the combination of grill shape and headlight position will likely uniquely identify a vehicle model. The proposed system will use VGG16 models in a bilinear fashion for vehicle make and model recognition.

5. IMPLEMENTATION AND TESTING

This section delves into the implementation details of the previously described vehicle monitoring system. First, the RFID system underwent initial testing in an outdoor environment on the NWU campus in Potchefstroom, North-West Province, South Africa, with minimal external interference. Subsequently, the system was further evaluated on actual roads to assess its performance in a real-world scenario. Tests were conducted on 3 different roads: a road on the NWU campus; a SANRAL test road on the campus of UP in Pretoria; on an offramp linking the N4 highway with the N1 highway in Pretoria.

5.1 RFID Lab Tests

Figure 2: RFID field test setup

Figure 2 displays the lab test setup used to measure the RFID signal illumination area in the horizontal plane. The setup consisted of an in-road RFID reader, IDePLATE. The reader housing is placed in a cavity in the ground with the antenna on top of a 2.4m x 2.4m aluminium gauze sheet that forms a ground plane. The plate is positioned 1m from the reader and 400mm above the ground (typical license plate heights are 200mm - 1.3m). The illumination area is determined by measuring the maximum tag read range for different angles relative to the reader; see Figure 3 (the tag approaches the reader parallel to the 0 - 180-degree line while the tag face is kept parallel to the 90 - 270-degree line). The maximum read range is given by (1), where r is the distance between the reader and tag in meters and $\overline{EIRP}$ is the average transmit EIRP required to activate the tag in dBm (GS1.org, 2008).

$$Read\ range(m) = r \times 10^{\frac{(35-\overline{EIRP})}{20}} \quad (1)$$

From the plot in Figure 3, we can determine the effective, readable distance as a function of the travel path with a lateral offset from the reader position. Figure 4 graphs this relationship, assuming a standard lane width of 3.5m and a reader placed in the centre of the lane. It is clear from the graph that a vehicle travelling along different lateral lines has at least 7m of illumination in each direction. Consequently, the detection system satisfies the required 4m reading zone defined in (Pretorius, Hoffman & Wang, 2015).

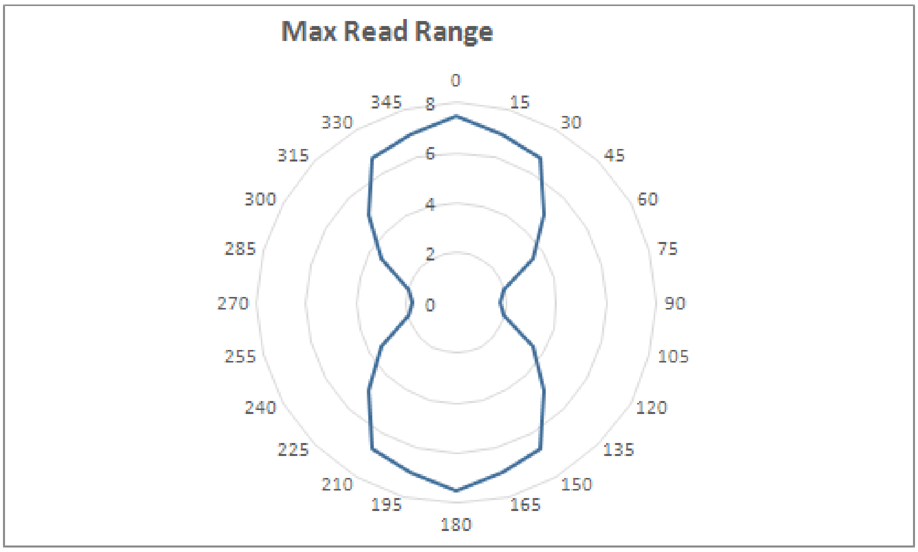

Figure 3: RFID signal illumination area. Source: Author

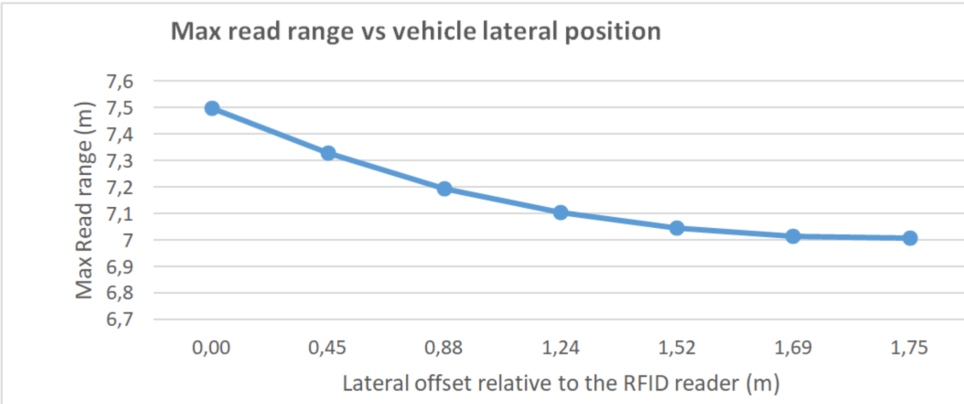

Figure 4: Effective reading distance vs. lateral vehicle offset. Source: Author

5.2 RFID In-Road Tests

Figure 5 displays the RFID reader installation in a section of pavement on the North-West University campus. The reader is placed in a cavity with a 2.4m x 2.4m ground plane. Various tests were performed to verify if the system meets the theoretical requirements. These tests were conducted on a stretch of road about 300 m in length, allowing a maximum vehicle speed of 70km/h.

Figure 5: RFID reader in-road setup. Source: Author

Reader mode test: The specific EVI application requires rapid reading of data from the tag. The ISO18000-6C specification provides different read modes that can optimize the readability of a tag for a particular application. Three different read modes are given in Table 1. The reader mode test aimed to identify the optimal reader mode for maximizing data retrieval from a tag moving at various speeds. In this experiment, a single tag was mounted on a vehicle 400mm above the road surface, passing directly over the reader. The reader's output power remained fixed at 30dBm.

Table 1: RFID reader modes

Reader mode	Modulation	TARI	PIE	BLF	M	DR
High throughput	DSB-ASK	6.25	1.5	640	1	64/3
Dense mode M4	PR-ASK	25	2	250	4	64/3
Dense mode M8	PR-ASK	25	2	250	8	64/3

Source: ISO 18000-3C Standard

Figure 6 graphs the relationship between the number of successful reads and the vehicle speed for different reader modes. The experiment was repeated for different data read sizes; however, the graph only displays the results for 96 bits. From this data, we can easily determine the RFID signal illumination distance. According to the High throughput mode (Fast Search Mode) setting of the ThingMagic M6E micro reader, the read rate is about 750 tags/sec for 96-bit tags. The graph in Figure 6 demonstrates that a tag moving at 20km/h can be successfully read 735 times in High throughput mode. This indicates that the vehicle tag received illumination for a duration of 0.98 seconds. Therefore, considering the vehicle speed, the effective tag illumination distance is calculated to be 5.4 meters. This conforms with the requirement of 4m as stated in (Pretorius, Hoffman, and Wang); however, it is still lower than the read range determined in the RFID lab test.

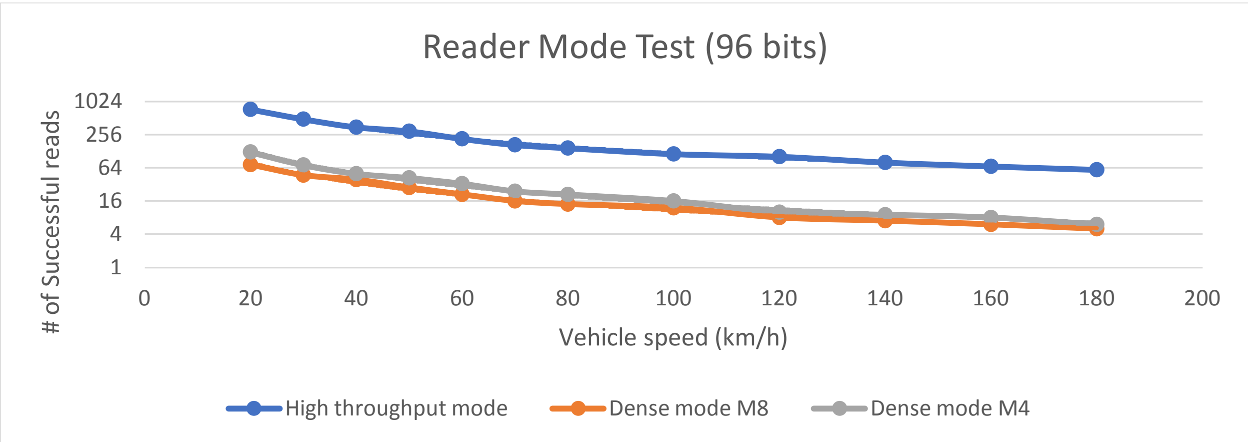

Figure 6: Reader mode test results. Source: Author

Multi-tag test: (Pretorius, Hoffman, and Wang) found that a reader will have to interrogate a maximum of five legal tags visible to the reader at one time. The multi-tag test determined how much data could be read when five tags were in the reading zone. The reader was set to High throughput mode with a tag height of 400mm. Figure 7 displays the results of a tag interrogation with four other tags also moving through the reading zone. We can see the reduction in read rate compared to Figure 6.

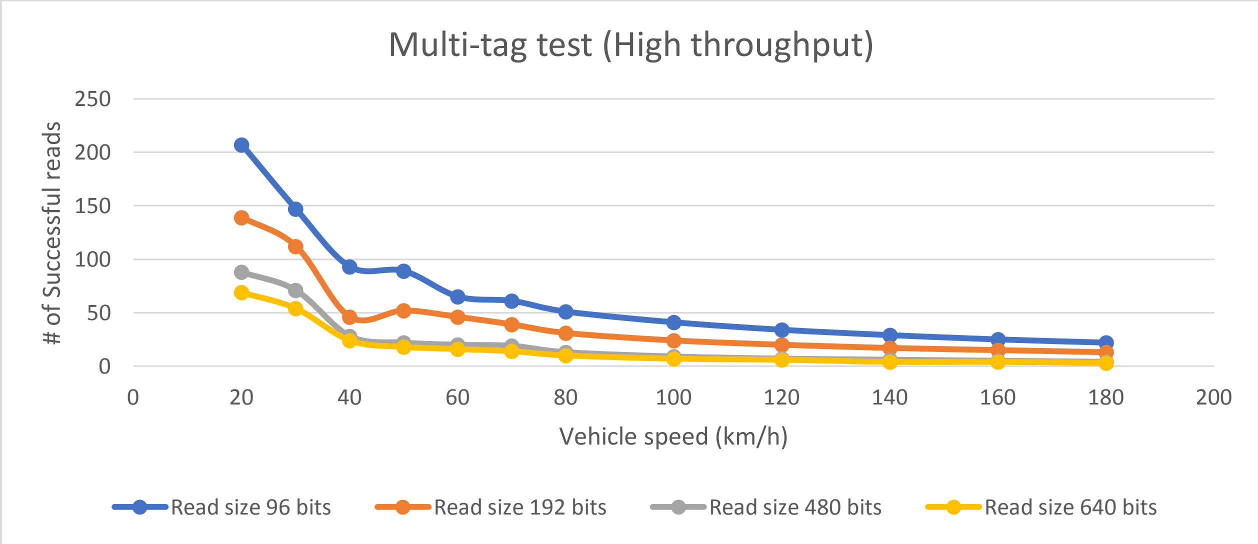

Figure 7: Multi-tag test results. Source: Author

Tag height test: The Tag Height test investigated the difference in tag performance for various license plate heights. Typical license plate heights range from 200mm - 1.3m; however, for this test, the height was limited to 0.6m. The reader operated in high throughput mode, and tests were conducted for various data sizes. Figure 8 depicts the relationship between the number of successful reads and vehicle speed, considering different tag heights and a data read size of 96 bits. The graph demonstrates that a height of 400mm above the ground yields the most favourable results.

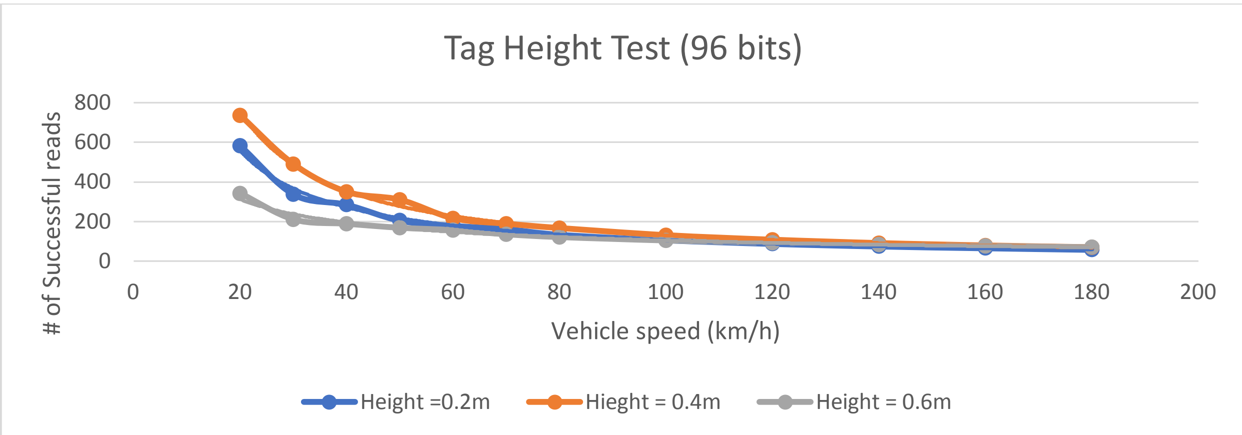

Figure 8: Tag Height test results. Source: Author

Vehicle lateral offset test: A standard lane width of 3.5m means the furthest vehicle offset relative to the reader is 1.75m (assuming the placement of a reader in the centre of each lane). The test revealed the in-road system's ability to detect a tagged vehicle for different lateral offsets. The reader operated in High throughput mode at 30dBm output power with a tag height of 400mm above the ground. The graph in Figure 9 displays the number of successful reads for different lateral offsets at incremental vehicle speeds. Performing a similar calculation as in the Reader mode test, it can be found that the illumination distance is 4.9m for a 1m offset and 4.2m for a 1.75m offset. Thus, the reader meets the theoretical requirement of a 4m reading zone.

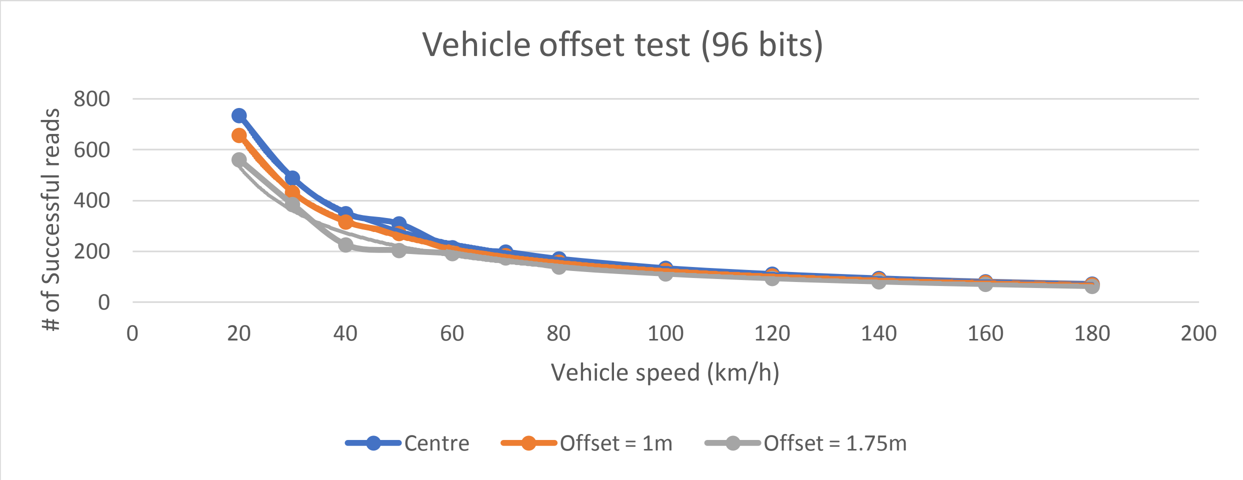

Figure 9: Vehicle lateral offset test results

Multi-reader test: In the field, multiple readers will be deployed in close proximity at different sections of a roadway. Tag-to-Reader interference can occur as a result of multiple readers trying to access the same tag. This can also lead to additional 'dead' time between reads. It is critical to achieve as low as possible interference, while maintaining a high read rate.

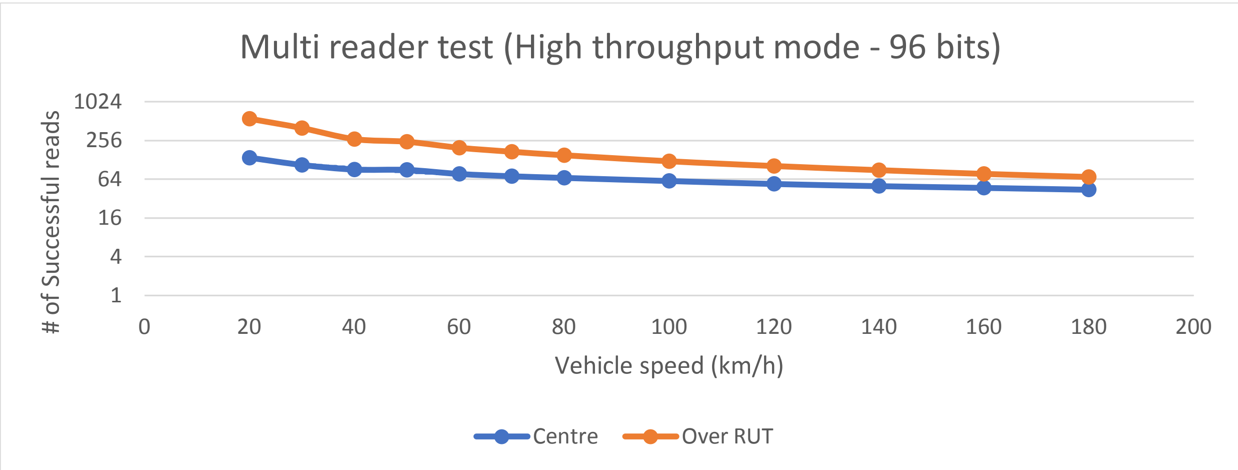

Figure 10: Multi-reader test results

Figure 10 represents a standard test with an additional reader positioned in a neighbouring lane. Comparing this graph with Figure 6, we can clearly see a reduction in the reading rate. Although the neighbouring reader is unable to read any tags, its mere presence affects the RUT's read rate. To counter this interference, adjusting reader placement from a collinear to a zigzag fashion may minimize radiation pattern overlap, expanding the detection zone's coverage. The zigzag spacing test forms part of future work.

5.3 Computer Vision Test

Fig. 11 demonstrates the output of the vehicle identification pipeline for a frame containing the tagged vehicle. The model accuracies for the validation datasets are displayed in Table 2. The ANPR model was pre-trained on the ImageNet dataset and fine-tuned using a custom ANPR dataset containing thirty thousand license plate images. These results closely resemble accuracies presented in (Besbes, 2021) on similar vehicle datasets. Vehicle make and model recognition was achieved using BCCNs consisting of two VGG16 networks whose outputs are combined using a bilinear pooling layer. The model was trained on a truncated version of the Stanford Cars dataset and contained 2,000 vehicle images from 196 different classes. The parts-based model described in (Besbes, 2021) achieved an average validation accuracy of 80.88%, having been trained on the CompCars dataset containing 136,727 images capturing the entire vehicle and 27,618 images capturing vehicle parts. This demonstrates the significant impact the size of a training set can have on a model's accuracy.

Table 2: Computer Vision model accuracies

Model	Accuracy (%)
LP detection	98.80
LP recognition	88.33
VMMR	77.25

Source: Author

Figure 11: Vehicle imaging road test Source: Author

<u>5.4 Data Fusion</u>

An RFID-enabled license plate tag that is issued to a vehicle owner will contain a unique identifier and additional vehicle information such as make, model, and registration number. When a vehicle enters the detection zone, an edge controller extracts the data from the RFID and traffic camera sub-systems and links it to a specific time slot (time slot sync). The vehicle registration number is cross-referenced within the designated time slot, and the vehicle's visual characteristics are compared. The connected edge controller can detect anomalies, such as mismatches or missed detections. Once an anomaly is identified, the edge controller reports it to an approved and controlled connected service using a best-practice access method. It is important to note that the specific details of this access method are not included in this study.

6. CONCLUSIONS

This study focused on designing and implementing a vehicle identification system that integrates two established object identification technologies. The aim is to detect and identify illegal vehicles while minimizing any impact on the experience of lawful road users. An in-road RFID reader and license plate tag provides an effective way to detect and identify in-traffic vehicles. At the same time, Computer Vision enabled traffic cameras can verify if the detected identity is true. Various tests performed on the in-road RFID system revealed that it complies with the theoretical requirements for reliable vehicle identification.

Additionally, the study verified that ANPR and VMMR achieved the anticipated levels of accuracy. However, it was observed that VMMR necessitated fine-grained classification for accurate vehicle model recognition. Future work includes further investigation of the system performance when additional readers are introduced in neighbouring lanes, testing the system in a high-density traffic environment with speeds up to 180km/h, and finally compiling a more extensive training dataset for both ANPR and VMMR, to enhance identification accuracy.

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