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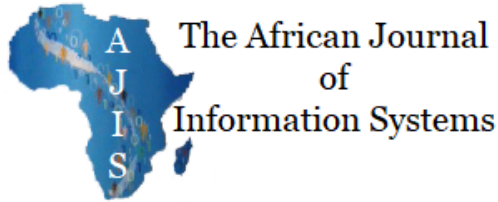
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Automated License Plate Recognition using Existing University Infrastructure and Different Camera Angles

Research Paper

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ABSTRACT

Number or license plate recognition has become an essential technology for traffic and security applications. Providing access control at any organization or academic institution improves the level of security. However, providing security personnel to manually control the access of vehicles at an academic institution is costly, time-consuming, and to a limited extent, error prone. This study investigated the use of an automated vehicle tracking system, incorporating experimental computer vision techniques for license plate recognition that runs in real-time to provide access control for vehicles and provide increased security for an academic institution. A vehicle monitoring framework was designed by using various technologies and experimenting with different camera angles. In addition, the effect of environmental changes on the accuracy of the optical character recognition application was assessed. The Design Science Research methodology was followed to develop the vehicle monitoring framework artifact. Image enhancement algorithms were tested, and the most viable options were evaluated and implemented. Optimal operating criteria that were established for the vehicle monitoring framework achieved a 96% success rate. The results indicate that a cost-effective solution could be provided by using an existing camera infrastructure at an academic institution and suitable license plate recognition software technologies, algorithms, and different camera angles.

Keywords (Required)

License plate recognition, university infrastructure, camera angles.

INTRODUCTION

The increasing population in today's society has resulted in countries experiencing an increase in licensed vehicles on the roads and access to premises (Bagade et al., 2011). As a result, validating a vehicle's presence manually, by recording the number or license plate, has almost become an impossible task. Law enforcement agencies and organizations require faster and more robust vehicle-monitoring systems. A Vehicle Monitoring Framework (VMF) or Automated Vehicle License Plate Recognition System (AVLPRS) can be described as software and hardware solutions aimed at the tracking of vehicles traveling on roads or entering or leaving premises. Identifying a vehicle's license plate (number plate) does not necessarily suffice in improving security, thus a VMF must be integrated into an IT architecture that incorporates a vehicle database, an alert system linked to mobile devices, and the possibility of the system being able to control external sensors (lights) and gates (Ullah et al., 2019; Khaparde et al., 2018).

A vehicle tracking system is one of numerous existing monitoring systems, such as burglar alarms and surveillance systems, which are placed in a specific environment to monitor or track activities or events (Choudhury & Abou El-Nasr, 2019). However, many of these systems require constant human intervention. Vehicle identification could aid in any organization's pursuit for increased security by controlling access to certain areas and by providing real-time alerts and logs of vehicular traffic. Simply recording security camera footage of vehicles entering an institution and storing the data does provide an increased level of security. An AVLPRS provides solutions that require minimal human interventions (Arafat et al., 2019; Fu, 2019).

Commercial and experimental AVLPRSs have been developed over the past years (Khaparde et al., 2018; Rajput & Som, 2015). An AVLPRS assisted with the identification of vehicles and provided a platform for further vehicle tracking and activity analysis. AVLPRSs generally use video cameras to capture the vehicle license plate and location. The license plate of the vehicle is located and the letters and numbers on the license plate are then extracted from the captured image by using an optical character recognition system or experimental technologies (Arafat et al., 2019; Humam et al., 2017). The identified vehicle license plate number is then used for further analysis, including vehicle tracking and for security purposes (Rajput & Som, 2015). AVLPRS applications have also been developed for mobile devices and smart phones (Gunawan, Mutholib, & Kartiwi, 2017). Research has indicated that AVLPRS on mobile phones, incorporating a multi-angle license plate character recognition model, can achieve up to 84% accuracy (Lin & Wu, 2019).

Environmental factors, such as weather and lighting conditions, play an important role in successful vehicle license plate recognition (Rajput & Som, 2015). Researchers have achieved up to 97% successful automated license plate recognition accuracy by using different methods, including combinations of edge statistics, morphology, and artificial neural networks (Fu, 2019; Rajput & Som, 2015). Numerous factors influence the effectiveness of a license plate recognition system, with one of the biggest risks being the quality of the video feeds and images captured by the system. Weather conditions also play a critical role. If it is too dark, the system may be unable to detect motion in the video and hence be unable to identify a vehicle's license plate correctly. Video camera placement and specifically the camera angle are also important, as the camera must be placed at the correct height or angle for successful image capturing to be achieved (Rademeyer, Booysen, & Barnard, 2018). The above factors are all detrimental to any automated surveillance system and care must be taken to achieve optimal operating criteria for the system.

Universities are monitoring vehicle access on campuses more frequently. University security personnel are required to identify staff and students entering campuses and check if the vehicles entering are permitted on the campuses. Video camera surveillance systems are being used increasingly at university entrances. The use of automated license plate recognition technologies is limited, however, due to the high cost involved in running a real time AVLPRS. The focus of this paper is the implementation and evaluation of an AVLPRS as part of a proposed VMF at a university, using existing technologies and university infrastructure.

The vehicle tracking framework developed and evaluated in this study used security camera feeds at the entrances of a university campus and identified vehicles entering the campuses. The credentials of registered vehicles were stored in the university vehicle database, and when a vehicle was identified by using a developed AVLPRS, security personnel were provided with automatic alerts triggered by the system, specifically if an unauthorized vehicle entered the premises. A registered mobile device was used to interface with the AVLPRS, and any alert generated was displayed immediately on the device.

The layout of the paper will include a literature review (Section 2), specify the research problem and research methodology applied (Section 3), provide a description of the proposed VMF (Section 4), and include an analysis of results of the evaluation of the VRF (Section 5). Conclusions and recommendations for future research are presented finally in Section 6.

BACKGROUND LITERATURE

License Plate Recognition Systems

Extensive research has been conducted on license (number) plate recognition (Arafat et al., 2019; Khare et al., 2019; Khaparde et al., 2018; Bakhtan, Abdullah, & Rahman, 2016; Arivu Selvi, Ramya, Kala, & SriDivya, 2016; Rajput & Som, 2015). Comparative studies have been done on effective approaches of automatic license plate recognition (Balamani & Kavitha, 2018). AVLPRS generally include a four-phase process, namely, image capture, image processing and enhancement, license plate localization, and license recognition using optical character recognition (Khaparde et al., 2018, Rajput & Som, 2015). Arafat et al. (2019) and Bakhtan et al. (2016) indicate that the four processes are image acquisition: license plate detection, character segmentation, and character recognition. Real-time applications have been developed incorporating the four phases that can identify a moving vehicle, extract the license plate, divide the characters, and recognize the characters (Arafat et al., 2019; Damayanti et al., 2019; Arivu Selvi et al., 2016).

Research into license plate recognition faces many challenges, as license plates differ in size, position, color, shape, size and, specifically in South Africa, background patterns (Rademeyer et al., 2018). Identifying letters and numbers on a license plate in real-time is further challenging in different weather conditions, lighting conditions, and the use of different camera angles. Additional challenges faced when capturing an image of a moving vehicle were image distortion or noise, license plate location, and license recognition by means of optical character recognition. Khare et al. (2019) introduced a new concept, called partial character reconstruction, to segment characters of license plates and improve the performance of an AVLPRS.

Motion detection, i.e., identifying a moving object, is an important research domain, and once the image has been captured, the image needs to be enhanced by using different photographic techniques and algorithms. The distance from the camera to the vehicle also influences the accuracy of the system (Noprianto, Wibirama & Nugroho, 2017). Noprianto et al. (2017) found that the accuracy of the system deteriorated from 88% at 1 meter, to 83% at 3 meters, and 65% at 5 meters by using a three-phase process. Wang et al. (2010) indicated that accuracy rates for license plate localization (98%), character segmentation (98%), and character recognition (96%), were obtained with an overall 96% accuracy rate by using Daubechies wavelet transform to overcome multiple limitations.

Rajput and Som (2015) have also achieved up to 97% success in automated license plate recognition accuracy. Different methods and algorithms have been used in an AVLPRS, including combinations of edge statistics, morphology, and artificial neural networks (Rajput & Som, 2015; Chuang, et al., 2014). Related research discussed by Bakhtan (2016) compares algorithm efficiency in license plate recognition. The research includes examples of using a backward propagating neural network on Thai license plates, where a 92% accuracy recognition rate was achieved. The Sobel algorithm, with morphological operations, was implemented in Saudi Arabia and achieved a 95% accuracy rate. The Turkish algorithm was used on edge detection, including morphological operations such as erosion, filtering, and convolution, and achieved a 95% accuracy rate. The use of neural networks and signal processing are popular techniques used for license plate and character recognition (Fu, 2019; Bakhtan et al., 2016).

License Plate Detection

Computer Vision (CV) is the science of computerising the ability to see and interpret images. It gives a machine the ability to interpret what it is seeing and allows the machine to make seemingly independent decisions or to perform actions similar to those that humans perform (Learned-Miller, 2011). It is important to note that there is a difference between image processing and computer vision. Image processing, while used to enhance images before being used in computer vision algorithms, differs from computer vision in that it deals with the enhancement of images for use by humans (Maxwell, 1998). Typical enhancements include noise cancellations, image enhancements, and image transformations. Figure 1 provides an example of an extremely grainy (noisy) image as well as the resultant image after a noise cancellation algorithm has been applied to it.



Figure 1: Image processing algorithms applied to reduce the amount of noise in an image.

CV deals with the manipulation of images that will be analysed and understood by a computer (Chuang, et al., 2014). CV topics include line finding, object representation, object recognition, edge detection, and character recognition. License plate detection can be divided into different categories (Chuang et al., 2014). The categories include using color as a main feature, using edge features to identify the number

plate block, and searching for the characters in the image. Two particularly important ways for the purpose of this study in which CV has been implemented are in motion detection and optical character recognition. These implementations of CV were used simultaneously to help create a system that tracks the movement of cars uniquely by license plate number recognition.

Motion Detection

The objective of motion detection is to determine the amount of change in position an object experiences relative to its surroundings (Alavi, 2012). An algorithm is applied to two closely related frames from video footage to produce a resultant image in which the differences between the first image and the reference image can be highlighted. These differences are regarded as motion that has occurred. Motion detection algorithms use a threshold value to determine if movement has occurred between frames. The threshold value is the amount by which an image differs from the reference image. A threshold value allows a system to be fine-tuned to detect motion only above a certain level and disregard unimportant events, such as the leaves on a tree moving with the wind (Myers, Eric, & Daniel, 2004). This threshold value is simply the number of pixels that differ between two input images.

Image subtraction is one of the most popular techniques for a motion detection algorithm. It operates by subtracting the numerical value of each pixel of one image, from the corresponding pixel of the reference image. Image subtraction is one of the fastest methods for motion detection. Two of the most common image subtraction techniques are the Two Frames Differences technique and the Background Subtraction technique (Cheung & Kamath, 2004).

The purpose of the *Two Frames Difference* technique is to find the difference in two consecutive frames, by comparing the current frame to the previous frame. The formula can be represented as: $\Delta I = I_{cur} - I_{prev}$ where ΔI is the number of pixels that are the difference between two consecutive frames (Alavi, 2012). A value of 0.1, for example, indicates that the two images are 10% different. Thus, the greater the value of ΔI , the greater the difference between the two frames and thus the greater the motion level in the video footage between those frames. The Two Frames Difference technique is one of the simplest and fastest techniques; however, this technique is not suitable when high accuracy is required, as it can produce areas of inaccurate results, as shown in Figure 3, where the algorithm does not show the entire area of movement, but only the general outline of the object (person).

Background Subtraction (BS) differs from the Two Frames Difference technique above in that it does not compare two consecutive frames, but rather it compares the current frame with a reference image. BS determines how the number of pixels in the current frame differ from the corresponding pixels in the background image. These pixels are classified as foreground pixels, which are considered part of a moving object. A large number of background subtraction algorithms are available, all generally sharing common processes, including Pre-processing, Background Modelling, Foreground Detection, and Data Validation, as shown in Figure 2.

Further detail into each step of the BS technique will not be covered, as it is not the primary focus of this paper. It is important to note that the BS technique offers much greater accuracy than that of the simpler Two-Frames Differences algorithm, as can be seen when comparing Figure 3 with Figure 4. Whereas Figure 3 only highlights the general silhouette of the person, Figure 4 highlights the entire person.

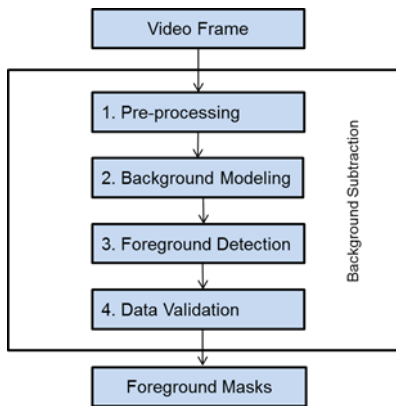


Figure 2: Flow diagram on a generic Background Subtraction algorithm.



Figure 3: Two Frames Difference technique. Figure 4: Background Subtraction technique.

Image Capturing and Enhancement

Factors that influence the capturing of an image, specifically a license plate, include camera angles, camera types, lighting, and the distance of the camera from the license plate. Rademeyer et al. (2018) found that a camera specification, specifically the focal length of the lens, was the most influential factor. Research has shown that AVLPRS that use a 5-meter distance of the camera from the number plate produces the highest accuracy (Noprianto, Wibirama & Nugroho, 2017).

Once the image has been captured, the image needs to be enhanced. There are four types of image enhancement algorithms used in the VMF developed. These include Sharpening, Gaussian Sharpening, Contrast Correction, and Brightness Correction, all of which are implemented by using the AForge.NET computer vision library. Post-processing algorithms for image enhancement are processor intensive, as the running times for these algorithms vary largely and can have a negative impact if used in a real-time system, such as the proposed VMF.

Image filtering allows for various effects to be applied to photos. For each filter, a two-dimensional matrix is required. For each pixel of the image, the sum of the product is taken where the product is the color value of the current pixel or a neighbor of it, multiplied by the corresponding value of the filter matrix. The center of the matrix is applied to the current pixel, while the remaining elements of the matrix are applied to the neighboring pixels (Vandevenne, 2004).

Sharpening. The sharpening filter performs a filter using the following kernel

$$\begin{vmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$

to produce a sharpened image as in Figure 5.



Figure 5: (a) before sharpening (b) after sharpening

Gaussian Sharpening. Gaussian Sharpening performs a convolution filter using the kernel where the kernel is calculated from an array of Gaussian function's values in the $[-r, r]$ range of (x, y) values, where $r = \text{floor}(\text{size}/2)$ and then converted to an integer sharpening kernel. Note that the difference in the images is small when the image is downscaled, as shown in Figure 6 (a); however, Figure 6 (b) provides a much clearer image of the process.



Figure 6: (a) Image before Gaussian Sharpening and (b) after Gaussian Sharpening.

Contrast Correction. The Contrast Correction filter operates in RGB color space and adjusts the pixels' contrast value by increasing RGB values of bright pixel and decreasing RGB values of dark pixels (or vice versa if contrast needs to be decreased). The filter is based on LevelsFilter, which performs linear correction of RGB channels by mapping specified channels' input ranges to output ranges (Figure 7).



Figure 7: (a) before contrast correction (b) after contrast correction.

Brightness Correction. The filter operates in RGB color space and adjusts the brightness of the pixels' by increasing every pixel's RGB values by the specified adjusted value (Figure 8). This filter is also based on LevelsLinear.



Figure 8: (a) before brightness correction (b) after brightness correction.

License Plate Recognition and Number Segmentation

Automatic License Plate Recognition (ALPR) is a practical application of Artificial Intelligence and there is a great demand for information systems to implement ALPR, which will allow for better management of traffic and security through access control (Fu, 2019; Bagade et al., 2011; Martinsky, 2007). ALPR has the following major steps, as shown in Figure 9. Character segmentation and recognition will be the only steps developed in this paper. Related research indicated the use of back propagating neural networks (Chuang et al., 2014) and feed forward artificial neural networks with sigmoidal activation functions for license plate character recognition (Fu, 2019; Wang, 2010).

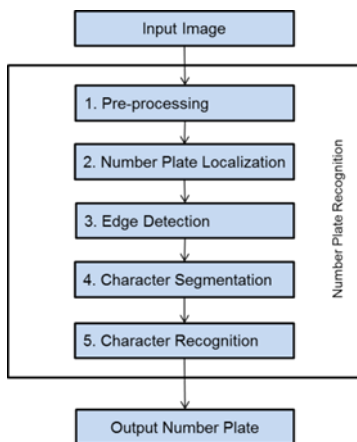


Figure 9: Process of License Plate Recognition.

The segmentation of the characters of the license plate is one of the most important steps in the algorithm and if it fails, a character can be improperly processed and either merged into another character, or split into two characters (Damayanti et al., 2019; Martinsky, 2007). The process of segmentation of the characters consists in finding the horizontal boundaries between each character. Damayanti et al. (2019) obtained 99% accuracy by using the k-nearest neighbor classification method.

Character segmentation algorithms need to determine undesirable elements, such as dots, dashes, or extra white spaces on the sides of characters, depending on the region from which the license plate originates. These elements may cause inconsistencies in the element segmentation process and there is thus a need to eliminate these elements and allow for only the characters to be extracted. In Figure 10, the resultant images consist of the individual characters of the license plate that need to be extracted from the image into text.

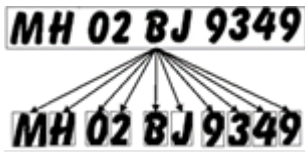


Figure 10: Character Segmentation.

For the purpose of this paper, backward propagating artificial neural networks were used to extract characters from the segmented images, as they allow for greater accuracy and faster recognition speeds over traditional Optical Character Recognition algorithms (Fu, 2019; Nagare, 2011). These neural networks are already trained with thousands of sample images of characters (Bagade et al., 2011), which are mapped to the most probable character for that area's license plate style in the training set.

Vehicle License Post-processing

After the vehicle number has been obtained and converted to a text format, the number can be used to retrieve vehicle information from internal databases (Khaparde, 2018). The identified vehicle provides a reference to its location at a specific point in time and can be used for further analysis, including vehicle tracking, activity analysis, and security and access control. The VMF developed in this study included the use of a graphical user interface on a mobile device used by a security officer at a university entrance. The vehicle number was compared to all the registered vehicles in the university database, and if the vehicle was not registered, an alert with a picture of the vehicle was sent to the mobile device of the security personnel at the entrance. The security personnel were then required to pull over the driver of the vehicle and investigate the reason for access and record the appropriate action taken. The user of the mobile application was further required to swipe and/or dismiss the alert, thereby triggering an 'EVENT_ALERT_CLEAR' event on the server, indicating that that particular alert had been dealt with.

RESEARCH METHODOLOGY AND RESEARCH PROBLEM

Internationally, university management is discouraging private vehicles from entering and parking on campuses and instead are encouraging staff and students to use public transportation. More specifically, students and staff are being encouraged to walk to campus and to make use of bicycles (Lyth, Peterson, & Singh, 2018). Walking and cycling for transport (active travel) is an important source of physical activity, with established health benefits. Universities in South Africa, however, have experienced an increase in the number of private vehicles and mini-bus taxis entering campuses, due to poor public transportation and limited student accommodation on campus.

Universities have further experienced an increase in student numbers, which implies an increase in the number of vehicles entering, leaving, or parking on campus. University security and access control has been upgraded on most campuses in South Africa, specifically after the 2016 student protests (Davids & Waghid, 2016). The use of video surveillance cameras at campus entrances has become standard practice. Due to an increase in traffic violations on campus, certain vehicles, and specifically specific taxi operators, have been banned from entering a campus.

Universities in South Africa are experiencing increasingly severe budgetary constraints (Calitz, Bosire, & Cullen, 2017). The budgetary constraints have had an impact on academic and infrastructure projects. A major problem identified in this research study is that security management has been affected

negatively by the inability to purchase expensive video surveillance hardware and software to allow the real time monitoring of vehicles and people.

A large number of AVLPRS have been developed by using different techniques to detect and recognize license plates (Arafat et al., 2019; Khaparde, 2018). The research objective of this study was to determine how the existing video camera infrastructure and camera angles at the entrances of a university could be used effectively as part of an inexpensive vehicle management system, using existing technologies and algorithms available in the research domain (Arafat et al., 2019). An integrated AVLPRS was developed, using existing available technologies, linking the output to mobile devices used by security personnel at the gates for real-time vehicle information retrieval, verification, and presentation.

The research approach applied in this study was a literature synthesis followed by an experimental assessment of an artifact, namely the VMF. The Design Science Research Methodology (DSR) was used to design and evaluate the VMF artifact (Hevner, 2007). The overall framework for DSR is illustrated in Figure 11, and consists of three main boxes, namely, from left to right, the Environment, Research, and Knowledge base.

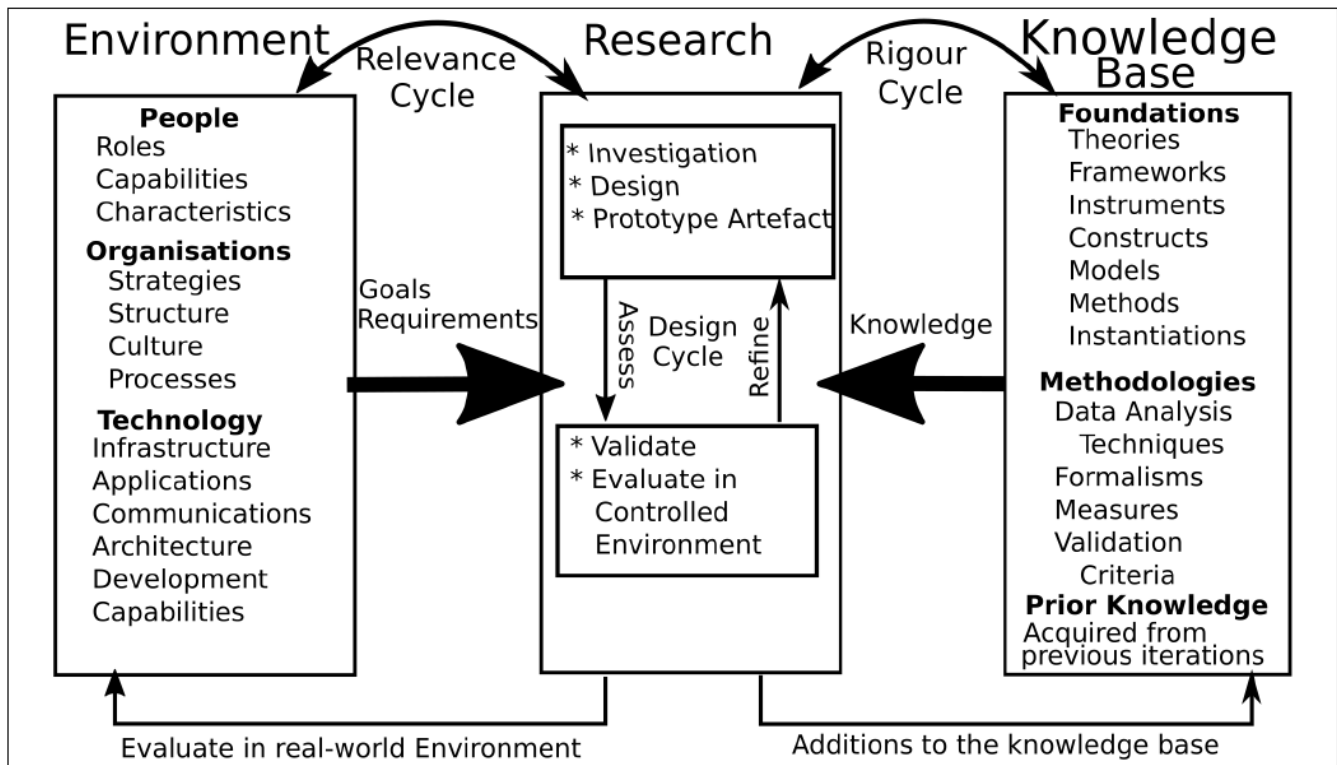


Figure 11: DSR framework adapted from Hevner [2007].

The Environment represents the problem area under investigation. The problem area includes the problem as well as problem related entities; for example, users of a proposed software artifact being designed as a solution for the problem. The bulk of the research is carried out here, where artifacts that address the problem are developed and evaluated. The design cycle is an iterative feedback cycle comprising several steps with knowledge flows in both directions, resulting in iterative improvement. The knowledge base comprises all external information sources concerning the problem area, including

prior research, related research, related disciplines and fields, and results from the previous Design Science cycle.

Design theories are the sciences of the artificial counterpart to scientific theories in the natural sciences. Baskerville and Pries-Heje (2010) differentiate between two forms of design theory:

- Design Practice Theory (DPT), which is prescriptive and describes in practical terms how to design an artifact; and
- Explanatory Design Theory (EDT), which relates generalized requirements to generalized components of a system. The generalizability means that a wide range of possible designs can be examined for different component combinations. The components are supplied by the design; relating specific component combinations to the requirements provides a means of evaluating the design.

The Design Practice Theory was used in this study to identify algorithms and software sub-systems, and to assist in the design the VMF. The Explanatory Design Theory was used to obtain the generalized combination of components for the VMF, specifically identifying components used in similar AVLPRSs discussed in literature.

In addition to the design cycle, Hevner (2007) describes two other cycles in the DSR framework. The Relevance Cycle provides a feedback loop between the Environmental context and the DSR context. Initial design goals form input to the DSR, and proposed artifacts are output from the DSR to the Environment. The Rigour Cycle continually verifies the research contribution of the artifact by monitoring the Knowledge base. The output from the DSR process is important, as it documents the research results and forms a theory of knowledge about the research area, which in turn, can be peer reviewed or used by other researchers when researching related areas. Unfortunately, there are no set standards in DSR output artifacts. However, the most widely accepted recommendations are constructs, models, methods, and applications, such as an AVLPRS or VMF.

PROPOSED VEHICLE MONITORING FRAMEWORK

One key aspect in the reliability of such a proposed VMF is the quality of the type of data that is used. In this case, the variability of video data specifically relates to the angle of the camera in relation to the vehicle being recorded and the quality of the video feed (Moreau, 2013). For the purpose of this paper, assumptions are made about the evaluating data to eliminate the problem of overlapping vehicles, as described in Section 2. These assumptions are that each camera monitors only a single lane of traffic in a particular direction, either entering or exiting the premises, and that the video camera footage is of a high quality.

This paper aims to investigate how various camera angles relative to the detected vehicle affect the reliability of the detection process. The camera angles included in this evaluation are the front, rear, and angled-front angles (Figure 12). Three camera angles which are not included in this evaluation are the side, top-down, and the highly elevated front angles. The reason for this is that top-down and side angles do not provide any view of the license plate and are thus not suitable for use in the VMF. A highly elevated front angle, such as when a camera typically would be located on the top of a street light, is also not considered, as the likelihood of incorrect plate identification would increase significantly, as well as a high angle would include vision of multiple traffic lanes.

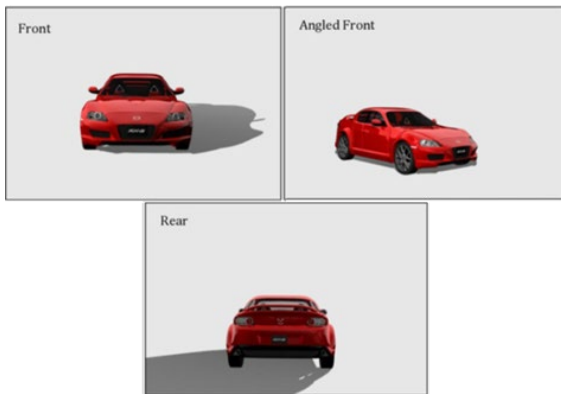


Figure 12: Different camera angles compared.

The front camera angle is used to record vehicles in a position directly in front of the camera. The advantage of this camera angle is the clear visibility of the license plate (Moreau, 2013). It would be most advantageous to place the camera at an angle of 0° — or perfectly in line with the vehicle's license plate. However, because of the nature of moving vehicles, this approach would likely cause a collision between the vehicle and the camera. Thus, the camera angle for the front view of the vehicle will be approximated at 15° . The front camera angle would likely yield the best results, as it provides a head-on view of the vehicle's license plate. Because it is not always possible to position a camera ahead of the vehicle, an angled-front and a rear angle were considered.

A rear camera angle is similar to the front camera angle whose primary goal is the clear view of the vehicle's license plate. However, this angle is more prone to having a secondary vehicle driving closely behind the first vehicle, obstructing the view of the primary vehicle's license plate. Similar to the front camera angle, placing the camera directly behind the vehicle was not feasible. Thus, the closest approximate angle that resembles the rear-view closely was chosen.

An angled-front camera angle is an approach to recording vehicles that includes a full view of the car itself, as well as the car's license plate. However, an issue could arise as to whether or not the clarity of the license plate is sufficient for the recognition process. An angle of 45° was chosen as a test parameter for the angled-front view for the system, since it should expose the license plate sufficiently for recognition.

Weather conditions also play an important role in license plate recognition and contribute to the effectiveness of the VMF. The test for each camera angle was performed using video footage from a clear (sunny) day as well as from a rainy (cloudy) day. To ensure the possibility of effective comparison of both weather conditions, each video recording was taken at the same location and within approximately a one-hour time span to ensure a consistent amount of lighting. The video footage was also recorded at midday to ensure adequate lighting conditions.

An analysis of various image enhancement algorithms was conducted to determine if the detected image could be enhanced to such an extent as to make an undetectable license plate detectable. Various image

enhancement algorithms were considered, which included Sharpening, Gaussian Sharpening, Contrast Correction, and Brightness Correction algorithms.

The VMF also incorporated a security feature by using a mobile client for the security personnel. The advantages of using a mobile device were the instantaneous relaying of data to the security personnel tasked with the admittance of vehicles onto the premises. The mobile application delivered the notification instantaneously to the security guard, using a wakelock (Android) that was obtained for the duration of the alert. The mobile application allowed for the dismissal of events, which consequently trigger an event on the servers to indicate that the pending alert had been handled. The VMF architecture developed is depicted in Figure 13.

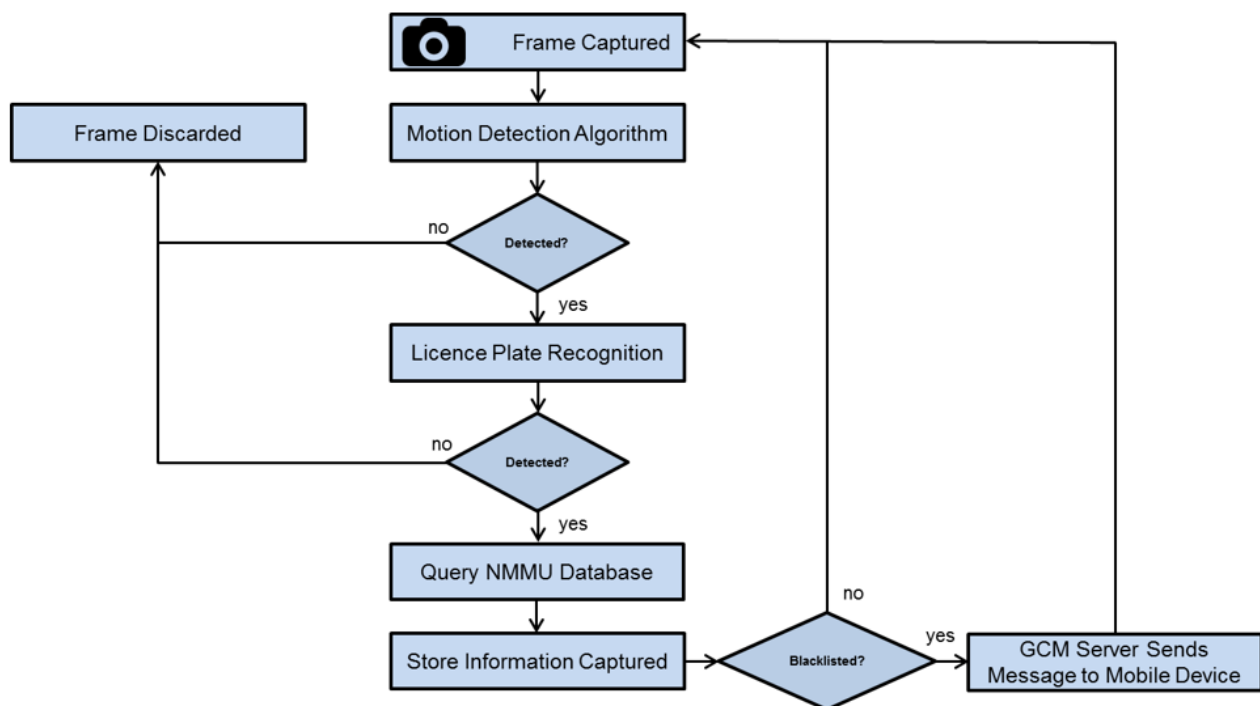


Figure 13: VMF Architecture.

The practical interface of the VMF is depicted in Figure 14. The camera provides a video stream and the VMF monitors and captures a vehicle’s image which is processed by the VMF (Figure 13). Once the numbers on the license plate have been segmented, the university vehicle database is queried (SQL query) to determine if the vehicle is registered in the university’s vehicle database. The VMF provides a notification to the security guard, including a picture of the vehicle, indicating whether the vehicle is registered.

The mobile application, written in Android, was capable of receiving alerts from the system and having all details about the alert viewable for the security guard. Each device was registered for a specific user to allow administrators of the system to obtain detailed logs of when an alert was sent out and which

user dealt with that alert. The system, as a whole, provided detailed logs of all vehicular traffic and provided statistics and graphs for reporting purposes.

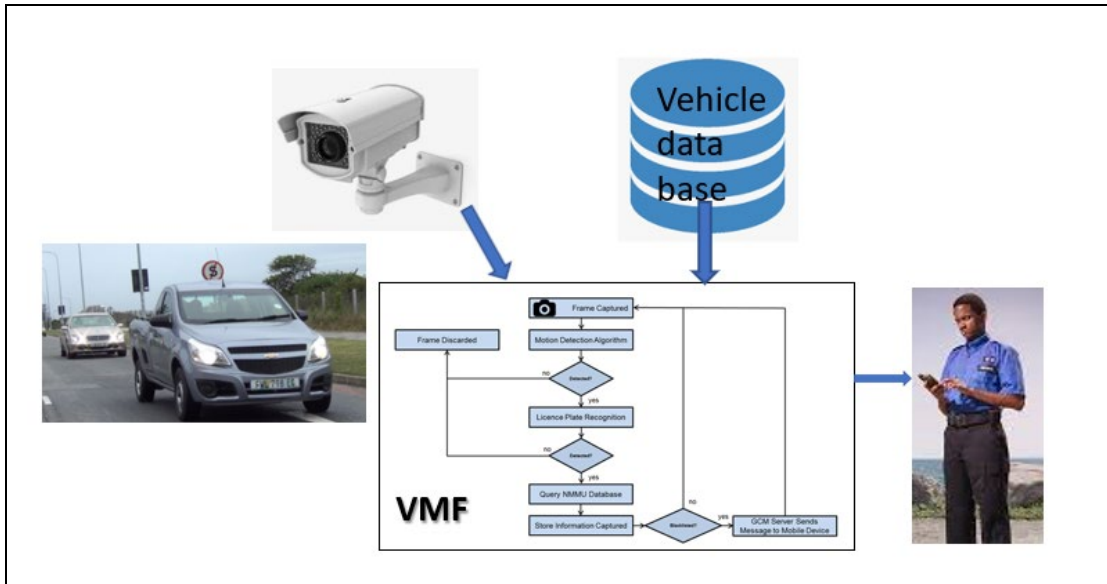


Figure 14: Practical view of the VMF.

EVALUATION OF RESULTS

In related research, the accuracy of commercial versus open source software for license plate recognition was compared (Khaparde et al., 2018; Balamani & Kavitha, 2018). It was established that since the open source software’s recognition module was trained with only UK and US style license plates, the accuracy was incredibly low for other areas and failed to detect even a fraction of the total sample size accurately. It is for this reason that open source software was excluded as a viable candidate for the VMF, and the following comparisons were done using commercial license plate recognition software, named SimpleLPR (<https://simplelpr.soft112.com/>). A sample size of 34 vehicles for each angle was used and the experiment was conducted at midday in both environments to standardize the amount of light the sun presented.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	31	3	91%
Angled-Front	28	6	82%
Rear	19	15	56%

Table 1. Detection Accuracy in a Sunny Environment using Two Frames Difference Motion Detection.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	28	6	82%
Angled-Front	16	18	47%
Rear	17	17	50%

Table 2. Detection Accuracy in a Rainy Environment using Two Frames Difference Motion Detection.

The accuracy of detection for each angle in the corresponding environment setting is presented in Tables 1 and 2. This process was repeated using both the Two-Frames Differences technique as well as the Background Subtraction technique of motion detection (Tables 3 and 4). This initial evaluation of the system was done using pre-recorded 720p video footage; however, the final evaluation was done using 1080p live footage.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	32	2	94%
Angled-Front	28	6	82%
Rear	20	14	59%

Table 3. Detection Accuracy in a Sunny Environment using Background Subtraction Motion Detection.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	28	6	82%
Angled-Front	17	17	50%
Rear	17	17	50%

Table 4. Detection Accuracy in a Rainy Environment using Background Subtraction Motion Detection.

The front-angle camera location proved to provide the highest accuracy. The detection accuracy of the system decreased when the results of the sunny environment were compared to those of the rainy environment. A comparison of the results of the front-angle location, obtained between the sunny environment and the rainy environment, yielded an understandable drop in accuracy. The light provided in a rainy environment has a particularly negative impact on detection accuracy when the license plate itself has defects, such as a crack in the license plate or a particularly dirty plate, which generally happens while driving in rain. In Table 1, two of the incorrect detections found in the front-angle were due to one of the plates having a crack along the vertical direction, which caused the recognizer to detect a 'C' as a 'K', as the crack was right before the letter 'C'. The other plate was so damaged that it was missing a letter at the end of it. The inaccuracies introduced by issues are understandable and cannot be attributed to the license plate recognition algorithm itself.

An unexpected result was the low accuracy of the angled-front camera location in rainy conditions. Upon review of the video camera footage, it was evident that the further the license plate was from the camera, the less likely it would be detected accurately. A common, incorrect analysis by the recognition

software often merged the two end characters of the license plate, namely 'EC' became 'B'. This incorrect merging of characters could be explained again by the lighting conditions during rainy conditions. There was simply not enough contrast between characters and non-characters when the camera was at such an angle to the vehicle in the specific lighting conditions.

The detection accuracy of the rear camera angle remained inherently poor in rainy conditions. This could be attributed to the overlapping of vehicles where the secondary car obscures the characters of the license plate of the vehicle in front of it. When vehicles were travelling at a high speed, it became difficult for the license plate recognizer and number segmentation modules to detect the characters accurately. The further the vehicles were from the camera, the smaller the license plate became. This affected the license plate localization process, causing the algorithm to not locate the license plate of a vehicle that was too far away. Both the Two-Frames Differences technique as well as the Background Subtracting technique of motion detection produced similar results (Tables 1-4).

The minor improvement in results using the Background Subtraction technique could be attributed to the increase in the accuracy of the algorithm. One case in which the Background Subtraction algorithm outperformed the Two Frames Differences algorithm was when a bus came to a complete halt while still present in the motion zone. Since the system relied on the detected motion levels being above a certain threshold for the license plate recognition module to be activated, the motion detection algorithm in these cases proved invaluable. The Background Subtraction technique proved that it detected motion in these cases due to the static background image being used for comparison with the current frame.

The Two Frames Differences algorithm in this case proved unable to detect that a vehicle was in the motion zone, as it had come to a complete stop. Other increases in accuracy, when using the Background Subtraction technique, came from when vehicles were moving very slowly. Again, because of the background image that the current frame was compared against, the Background Subtraction technique was able to detect the vehicle even while it was moving very slowly. The same detection for slow moving vehicles could be achieved using the Two Frames Differences technique by simply lowering the threshold value slightly. However, in doing so, unwanted movement from pedestrians and foliage were also detected, which increased CPU utilization, as the license plate recognition module was incorrectly activated more often.

It is important to improve the system's performance so that the character recognition module would detect characters only when a certain level of motion has occurred. Unwanted occurrences, increased the CPU utilization of the system considerably. While the Background Subtraction technique was more computationally expensive compared to the Two Frames Differences technique, the increased CPU usage, while using the Background Subtraction technique, was comparably negligible, since it increased the accuracy of the entire system. In order to provide the most accurate detection possible, the Background Subtraction technique was used as the final motion detection algorithm for the VMF.

As stated earlier, the decrease in the accuracy of the results when comparing a sunny environment to rainy conditions could be explained by the lack of sufficient lighting conditions during rainy conditions. This lack of light could be compensated for somewhat by applying various post-image processing

algorithms to the detected frame. To determine whether applying post-image enhancement algorithms to images from both sunny and rainy conditions increases the overall detection rate, all previous tests were re-run using:

- a) A Contrast Correction algorithm (Tables 5 and 6)
- b) A Brightness Correction Algorithm (Tables 7 and 8)
- c) A Sharpen algorithm (Tables 9 and 10)
- d) A GaussianSharpening algorithm (Tables 11 and 12)

A combination of each algorithm was also applied to a variety of test cases, but proved to decrease the accuracy of the license plate recognition considerably, and thus it was decided that no further testing of the combinations of algorithms would be conducted. However, Tables 5 through 12 indicate the results of applying each algorithm to the video feed using the Background Subtraction technique separately.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	32	2	94%
Angled-Front	26	8	76%
Rear	20	14	59%

Table 5. Contrast Correction in a Sunny Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	30	4	88%
Angled-Front	20	14	59%
Rear	17	17	50%

Table 6. Contrast Correction in a Rainy Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	29	5	85%
Angled-Front	24	10	71%
Rear	20	14	59%

Table 7. Brightness Correction in a Sunny Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	20	7	79%
Angled-Front	24	14	59%
Rear	19	15	56%

Table 8. Brightness Correction in a Rainy Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	31	3	91%
Angled-Front	29	5	85%
Rear	21	13	62%

Table 9. Sharpening in a Sunny Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	30	4	88%
Angled-Front	20	14	59%
Rear	16	18	47%

Table 10. Sharpening in a Rainy Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	29	5	85%
Angled-Front	32	2	94%
Rear	20	14	59%

Table 11. Gaussian Sharpening in a Sunny Environment.

Angle	Correctly Detected	Incorrectly Detected	Detection Accuracy
Front	31	3	91%
Angled-Front	21	13	62%
Rear	17	17	50%

Table 12. Gaussian Sharpening in a Rainy Environment.

Performing a Contrast Correction algorithm to the input images slightly improved accuracy or produced the same result in all camera angles in both environments, with the exception of the angled-front view in the sunny environment (Tables 5 and 6). The filter, when applied to the angled-front view in the sunny environment, tended to over-expose the more distant letters on the license plate, causing more missed detections than when the filter was not applied.

Performing a Brightness Correction on the input images proved to yield significantly worse results across the most important camera angle, the front view (Tables 7 and 8). The cause was a darkening of the sunny environment images due to the increased amount of light in the image. In the rainy conditions, however, it brightened up images to the point where the accuracy of detection increased in the angled-

front view as well as the rear-view. Brightness Correction tended to slightly affect the front camera angle in both environmental settings negatively.

Performing the Standard Sharpening algorithm to the images provided increased accuracy, except for the rear camera angle (Tables 9 and 10). As this camera angle's accuracy was already considerably low, ignoring the negative effect of the algorithm on its accuracy is recommended. With results similar to those of the Contrast Correction algorithm, this algorithm could be considered the likely candidate for implementation into the proposed system.

Gaussian Sharpening proved to be the most effective algorithm to enhance an image, to the point where it made a once undetectable plate detectable (Tables 11 and 12). Once again, an overall average accuracy of 73% during both sunny and rainy environments was obtained. Unfortunately, performing Gaussian Sharpening took around one second for each image, which is unacceptable for a system to perform in real time.

A Standard Sharpening algorithm was the next best performer, with an average accuracy of 72% during both sunny and rainy conditions with Contrast Correction (71%), and then Brightness Correction (69%), providing the next best performance. Considering the front camera angle, it is evident that the Contrast Correction algorithm offered the best accuracy in both sunny and rainy conditions. The processing time of the algorithm was also acceptable for a real-time system, showing that image enhancement using Contrast Correction allows for an increase in the accuracy of the entire system.

The above analysis of the system was performed using pre-recorded footage in order to establish a base level of accuracy for the system as well as to tweak parameters used in the detection process. The final evaluation, however, was performed in a live environment over a five-day period. The weather conditions varied during that time, which meant the system was tested in the most common lighting conditions, which included: Sunny, Overcast, and Rainy conditions.

Individual camera specifications influence the geometric detection pattern of an AVLPRS (Rademeyer et al., 2018). The camera used in this evaluation was a Hikvision DS-2CD2232-I5. This camera features a 3.0-megapixel sensor to produce 1080p full HD real-time video. This camera was also equipped with a fixed light mounted onto the unit itself for illumination in low light scenarios. It should be noted that this light increased detection rate during times when illumination was low, such as in the early morning and during rainy conditions. For each recorded day, a total of 120 vehicles were considered, making a total sample size of 700 vehicles. The considered vehicles were chosen at random during a period of 12 hours, from 6 A.M. to 6 P.M., with 10 vehicles tracked each hour. There were also stages during evaluation where vehicles came onto the campus at midnight, and while that time was not included in the evaluation data, it should be noted that the majority of those license plates were captured correctly as well, with the exception of a scooter, which does not have a front-mounted license plate..

Day	Conditions	Day total	Correct	Accuracy
1	Overcast	120	114	95%
2	Overcast	120	116	97%

3	Sunny	120	117	98%
4	Raining	120	110	92%
5	Overcast	120	115	96%

Table 13. Results of LPR system in a live environment.

Table 13 shows that while the accuracy of the system does indeed decrease between an extremely well-lit environment (sunny environment) and a darker environment, such as the overcast and extremely wet days, this decrease is so slight that it is seemingly insignificant. However, it should be stated again that the light of the camera shining on the vehicles' license plates helped improve the performance of the license plate recognition module in dark environments.

CONCLUSIONS AND FUTURE WORK

AVLPRS assist in identifying vehicles and provide a reference for further vehicle tracking and activity analysis. The challenges researchers face when implementing successful AVLPRS include the large variety of license plates and their location on the vehicle, environmental and lighting conditions, and camera angles. The objective of this study was to investigate the development and implementation of a VMF that could assist security personnel using mobile devices at the entrances of a university, with real-time vehicle identification.

The Design Science Research Methodology (Hevner, 2007) was used to design and evaluate the VMF artifact (Figure 11). The Design Practice Theory was used in this study to identify the requirements and the design of the VMF. The design included the identification and use of existing open-source algorithms and neural networks used in existing AVLPRS (Arafat et al., 2019; Fu, 2019; Bakhtan et al., 2016). The Explanatory Design Theory was used to obtain the generalized components and sub-systems for the VMF. The sub-systems, such as acquisition, license plate detection, character segmentation, and character recognition, were identified from similar components used in AVLPRS discussed in literature (Ullah, et al., 2019; Khaparde, et al., 2018).

Universities are faced with diminishing funds, thus, the aim of the study was to use existing infrastructure available on campus and existing technologies and available (open source) algorithms. A 98% vehicle license plate recognition was achieved in sunny conditions. This study further aimed to investigate the effect of different camera angles as well as the environmental effects of lighting. The accuracy dropped to 92% in poorer and rainy lighting conditions. The rear camera angle remained the worst overall performer for the license plate detection and recognition accuracy. The overlapping of vehicles was the main cause for the poor accuracy, even with the assumption of a single lane of traffic made at a university entrance.

At an angle of approximately 45°, the angled-front camera location made the accuracy of the license detection process extremely volatile. It was shown that in a sunny environment, by using the Two Frames Differences technique and a front-angled camera located at about 15° relative to the oncoming vehicle, an accuracy percentage of 91% was achieved. The same camera angles were then used in a

rainy environment where due to the environmental changes, there was a drop of 35% in accuracy between a sunny environment and a rainy environment. This drop in accuracy was caused by the license plate recognizer, which incorrectly merged characters when the vehicle was far away from the camera and also due to the poor lighting and rainy conditions.

The same experiment was re-run using the Background Subtraction technique of motion detection and the accuracy increased slightly from 91% to 94% in the sunny environment for the front camera angle, while there was no change in the rainy environment. The Contrast Correction algorithm, which is an image enhancement algorithm that adjusts the RGB values of the bright and dark pixels accordingly, proved to yield the highest increase in accuracy over the front facing camera angle. This increase caused increased CPU usage; however, this was acceptable in the effort to provide increased accuracy.

It could be concluded that a front-angled camera location at an angle of 15° with respect to the vehicle was the best all-around performer in terms of detection accuracy. The major deciding factor in the accuracy of the system was the lighting conditions in which the camera operated. Character recognition algorithms are highly sensitive to environmental light conditions, and care should be taken to provide the ideal lighting conditions.

Detection accuracy was improved by using the Background Subtraction technique of motion detection to ensure that the system accurately captured even slow-moving cars. The image enhancement technique of Contrast Correction was also found to greatly improve the accuracy of the results in the rainy environment. During a live evaluation of the system, the accuracy ranged from 92% in a rainy condition to 98% in a sunny condition. These findings compare favorably with studies discussed by Bakhtan (2016), achieving 92%-95% accuracy. While this decrease during rainy conditions was expected, the system outperformed initial estimates of accuracy during dark conditions, mainly due to the light source attached to the video camera. Even during the darkest hours at night, around 12 A.M, the system outperformed initial expectations, except for scooters and motorbikes, which the system was unable to detect, since they do not have front-mounted license plates.

The detection accuracy of the system could be improved further if the university would install an effective external light source at the entrance of a campus. Future research should investigate the use of new machine learning algorithms and technologies. Moreover, future research should investigate further the inclusion of the VMF into the university security environment.

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