AN AUTOMATIC TECHNIQUE FOR MALAYSIAN NUMBER PLATE RECOGNITION

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2018

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DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF COMPUTER SCIENCE

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

UNIVERSITI MALAYA

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ABSTRACT

License plate recognition is useful for several real time applications, such as traffic monitoring, security issues, tracing transport rules violated vehicles, toll fee payment and intelligent vehicle movement without pilot etc. In order to find solution to license plate recognition, there are many methods developed in literature. However, the existing methods suffer from their own inherent limitations for addressing challenges posed by Malaysian license plate number. One such challenge is that Malaysian license plate where normal plate represented by dark-background, white-foreground (number) and taxi plate represented by white-background and dark-foreground. In addition, some Malaysian license plate suffer from blur, noise, degradations, low contrast and illumination effect. Hence, achieving best recognition rate for the Malaysian license plate number is hard. To alleviate the problem of Malaysian license plate recognition, the work proposes classification of Normal and Taxi plates such that each type can use different recognition method rather than single method for both the type images. The proposed classification method works based on the fact that the values which represent white colour have values near to 255 and the values which represent dark colour have values near to zero. Besides, it is true that the number of background pixels is larger than the number of foreground pixels. Based on these two observation, the proposed classification explores canny edge images of the input image and clustering to differentiate them. For the classified license plate images, The proposed work explores Maximally Stable Extremal Regions (MSER) which perform operation over Canny edge image of the input image unlike existing MSER perform only on grey colour images. This combination outputs character components for license plate images. The components are considered as connected components to separate from the license plate images. The segmented characters are feed to OCR, which is available publicly for recognition. In summary, there are two contributions

from the proposed work. One is exploring classification of normal and taxi plate images and another one is use of MSER for character component segmentation. Furthermore, experimental results for classification and recognition on our image dataset show that the proposed method works is better than existing methods.

ABSTRAK

Pengiktirafan plat lesen berguna untuk beberapa aplikasi masa nyata, seperti pemantauan lalu lintas, isu keselamatan, peraturan pengangkutan yang melanggar kenderaan, bayaran tol dan pergerakan kenderaan pintar tanpa perintis dll. Untuk mencari penyelesaian untuk pengecaman plat lesen, terdapat banyak kaedah dibangunkan dalam kesusasteraan. Walau bagaimanapun, kaedah sedia ada menderita batasan mereka sendiri untuk menangani cabaran yang ditimbulkan oleh nombor plat lesen Malaysia. Satu cabaran sedemikian ialah plat lesen Malaysia di mana plat normal diwakili oleh latar belakang gelap, plat depan (nombor) dan plat takrif yang diwakili oleh latar belakang putih dan latar gelap. Di samping itu, beberapa plat lesen Malaysia mengalami kabur, bunyi bising, degradasi, kesan kontras dan pencahayaan yang rendah. Oleh itu, mencapai kadar pengiktirafan terbaik bagi nombor plat lesen Malaysia adalah sukar. Untuk mengatasi masalah pengiktirafan plat lesen Malaysia, kerja mencadangkan klasifikasi plat Normal dan Teksi supaya setiap jenis boleh menggunakan kaedah pengiktirafan yang berlainan dan bukan satu kaedah untuk kedua-dua jenis imej. Kaedah pengelasan yang dicadangkan berfungsi berdasarkan fakta bahawa nilai-nilai yang mewakili warna putih mempunyai nilai-nilai yang dekat dengan 255 dan nilai-nilai yang mewakili warna gelap mempunyai nilai-nilai yang hampir kepada sifar. Selain itu, benar bilangan piksel latar belakang lebih besar daripada bilangan piksel latar depan. Berdasarkan kedua-dua pemerhatian ini, klasifikasi yang dicadangkan meneroka imej kelebihan cendawan imej input dan kluster untuk membezakannya. Untuk imej plat lesen dikelaskan, Kerja yang dicadangkan ini meneroka Kawasan-kawasan Extremal Stabil Maximally (MSER) yang melakukan operasi terhadap imej tepi Canny dari imej input tidak seperti MSER sedia ada yang hanya dilakukan pada imej warna abu-abu. Kombinasi ini menghasilkan komponen

watak untuk imej plat lesen. Komponen ini dianggap sebagai komponen yang tersambung untuk dipisahkan dari imej plat lesen. Watak bersegmen adalah suapan kepada OCR, yang tersedia secara terbuka untuk pengiktirafan. Ringkasnya, terdapat dua sumbangan dari kerja yang dicadangkan. Salah satunya adalah meneroka klasifikasi imej plat biasa dan teksi dan satu lagi menggunakan MSER untuk segmentasi komponen karakter. Selain itu, hasil eksperimen untuk klasifikasi dan pengiktirafan pada dataset imej kami menunjukkan bahawa kaedah yang dicadangkan berfungsi lebih baik daripada kaedah sedia ada.

ACKNOWLEDGEMENT

I give thanks to Almighty Allah for his provision and protection upon me, during my studies in the University of Malaya, and peace is upon his prophet, prophet Muhammad (S.A.W). I also express my profound gratitude to my parents for their nurturing and assistance at the beginning of my life until today. May Almighty Allah makes them eat the fruit of their labour. I also appreciate my family and friends especially my uncles for their assistance on my studies. I can’t forget my friends in school and home such as: Maryam Asadzadeh, Atif Ahmed and others in Multimedia Lab, may Almighty Allah be with each and every one who contributed to the success of my studies. I thank all my lecturers in my department especially my supervisor, Dr P. Shivakumara for his enormous contribution upon my thesis, your works shall be rewarded abundantly. I also appreciate all lecturers in my faculty and school generally.

DEDICATION

This research work is dedicated to almighty Allah and his prophet, prophet Muhammad (S.A.W). It also dedicated to my late grandfathers and grandmothers, may Almighty Allah grant them paradise. It also dedicated to all Muslims that have gone, may Almighty Allah forgive their sins and grant them paradise.

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LIST OF SYMBOLS AND ABBREVIATIONS

ALPR	:	Automatic License Plate Recognition
ANPR	:	Automatic Number Plate Recognition
AVI	:	Automatic Vehicle Identification.
CCA	:	Connected Component Analysis
CCL	:	Connected Component Labelling
CCTV	:	Closed Circuit Television.
CPR	:	Car Plate Recognition.
DCBV	:	Dense Cluster Based Voting
DP	:	Driving Permit
GB	:	Grey Background
GF	:	Grey Foreground
GPS	:	Global Positioning System
HMM	:	Hidden Markov Model
HOG	:	Histogram of Oriented Gradient
LPR	:	License Plate Recognition.
MLPR	:	Mobile License Plate Reader or Mobile License Plate Recognition.
MNPN	:	Malaysian Normal Plate Number

MSER	:	Maximally Stable Experimal Region
MTPN	:	Malaysian Taxi Plate Number
NN	:	Neural Network
NNC	:	Neural Network Classifier
OCR	:	Optical Character Recognition
RFID	:	Radio Frequency Identification.
RGB	:	Red Green Blue
SWO	:	Sliding Window Operation
SVM	:	Support Vector Machine.
VLPR	:	Vehicle License Plate Recognition.
VRI	:	Vehicle Recognition Identification.

CHAPTER 1: INTRODUCTION

1.1 Introduction

ALPR (Automatic License Plate Recognition) can be traced back as early as 1976, it was invented at the police scientific development bank in United Kingdom, and the original systems were working by 1978 (David et al, 2012). ALPR is a technology of mass surveillance algorithm that implements optical character recognition on an images to read the LP (License Plates) on vehicles, by getting the License Plate information extracted from an image for a specific reason. It normally reads and processes image as input, which has vehicle number plate and recognizes automatically the number plate as output. ALPR also have some other names, such as: Automatic Number Plate Recognition (ANPR), Automatic Vehicle Identification (AVI), Car Plate Recognition (CPR), License Plate Recognition (LPR), Automatic license-plate reader (ALPR), Mobile license-plate reader (MLPR), Vehicle license-plate recognition (VLPR) and Vehicle Recognition Identification (VRI).

There are lots of real time applications where license plate recognition play a vital role (Ranglani et al, 2016), such as: traffic control, speed control, tracing the stolen cars, nearing toll gates, electronic payment systems, automatic vehicle ticketing, traffic violations detection, security application, traffic activity monitoring and so on (Saha et al, 2015).

Application of ALPR

- **ALPR for Law Enforcement:** One of the main application of ALPR is law enforcement by government in the country especially when the crime is committed, this can deny criminal's use of the road when their plate number has been recognized. For instance, on 18 November 2005 Sharon Beshenivsky (British police) was gun down during a robbery operation in Bradford (Independent, 2005). ANPR system was able to recognize the car and track its movements, and six suspects were arrested. This kind of system recognizes unregistered vehicles, drivers who are not qualify, also suspended drivers as well as other such as persons having outstanding warrants. It based on government policing strategy.
- **ALPR for Theft Car Detection:** ALPR has been applied for theft detection of the car, this can be traced back as early as 1981, (David et al, 2012). Theft car detection is the recognition of the stolen car, in this scenario, first of all, the number of stolen car is given to the system, if the system detect it, the system detects the front plate number of the car, and captures the plate number for further process then it segments and recognizes the characters, this appears in graphical user interface and store it in database with time and date. Immediately the theft car is detected and alarm ring, the policemen receive notification in order to trace the car and do their job.
- **ALPR for Access Control:** ALPR also using for access control in some countries, since each country has different type of plate number for citizen with their status, or private and public. Some vehicle may allow to access specific place while some may not allow to access that place. Automatic License Plate Recognition has been using to solve this kind of access control problem. For instance; ALPR has been used to manage the access of different kinds of vehicles to some area of (Saudi Arabia)

Makkah, during the season of Hajj (Pilgrimage). This small area usually has traffic jam with huge number of vehicles. At the beginning of the season, vehicles given permission to access the region are assigned passive RFID (Radio Frequency Identification) tags, this specify their permission schedule of entry. Any vehicles which doesn't have the tags is detected and also identified using ALPR. The system tested for like two years during the pilgrimage season, and it achieved 94 % recognition accuracy, (Mohandes et al, 2016).

- **ALPR for Traffic and Speed Control:** ALPR is also used for the control of the traffic and speed, many countries, districts and cities have developed traffic and speed control systems. This can assist to manage the flow and movement of vehicles around the road network. Using CCTV cameras can help traffic control centres. By implementing ANPR in this scenario, it is easy and possible to manage the movement of individual vehicles, by providing information and measurement about the speed automatically, and flow of various roads. These details can figure out the problem areas as they occur and assist the centre to make informed incident management decisions.
- **ALPR for Electronic Toll collection:** Implementation of ALPR for the electronic toll collection is one of the ALPR technology, this is automatically charge for toll payment. It sometime combine the ANPR with radio transponder, the main aim is to stop the delay that may occur on toll roads via collecting tolls in electronic method, sometime it determines if the cars passing are registered or not, those unregistered cars would not allow, but registered cars would not stop, but their invoice are debited, (Kelly, 2006). Using ANPR for electronic toll collection system charges vehicles that pass every day, and both front and back number plates are being captured, on vehicles

going both in and out, this is a chance to capture plate number of a vehicle that is going out and coming in.

From the discussion on the above real time applications, it is noted that license plate recognition system is useful. For this purpose, there are systems available in literature (Kim et al, 2017), which detect the license plate from the input image as shown in Fig. 1.1 where one can see license plate number is fixed by rectangle. At the same time, over view of license plate recognition can be seen in Fig. 1.2 where general steps and flow of the recognition process are shown.

Figure 1.1: License Plate Image

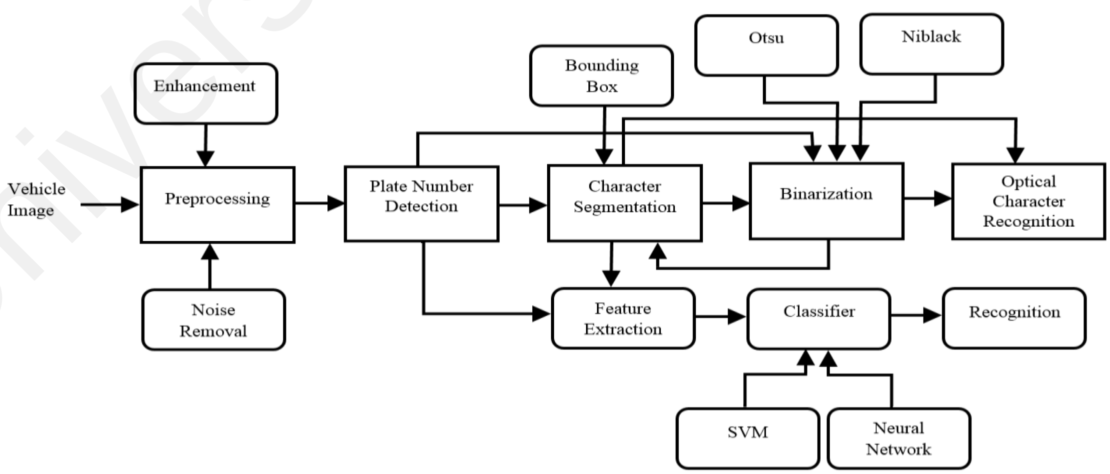


Figure 1.2: Block Diagram of an ALPR System.

Overview of General License Plate Recognition System

1. **License Plate Image:** The steps of Automatic License Plate Recognition starts with the input of license plate image, this is an input data for recognition engine or ALPR system, the vehicle image may contain unwanted boundary in plate number, system will find the area of plate number, there must be an input image which is License plate as shown in Fig 1.1.
2. **Pre-processing:** In order to get the high recognition rate in license plate recognition, several pre-processing techniques need to be performed, such as elimination of shadows and noises, this will help to make next step easy. Various filters are adopted to minimize or eliminate these elements. When there is too much contrast between the background and text, a common filtering technique for license plates is edge detection, this works well when there is above issues. In some other expert systems, multiple images of the same plate are blended together to make it easier for the processing engine (Demmin & Zhang, 2003). In this step there is adjustment the contrast and brightness of the image. At times, plate number may need a little bit adjustment, although it depends on its angle, so therefore angular correction may need some mathematical operation, which will help in decoding plates which are taken from overhead camera, parallel, side and they correct for perspective and rotation.
3. **License Plate Number Detection**: In this step the system will make attempt to find the plate number area in the image, in order to focus on it and ignore other area which is not plate number in boundary, any extraneous boundary will be disregarded, this is called detection, localization or framing. Although some of the LPR system may also look at information outside the license plate frame, like vehicle model, logo, colour and so on. One such example is shown in Fig. 1.1.

4. **License Plate Character Segmentation:** This steps considers the output of the previous step as input for character segmentation. To recognize the license plate number, it is necessary to segment the character from the license plate number because OCR accepts individual character for recognition. There are two ways for segmentation as shown in Fig. 1.2, segmenting character after binarizing the license plate number and segmenting character without binarization. For binarization, there are popular thresholding techniques as mentioned in subsequent step then the methods uses simple connected component labelling for character segmentation. If there is no binarization, the methods extract features to find space between the characters.
5. **License Plate Number Binarization:** The grayscale of the plate number will be binarized. In this stage there are processes of conversion of the plate number image to a binary image, the plate number will have two colours, white and black, one colour for background, and another colour for foreground, with the pixel value of 1 and 0. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit. There are different methods which can be adopted for binarization, such as: Otsu, Niblack, Sauvola and so on (He et al, 2005).
6. **Optical Character Recognition**: After the individual character has been segmented, and binarized, the next step is to recognize the character one by one through the OCR (Optical Character Recognition) algorithm (Du et al, 2013). Pattern matching, pixel repetition, proportion and edge tracing are common technique for character recognition. In OCR there is conversion of licensed plate text into machine-encoded text. There are methods in literature which accepts the detected license plate for recognition without going through character segmentation and binarization. In this case, the methods extracts features for the license plate number directly and then use

classifier such as Support Vector Machine (SVM) and Neural Network Classifier (NNC) for recognition.

Challenges in ALPR

However, it is noted from the literature that there are flaws for every step shown in block diagram as applications and requirement changes. The challenges are listed below according to steps in the Fig 1.2.

- **Pre-processing:** ALPR faces some challenges during the pre-processing such as: blur or noise, when the vehicle plate is too blur and noisy, it will difficult for system to read it. Also, dirty plates, loss of information, illumination effect, head light effect, Night effect, Occlusion and so on. These are big challenges, these make it difficult to accomplish good result in ALPR, for example if there is night effect, illumination or occlusion, the plate number will have additional background, this is a challenge because it will lead to unwanted result when proceed with other steps in ALPR.
- **License Plate Number Detection**: During the plate number detection, there are other challenges that ALPR encounters, such as: complex background, this will make it difficult to locate the boundary of license plate, unwanted boundary may detected as part of plate number, also the plate number patch may neglected as unwanted boundary, the Fig 1.3(a) show the plate number with complex background. Night condition is also a big challenge for plate number detection, this is difficult to detect the plate number in darkness, especially if there is no light, or the driver off the vehicle's light, as shown in Fig 1.3(b), this may lead to poor result. Car bending condition is also a challenge to detect plate number accurately, if this happen some

other character may miss, and system may not recognize it properly, as shown in Fig 1.3(c). License plate at different locations of the vehicle, raining, fog, Snow and so on are also part of these challenges in plate number detection. When these aforementioned occur, they are challenges to achieve good detection results.

Figure **1.3:** Some Challenges in Plate Number Detection.

- **License Plate Character Segmentation**: Also there are other challenges that erupt when segmenting the plate number character, when characters touch each other or laying on top of each other, it will difficult to segment, and recognition engine will segment them as one character, this is a challenge because after the recognition step, the number of character will decrease. Also, broken character is part of challenges in character segmentation, because after the recognition step, the number of character will increase and misrecognition will happen, which lead to poor result.
- **License Plate Number Binarization**: There are other challenges that arise during the plate number binarization. For instance different background and foreground colour is a challenge during the plate number binarization, this is one of the problems of this research work, because the adopted method may work for one background and may fail for another background. Contrast and illumination variation is also a big challenge, this results to poor binarization, and after the binarization the binary image

may lose some character, Therefore, it is a challenge to get good and high recognition rates.

- **Optical Character Recognition:** There are other challenges during the character recognition such as different font and size, sometime if the font in template match is different from plate number, misrecognition may occur. Missing shape also a challenge, if this happened some character may be recognized as another. For instance if letter B misses the shape, there is a tendency of recognizing it as 8, this is a challenge to accomplish the desire result.

Sample images for the above mentioned challenges are shown in Fig. 1.4. Fig 1.4(a) shows the plate number that has background illumination, this may result to poor recognition rate. Fig 1.4(b) also shows the plate number that is blur, this may cause the character to loose original shape and it may recognize as something else. In Fig 1.4(c) this plate number is too dirty which is not easy to recognize, this can affect the binarization because dirty patch may misbinarize as character and lead to poor result. Fig 1.4(d) demonstrates a foggy and noisy plate number, this will increase the plate number pixel's value and may lead to poor result if implement for classification. Fig 1.4(e) has unclear plate number, the character may not recognize properly and may affect the recognition rate. Fig 1.4(f) shows a complex background, this may lead to poor binarization result, because of complexity of the plate number.

Figure 1.4: Plate Numbers that are Affected with the Challenges in Research Work

1.2 Motivation

As discussed in the above sections, ALPR systems are developed using various intelligent computational techniques to obtain accuracy and efficiency (Polishetty et al, 2016). However, these methods may not perform well for Malaysian License Plate Images. This is because Normal and Taxi plat number usually have different backgrounds and foregrounds. Normal Plate Number has black background with white text, while Taxi plate Number has white background with black text as shown in Fig. 1.5 and Fig. 1.6. Fig 1.5(a) shows a Malaysian Normal Plate Number with blur, and this is not show clearly, this may difficult to classify properly. Fig 1.5(b) shows a Malaysian Normal Plate Number, this is clear, and can be easily seen, both of them have black background and white text. Fig 1.6(a) shows a Malaysian Taxi Plate Number with blur, and this is not show clearly, this may difficult to classify properly. Fig 1.6(b) shows a Malaysian Taxi Plate Number, this is clear, and can be easily seen. The main reason of the existing systems to fail for the above normal and taxi plates is that in general, binarization work well when the image contains fixed colour background. Therefore, OCR which accepts the output of binarization fail to recognize the characters. Hence, there is a necessity of classifying taxi and normal number plate such that the developed OCR can be modified to recognize the Taxi and Normal plates. It is also noted from Fig. 1.5 and Fig. 1.6 that both taxi and normal plate number suffer from different cause. Therefore, there is a demand for developing robust method for recognizing such characters.

a


b


Figure 1.5: Malaysian Normal Plate Numbers

a


b


Figure 1.6: Malaysian Taxi Plate Numbers

1.3 Problem Statements

Automatic classification of Malaysian normal and taxi plate number to overcome the problem of background and foreground variations is existing problem in Malaysian plate Number Recognition.

Achieving good recognition rate for the images affected by blur, noisy, illumination and so on. Some plate number images are affected by blur, noisy and illumination, this make it difficult for system to recognize them properly. Some of existing algorithm may good for normal plate number, but this may not suitable for taxi plate number. While some may good for taxi plate number but may not suitable for normal plate number because of variation in text and background, and the plate numbers need to be recognized properly, this problem requires solution so we can accomplish the good recognition rate from plate number with aforementioned challenges.

1.4 Research Questions

- How to differentiate Malaysian normal and taxi license plates?
- What is the method for separating foreground and background of input license plate images?
- What is the best method for recognition of multi-type license plate images?

1.5 Research Objectives

The objectives of this research work are mentioned below, and these are:

1. To develop a new algorithm for classifying the Multi-type plate number (Malaysia Normal Plate Number and Taxi Plate Number) based on foreground and background information.
2. To propose a method for recognizing plate number characters based on MSER concept in license plate that is affected by blur, noisy, illumination and so on.
3. To conduct comparative study with existing recognition methods to show superiority of the proposed method.

1.6 Contribution of the Research

This research work has contribution by getting the dataset of Malaysian normal plate number and taxi plate number in order to execute the research experiment. It has salient contribution to the field of image processing and pattern recognition by adopting the k-means algorithm and foreground information and background information of Malaysian plate number to classify the normal plate number and taxi plate number in a new way. Also it is applicable to classify any plate number that has white background with black text and the one that has black background with white text.

In addition it implemented the MSER (Maximally Stable Experimal Region) on plate number with aforementioned challenges by achieving good recognition rate and also applicable in ordinary scene text recognition. In the comparative studies, adjustment of threshold of existing recognition methods is enormous contribution that accomplish better recognition rate than existing thresholds.

1.7 Outline of Dissertation

- Chapter 1 of this dissertation elucidates the introduction of the research and justifies it. It includes the research problem, also explains the objectives of this research, research motivation, contribution of the research, scope and organization of research.
- Chapter 2 analyses the literature review of this research work. It explains the background of the studies, Classification of Multi-Type Text, Classification of Multi-Type Text in Video, Classification of Multi-Type Text in License Plate Images, Recognition of Text in Images, Text Recognition in Video, Text Recognition in Natural Scene Images, Text and Recognition in License Plate Images.

- Chapter 3 simplifies the research methodology in plate number classification which is Dense Cluster Based Method for Classification of Multi-Type License Plate Images. It includes background, Foreground and Background Separation, Dense Cluster Voting for License Plate Classification, Experimental Results, Evaluating Classification Method, Evaluating Usefulness of Classification Method, Comparative Study and Summary.
- Chapter 4 simplifies the research methodology in plate number recognition which is MSER Based Method for License Plate Recognition. It includes background, MSER for Character Components Extraction, OCR for Character Recognition in License Plate Images, Experimental Results, Comparative Study and the Summary of the chapter.
- Chapter 5 contains the summary of research and future work.

CHAPTER 2: LITERATURE REVIEW

2.1 Background

The previous chapter presents importance and motivation of license plate recognition in general, Malaysian license plate recognition in particular. This chapter describes the review of general classification of different type of text images and Malaysian license plate images. In addition, the current chapter reviews recognition of natural scene images and video images along with the license plate images.

This chapter is organized as follows. Section 2.2 explains the classification of multi-type text which includes natural scene, video text and Malaysian license plate images, and Section 2.3 presents review on recognition of natural scene images, video images and Malaysian license plate images.

Brief History of License Plate

LPN (License Plate Number) is a plastic or metal plate that is attached to a motor vehicle, motor bike or trailer for the purpose of official identification. The first country that introduces the license plate is France, with the passage of the Paris Police Ordinance on August 14, 1893. Later Germany also superseded it in 1896, but it was not famous and commonly use as it is nowadays. In 1898 Netherland introduced National License Plate, named (Driving Permit). In US, New York became the first state to require license plates in 1901, it has been enacted by New York Governor, Benjamin Odell Jr, requiring owners of motor vehicles to register with the state. The plate were made by owners, with owner initial names and some number, rather than being issued by government agencies in modern times. Those first plates were typically handcrafted by metal and leather to indicate the ownership by initials. After 2 years that the vehicle started increasing, confusion occurring and some people are bearing the same names. In 1903 the state agencies issued licensed plate (State-Issued) and distributed it in Massachusetts (Patrick, 1974). Other states also followed until every country superseded the License Plate Number Implementation, including Malaysia.

The plate number registration system in Malaysia can be traced back to the time of introduction of the motor vehicles in the early 1900s in Malaya British, it was introduced by Malaysian British Colonial Governments (Kheng, 1983). Later, it was control by Malaysian Road Transport Department. The issuing of the plate numbers to Malaysian is administered and regulated by the Malaysian Road Transport Department, According to the transportation's law, their cars has plate numbers with initial, each state has initials for their cars, the normal car has black background and white text. Usually Taxi plates start with a constant of H (Hire) prefix and have opposite colours (white background that contains black characters) for the purpose of differentiation between them.

Automatic License Plate Recognition becomes more interesting after the improvement of digital camera and enhancement of computational capacity (David et al, 2012). ALPR system has been developed for different purpose, such as: traffic control, speed control, identifying the stolen cars, nearing toll gates, electronic payment systems, automatic vehicle ticketing, traffic violations detection, security application, traffic activity monitoring and so on (Saha, et al 2015). ANPR recognizes a vehicle's license number plate from an input image or images taken by either a colour, white and black, or infrared camera. It is carried out by the formulation of a lot of computational techniques, such as object detection, artificial intelligent techniques, image processing, and pattern recognition (Du et al, 2013).

2.2 Classification of Multi-Type Text

As discussed in chapter-1, there are many types of text in the field of classification, such as video text, natural scene text, mobile video text and born digital text for the purpose of improving recognition performance of the methods or systems. Furthermore, video frame contains two types of text, namely caption text that is edited one and scene text that is natural text. It is noted that text in natural scene images and scene text of video frames are same as license plate images. Therefore, this section presents review on classification of multi-type video text and classification of Malaysian license plate images in subsequent sections.

2.2.1 Classification of Multi-Type Text in Video

Shivakumara et al (2014) proposed a method for classification of graphics (caption) and scene text in video, to get good and high recognition rate as based on the assumption that common properties are share by Sobel and Canny edge pattern for text. Their proposed method implements Ring Radius Transform in order to identify the radius that represents the medial axis in the edge image. The method explores the relationship within the histograms bins over respective values of radius, this resulting in intra line graphs. Therefore, this method can detect line graphs between both Sobel and Canny edge images of the input text lines. For the purpose of identification of the unique distribution for separation of scene and graphics texts, they explore the inner relationship that exist between intra line graphs of Sobel and Canny edge image with related medial values of the axes. This results in Gaussian distribution for graphics and non-Gaussian distribution for scene text.

Xu et al (2016) presented a method for the classification of graphics texts and scene texts by adopting related information of the texts and finding the relationship that exist between these texts in the video. This method proposes an iterative way to classify the Graphics Text Candidates and the Scene Text Candidates, generally graphics texts don't have very large movements when compare to scene texts, and these are usually embedded on background. This method later studies the symmetry between inter and intra feature components to identify graphics text candidates and scene text candidates. Boundary growing method is implemented to restore the text line completely. For each and every segmented text line, this method finally use Eigen value analysis in order to classify graphics and scene text lines, based on the distribution of respective Eigen values.

Qin et al (2016) proposed a new method for categorizing different types of video text frames, such as: videos containing advertisement, signboard, license plate, front page of book or magazine, street view, and video of general items, in order to accomplish better text detection and high recognition rate. The method also proposes symmetry features by adopting gradient vector flow for Sobel and Canny edge images of each input frame to identify candidate edge components. Then for a candidate edge component image, it extracts both global and local features using colours from different channels in a new way. Besides, the proposed method extracts statistical and structural features from the spatial distribution of candidate pixels in a multi-scale environment. Lastly, the extracted features are sent to a logistic classifier for categorization.

In summary, according to the observation from the above review, it's obvious that none of the methods focused Malaysian license plate classification. In addition, the methods considers the images affected by particular cause but not the kinds of images like Malaysian license plate which usually affected by different and multiple adverse factors, such as low contrast, illumination effect, blur effect, background complexity effect.

2.2.2 Classification of Multi-Type Text in License Plate Images

Sheng et al (2015) proposed another algorithm for License Plate Classification from a Binarization Perspective, this method is a stroke-width-transform-based method. It calculates the stroke width transform by adopting the greyscale image of input image and the inverted one. The histograms of the corresponding stroke width transform images are generated. Also, the image, corresponding to the maximum value of the histograms is chosen. Finally, if the original image is selected, the license plate is the "A" type and vice versa.

Raghunandan et al (2016) proposed a novel sharpness based features method of textual portion of each input text line image by adopting HSI colour space for the classification of an acquired image into one of the four classes, such as: video, scene, mobile or born digital. This method works well in selecting a suitable method based on the kind of the text acquired for its enhanced recognition rate. For any accomplished input text line image, this method acquires H, S and I images. After that, edge detection (canny) images are achieved for H, S and I spaces, this ends up in text candidates. This method used sliding window operation (SWO) on the text candidate image of each text line of each HSI colour space to evaluate novel sharpness via the computation of the stroke width and gradient information. The sharpness values of the text lines of these three colour spaces are then given to k-means clustering with k=3, these are maximum, average guesses and minimum, which leads to three respective clusters. The mean of each cluster for respective colour spaces outputs a feature vector encompassing 9 feature values for the classification of the image with the implementation of SVM classifier.

Al-Shami et al (2017) proposed Number Plate Recognition for the Saudi License Plates by implementing the Clustering and Classification techniques, this method propose to adopt a clustering method called X-Means in order to rearrange the numbers that have the similar features. Later, it develops a particular classification method for each cluster. The experiment of the proposed method is applied on their created dataset gave them some limitation in classification. The results of experiment accomplish more improvement by building a reference image for each and every class selected using a specific criteria from the training dataset.

In summary, it is noted from the above discussion that there are methods for classifying different types of license plate images. However, none of the methods focused on Malaysian license plate image which have different background colours to represent normal plate and taxi plate. This leads to poor recognition performance. Therefore, Malaysian license normal and taxi plate classification is a research issue in this work.

2.3 Recognition of Text in Images

As mentioned in Section 2.2, the same different types of text can be found for text recognition. Since it is hard to develop universal method for recognizing text which affected by many adverse factors, the methods prefer to classify them as different categories such that an appropriate method can be developed for achieving good recognition rate. This section reviews text recognition of different types, such as video, natural scene images and Malaysian license plate images.

2.3.1 Text Recognition in Video

Shetty et al (2014) proposed Ote-Ocr based method for text recognition and feature extraction from video frames. This provide a new method in order to detect and recognize the texts from the video frames. The task committed is divided into three steps approach that formulates the texts detection and texts recognition from the video frame. This video frame creation involves in dividing the video into an individual frames. The individual frame is grabbed and sent to the rest two phases. The text detection has two-steps approach, which involves text localization phase and the text verification phase. The text recognition involves in text verification phase and the optical character recognition phase.

Roy et al (2015) develop another algorithm to recognize the text in video via binarization by adopting a Bayesian classifier. This method explores wavelet decomposition and gradient sub-bands to improve text information in video. The improved information is implemented in another ways to compute the Bayesian classifier requirement, such as a priori probability and also conditional probabilities of text pixels to measure the posterior probability automatically, this ends up in text components. (CCA) Connected Component Analysis is then adopted to restore the text information that were missing before forwarding it to a recognition engine, if there is any disconnection in the component of the texts.

Khare et al (2016) proposed a blind deconvolution model for scene text detection and recognition in video. This method demonstrates a quality metric that is combined for measuring the level of blur in the image or video. The proposed method then present a blind deconvolution model that improve the edge intensity by suppressing blurred pixels.

In summary, it is found from the above review that since the primary goal of the methods is video text and natural scene texts, the methods focused on low contrast, high contrast and background complexity but not the effect of illumination, blur and noisy images as Malaysian license plate images.

2.3.2 Text Recognition in Natural Scene Images

Pise and Ruikar (2014) present Text Detection and Recognition in Natural Scene Images. In this method, there is a development of a text region detector by adopting a widely used feature descriptor named histogram of oriented gradients (HOG). Local binarization is used for connected components segmentation. For text extraction, the parameters such as normalized height width ratio and compactness are brought into consideration in order to filter out text and non-text components. Text recognition is followed using zone centroid and image centroid based distance metric feature extraction system.

Cherian and Sebastian (2016) proposed an automatic localization and recognition of perspective distorted text in natural scene images, they formulate a new algorithm to recognize text in a natural scene images which are perspective distorted. This method adopts the Hough Transform in order to correct the scene images orientation and implements efficient effective character detection and localization method. SVM classifier is adopted in order to filter the non-text components from the detected components, then after filtering, character recognition is adopted to recognize the text accurately.

Bai et al (2016) proposed a learned multi-scale mid-level representation for scene text recognition. This method contains a set of mid-level primitives, also termed strokelets, this attain the basic substructures of characters at any kind of coarse. The strokelets has 4 different advantages: 1, usability: automatically learned from character level annotations; 2, robustness: insensitive to interference factors; 3, generality: applicable to variant languages; and 4, expressivity: effective at describing characters.

In summary, the above discussion show that the methods work well for the images of high contrast text but not low contrast text because most of the methods work based on descriptors. It is true that descriptors work well when character preserved shape. For low contrast images, it is hard to expect character shape. Therefore, the methods may not perform well for Malaysian license plate images.

2.3.3 Text Recognition in License Plate Images

Sa et al (2013) Proposed robust document image binarization algorithm for degraded document images. In this paper the researchers presented an adaptive image, which is contrast based document image binarization method. This is applicable to different types of document degradation. This method is robust for document binarization and help to increase the recognition accuracy. The method is good for degraded document images but the output is poor for Malaysian license plate images.

Balamurugan et al (2015) proposed automatic number plate recognition system using super-resolution technique. The proposed method identifies the number plate of any vehicle from video input and then adopts the super resolution method. Applying the (OCR) Optical Character Recognition Technique it accomplish the text from the super resolution input image of vehicle number plate by comparing it with the RTO database and then it display the details of the vehicle such as owners name, vehicle registration. Super resolution is a method that is used to improve the visual quality of a sequence of low resolution image by constructing a single high resolution image, this method will fail if input image is not affected with any challenges, because the method will increase the resolution.

Saghaei (2016) propose another method, called proposal for automatic license and number plate recognition system for vehicle identification. This can extract the license plate number of the cars passing through a given location using some algorithm in image processing. There is no additional devices like GPS or radio frequency identification (RFID) need to be installed for implementing this system. Using special cameras, the system acquire the pictures from each passing vehicle and send the image to the computer for being processed by the LPR software. Plate recognition software uses different algorithms such as localization, orientation, normalization, segmentation and finally optical character recognition (OCR). The resulting data is applied to compare with the records on a database. But this method assumes the background is known, otherwise the recognition will fail to recognize unknown background.

Keong and Iranmanesh (2016) proposed Malaysian automatic number plate recognition system by implementing Pearson Correlation, according to them: Automatic Number Plate Recognition (ANPR) system used in order to track down and monitor a huge number of vehicle registration number plates by reading the vehicle plates as input and automatically recognize the plates' characters as output. In fact, inaccuracy of recognition can be caused by numerous factors such as: rotation of the plate and non-uniform illumination during image acquisition. So therefore, this method proposed the de-skewing operations and template matching technique in order to maintain the accuracy of the car plate at the high level. This method is good for vehicle that is in bending position, it can detect it properly, but it doesn't achieve high recognition rate for affected plate numbers according to the challenges.

Panahi and Gholampour (2016) proposed an accurate detection and recognition of dirty vehicle plate numbers for high speed applications. This implements the intensity values in different domains for feature extraction, but the performance of this method depending on the images captured by specific devices.

Kim et al (2016) proposed effective character segmentation for license plate recognition under illumination changing environment, this method is a new image segmentation way for license plate recognition (LPR) in video based traffic surveillance system. The license plate character segmentation is most important procedure in LPR system. However, in real situation, the character segmentation algorithms are challenged by drastic performance decrease due to sudden local illumination changes, especially when the colour of characters is similar to that of background in LP. To mitigate this problem, they introduce a novel LP character segmentation algorithm by employing an adaptive binarization method. This is good for character segmentation, but what about character recognition, if the plate number is not clear, this will fail to recognize the character.

Paul and John (2017) proposed Principle of Automatic Number Plate Recognition. The proposed method used Morphological operations, Histogram manipulation and Edge detection Techniques for plate localization and characters segmentation. This method is good for plate number without aforementioned challenges according to the research problem, but it fails to recognize the aforementioned challenges.

Bulan et al (2017) proposed segmentation and annotations free license plate recognition with deep localization and failure identification, which explores Hidden Markov Model for recognition. Since HMM requires predefined lexicons, it may not work well for different datasets especially for the images with background variations.

2.4 Summary

Overall, though there are plenty of methods for classification and recognition of different type of texts in literature, none of the methods give satisfactory results for the Malaysian license plate images. The main reason is that Malaysian license plate images suffer from different background to represent normal and taxi in addition to other challenges as in other text types. Therefore, we can conclude that classification and recognition of Malaysian license plate images are challenging and interesting.

CHAPTER 3: DENSE CLUSTER BASED METHOD FOR CLASSIFICATION OF MULTI-TYPE LICENSE PLATE IMAGES

3.1 Background

The previous chapter presents literature review on classification of multi-type text images, such as video text images, natural scene image, born digital image and license plate images. In addition, the review on recognition of natural scene, video and license plate images is also provided. It is noted that classification of license plate images is essential to increase the recognition rate of the license plate images. This is because license number plate images affected by different and multiple adverse factors especially Malaysian license plate images which suffer from background variations. The same adverse factors affect overall performance of the recognition of license plate image.

This chapter presents the method for the classification of the Multi-type license plate, this is MNPN (Malaysia Normal Plate Number) which has the black background with white text, and MTPN (Malaysian Taxi Plate Number) which has white background with black text. To achieve this, the chapter explores dense cluster concept using canny edge detection of the input images to identify a given license plate as taxi or normal plate.

The rest of the chapter is organized as follows. Section 3.2 presents foreground and background separation based on canny edge detection components. Section 3.3 describes license plate classification based on dense cluster voting. Section 3.4 demonstrates the experiment to validate the propose classification method. Section 3.5 provides the comparative studies between the existing methods and proposed method to show the superiority and Section 3.6 summarize the whole technique proposed in this chapter.

3.2 Foreground and Background Separation

As discussed in previous section, Malaysian normal license plate contains white colour as background and dark colour as foreground (number) while taxi plate contains dark colour as background and white colour as foreground (number) as shown in Fig 3.1 (a) shows the image of Normal plate Number and Fig 3.1 (b) shows Taxi plate number.

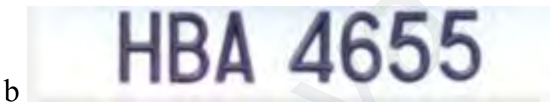
a  b 

Figure 3.1: Malaysian Plate Number (a) Normal (b) Taxi

To separate the background and foreground colours of the license plate images, the method uses canny edge detection. It is true that Canny edge detector gives fine edges irrespective of background and foreground colour changes by representing text as white pixels and background as black pixels, (Mayur et al, 2015). Therefore, the method considers pixels which represent white pixels as foreground and the pixels which represents black pixels as background. Finally, grey information in the input image is extracted for respective pixels foreground and background images. The steps for foreground and background separation are shown in Fig. 3.2. To extract the above observation, the edge pixels was separated as foreground and non-edge pixels as background for the input image as shown in Fig 3.4 (Foreground) and Fig 3.5 (Background).

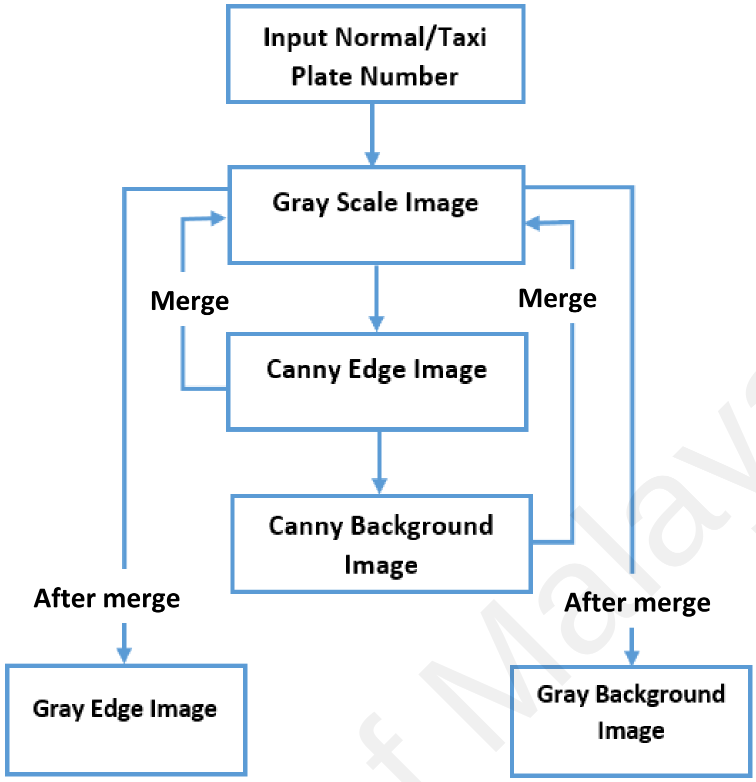


Figure 3.2: Flow Diagram of Foreground and Background Separation

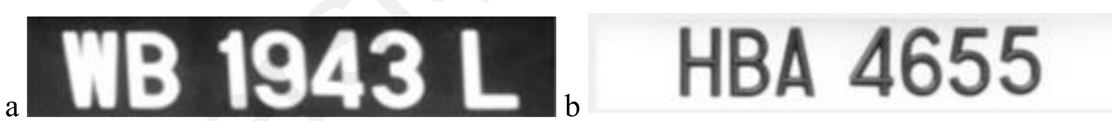


Figure 3.3: Grayscale Malaysian Plate Number (a) Normal (b) Taxi.

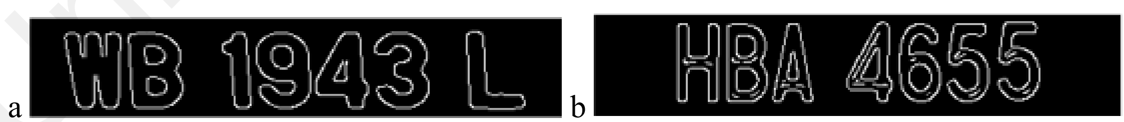


Figure 3.4: (Foreground) Canny Edge of Plate Number (a) Normal (b) Taxi.

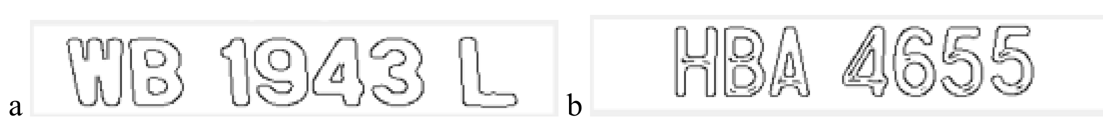


Figure 3.5: (Background) Canny Background of Plate Number (a) Normal (b) Taxi.

The proposed method extracts intensity values corresponding to foreground and background pixels from the gray image Fig 3.3 of the input image as defined in equation 3.1 and equation 3.2.

$$GF_{x,y} = \begin{cases} G_{x,y}, & \text{if Canny}(x,y) = 1 \\ 0, & \text{else} \end{cases} \quad (3.1)$$

$$GB_{x,y} = \begin{cases} G_{x,y}, & \text{if Canny}(x,y) = 0 \\ 0, & \text{else} \end{cases} \quad (3.2)$$

3.3 Dense-Cluster Voting for License Plate Identification

As noted from Fig. 3.3-Fig. 3.5 that the values which represent white colour have intensity values near to 255 and the values which represent dark colour have intensity values near to zero. In order to visualize this observation, the method performs histogram operation on intensity values of foreground and background of the normal and taxi plate images as shown in Fig. 3.6, 3.7, 3.8 and 3.9. It is observed from Fig. 3.6 and Fig. 3.7 that the dense distribution can be seen for the pixels which have intensity values near to 255 in case of foreground-normal plate, while the dense distribution can be seen for the pixels which have intensity values near to 0 in case of background-normal plate image. It is vice versa for the foreground-taxi and background-taxi as shown in Fig. 3.8 and Fig. 3.9. This is the main basis for classification of normal and taxi number plate images.

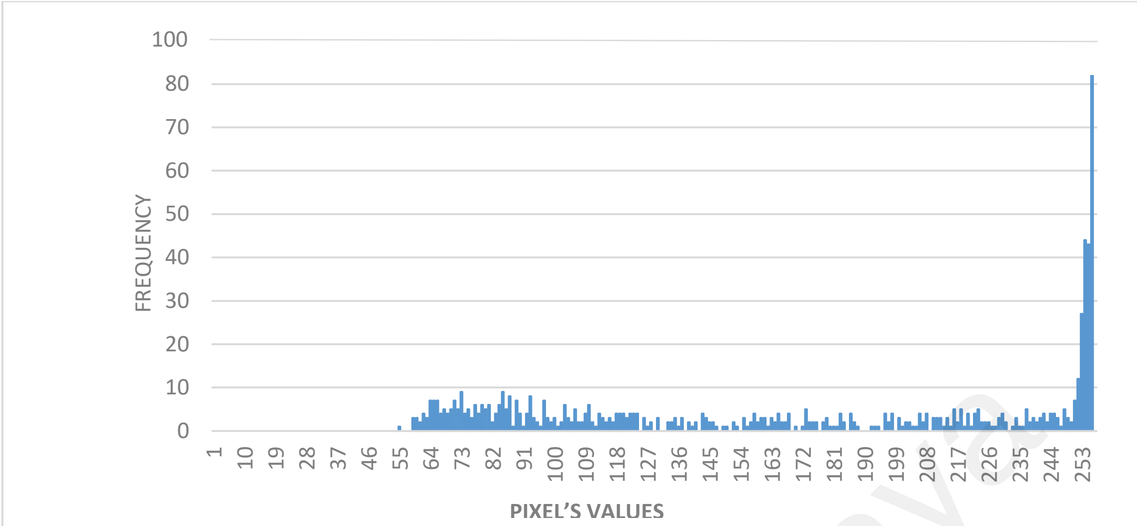


Figure 3.6: Histogram for Gray of Foreground of Normal Plate

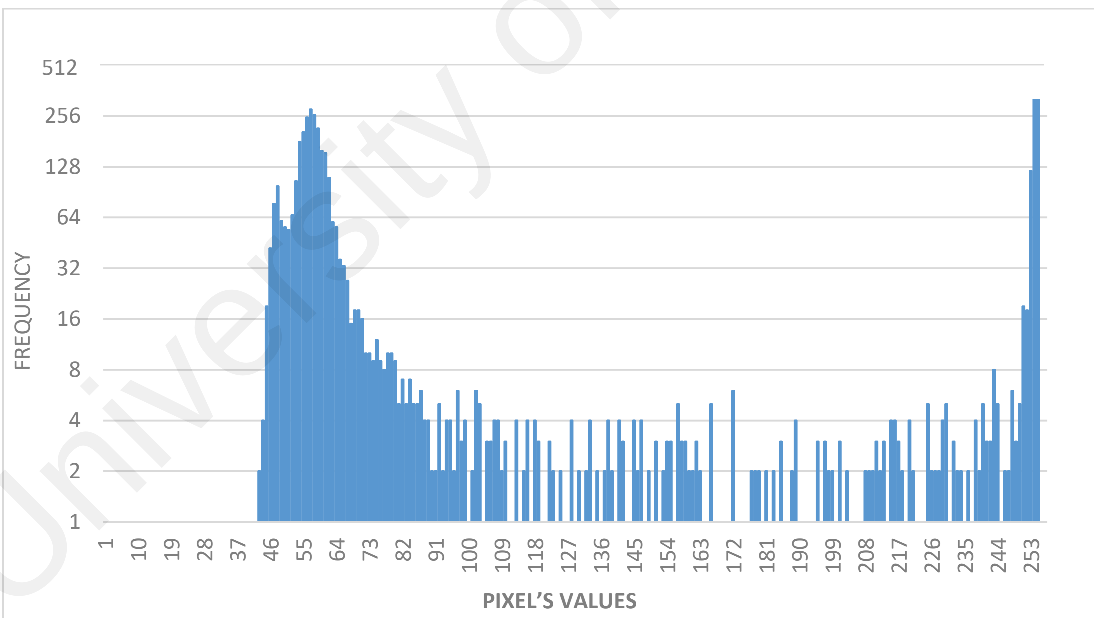


Figure 3.7: Histogram for Gray of Background of Normal Plate

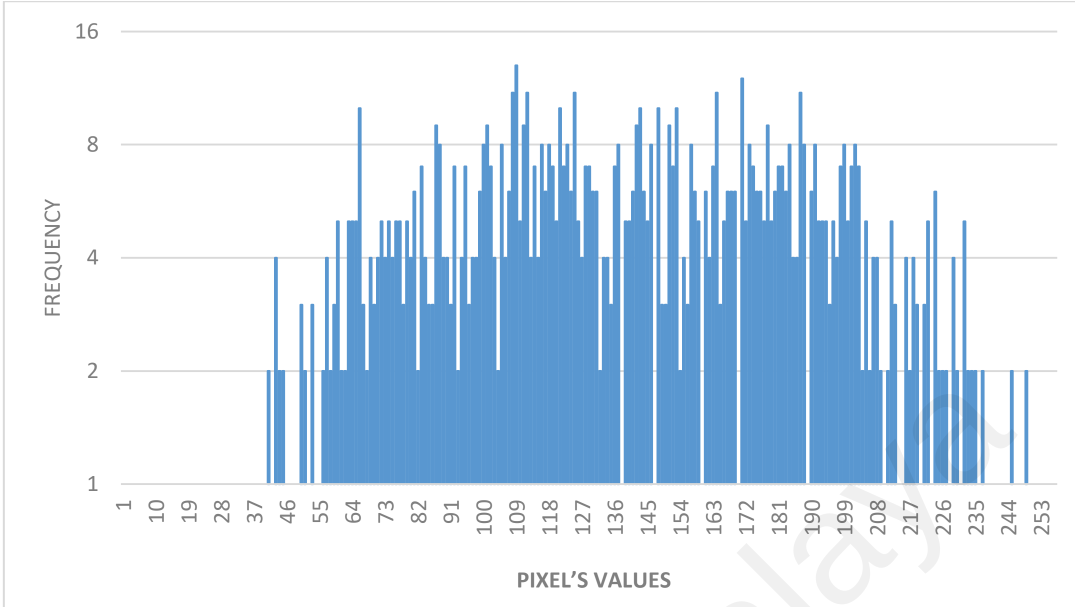


Figure 3.8: Histogram for Gray of Foreground of Taxi Plate

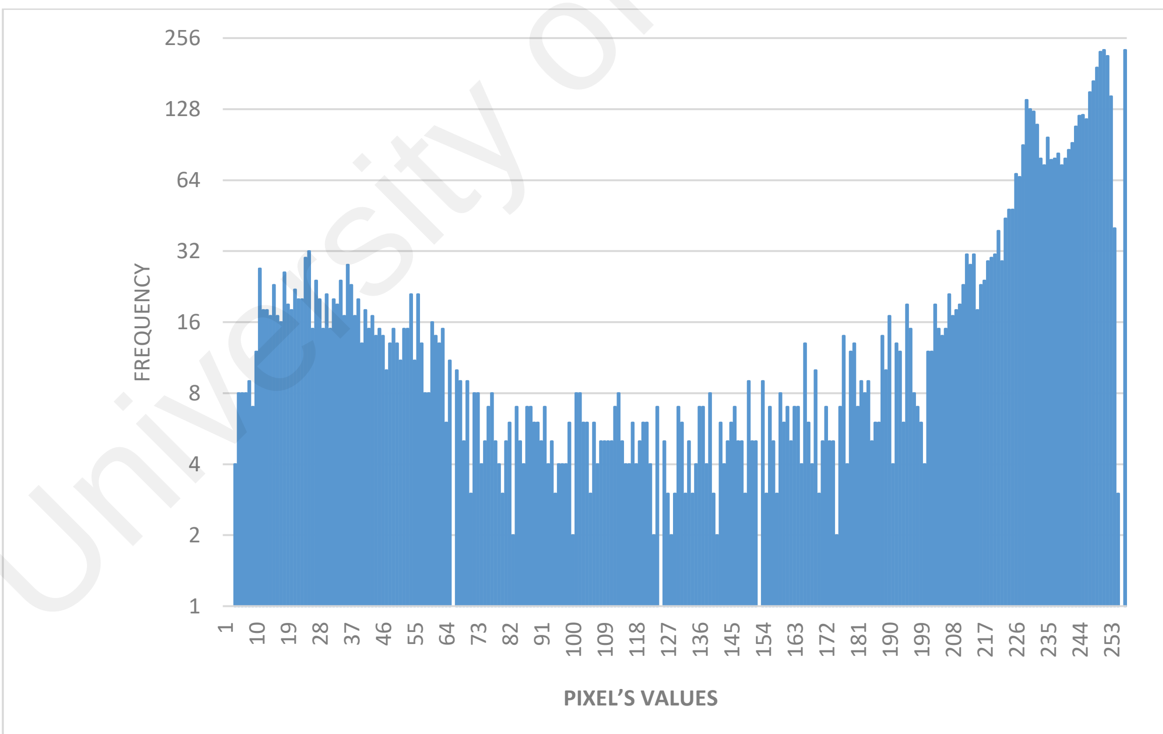


Figure 3.9: Histogram for Gray of Background of Taxi Plate

To extract the above mentioned observation, the method performs K-means clustering with K=2 on the values of foreground and background of normal and taxi plate images. This results into two clusters, namely Max cluster which gets high pixel's values and Min cluster which gives low pixel's values. In other words, the cluster that gives highest mean is considered as Max cluster and another one as Min cluster. This process outputs four clusters for the input image, namely, Foreground-Max cluster, Foreground-Min cluster, Background-Max cluster and Background-Min cluster. For each cluster, the proposed method computes mean, standard deviation and the number of pixels (density) to derive hypotheses to identify license plate images. For example, the product of standard deviation and the number of pixels of background-min cluster is greater than the product of standard deviation and the number of pixels of background-max cluster for normal plates. This results in response "1". In this way, the proposed method derives three hypotheses and finds the responses. If the hypothesis gives two responses as "1" out of three, it is identified as a normal plate else taxi plate. The whole logic of normal and taxi plate is shown in Fig. 3.10. The intermediate results of the steps are shown in Fig. 3.11 to 3.14. It is observed from Min and Max foreground of Normal and Min and Max background of normal, that the number of pixels classified into the Min cluster are higher than that of the Max cluster. Although the Max cluster gets high values, the number of pixels in the cluster is lower than the number of pixels in the Min cluster. Therefore, the number of pixels in the cluster as considered as weight and it is multiplied with the standard deviation. On the other hand, it is noted from Min and Max foreground of Taxi and Min and Max background of Taxi that the number of pixels which are classified into the Min cluster is lower than that of the Max cluster. This cue helps to derive hypothesis using the number of pixels in clusters and the standard deviations to identify normal and taxi plate images.

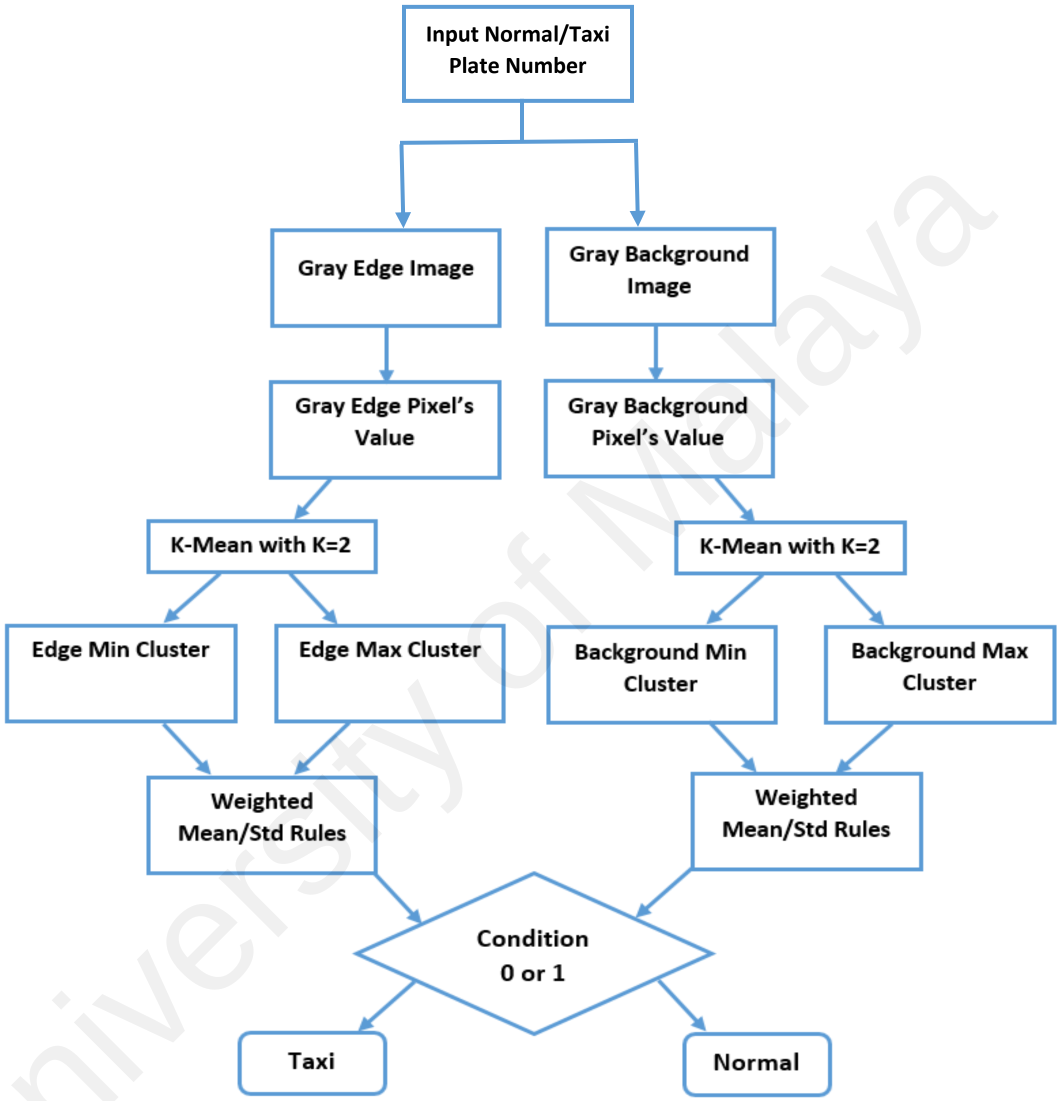


Figure 3.10: Block Diagram for Dense-Cluster Voting for License Plate Identification

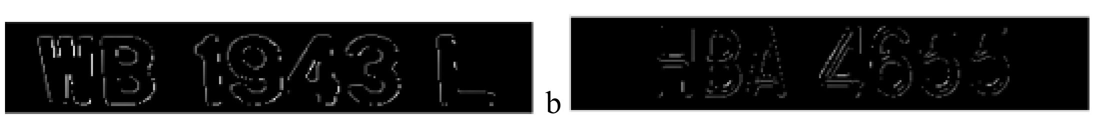
a  b

Figure 3.11: Min Cluster of Foreground of Plate Number (a) Normal (b) Taxi

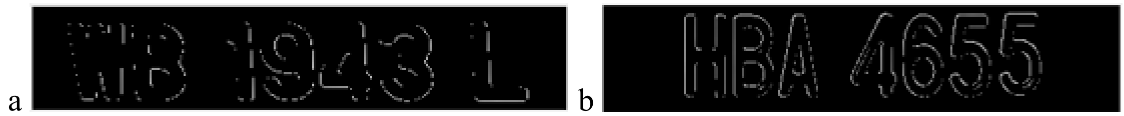


Figure 3.12: Max Cluster of Foreground of Plate Number (a) Normal (b) Taxi

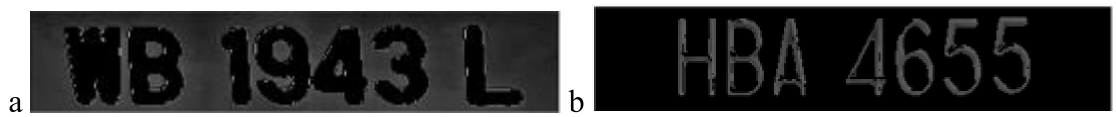


Figure 3.13: Min Cluster of Background of Plate Number (a) Normal (b) Taxi

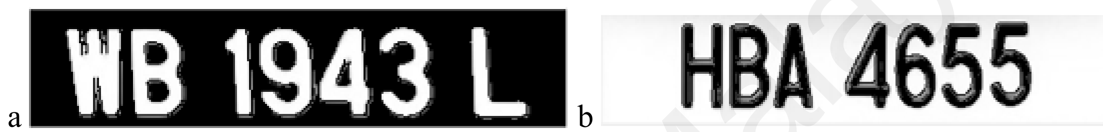


Figure 3.14: Max Cluster of Background of Plate Number (a) Normal (b) Taxi

To make it clear, the hypotheses are illustrated in Fig. 3.15 to 3.18, where one can see the number of pixels in background-min cluster (BN_{min}) is greater than that in background-max cluster (BN_{max}), the product of the number of pixels in background-min cluster (BN_{min}) and the standard deviation of background of min-cluster ($BStd_{min}$) is greater than the product of the number of pixels in background-max cluster (BN_{max}) for the normal image as shown in Fig. 3.16. However, the number of pixels (dense) in foreground-min cluster (FN_{min}) is less than that of pixels (dense) in background-max cluster (FN_{max}) for the normal image as shown in Fig. 3.15. This results in three hypotheses (H-1, H-2, H-3) as defined in equation 3.4-equation 3.6, respectively. The proposed method considers each response of hypothesis as "1" if it satisfies the condition, else it is considered as response "0". Out of the three responses, if two responses are "1", the input image is identified as a normal one, else it is a taxi image. Fig. 3.17 and Fig. 3.18 show that H-1 and H-2 do not satisfy the conditions, while H-3 satisfies the condition. Therefore, if two responses are "0", the image is identified as taxi. In this way, the proposed method tests all eight combinations of three responses for the input image. The researcher called this process voting, as defined in equation 3.7, where ∂ is the majority variable, which is set to be greater than or equal to 2 for normal and less than 2 for taxi.

$$Std_j = \sqrt{\frac{\left(\sum_{\gamma=1}^{m} M_j - X_\gamma\right)^2}{m}} \tag{3.3}$$

Where *Mj* is the mean of the *j* cluster, X denotes intensity values, and *m* is the total number of the pixels in cluster *j*.

$$H-1 = \begin{cases} 1 & if \;\; FN_{min} > FN_{max} \\ 0 & else \end{cases} \tag{3.4}$$

$$H-2 = \begin{cases} 1 & if \;\; BN_{min} > BN_{max} \\ 0 & else \end{cases} \tag{3.5}$$

$$H-3 = \begin{cases} 1 & if \;\; BN_{min} * BStd_{min} > BN_{max} * BStd_{max} \\ 0 & else \end{cases} \tag{3.6}$$

$$Voting = \begin{cases} 1 & if \;\; (H-1) + (H-2) + (H-3) > \partial \\ 0 & else \end{cases} \tag{3.7}$$

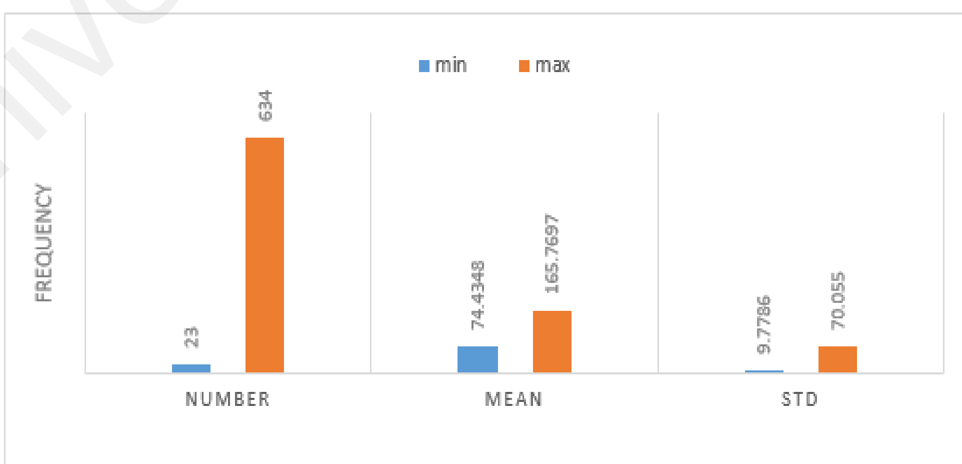


Figure 3.15: Number of Pixels, Mean and Standard Deviation for Min and Max Clusters of Foreground of Normal Image

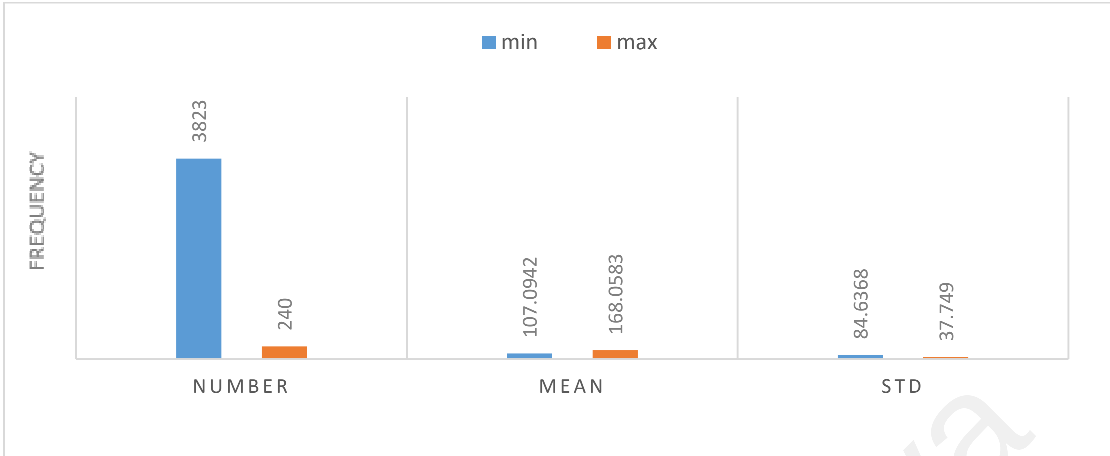


Figure 3.16: Number of Pixels, Mean and Standard Deviation for Min and Max Clusters of Background of Normal Image

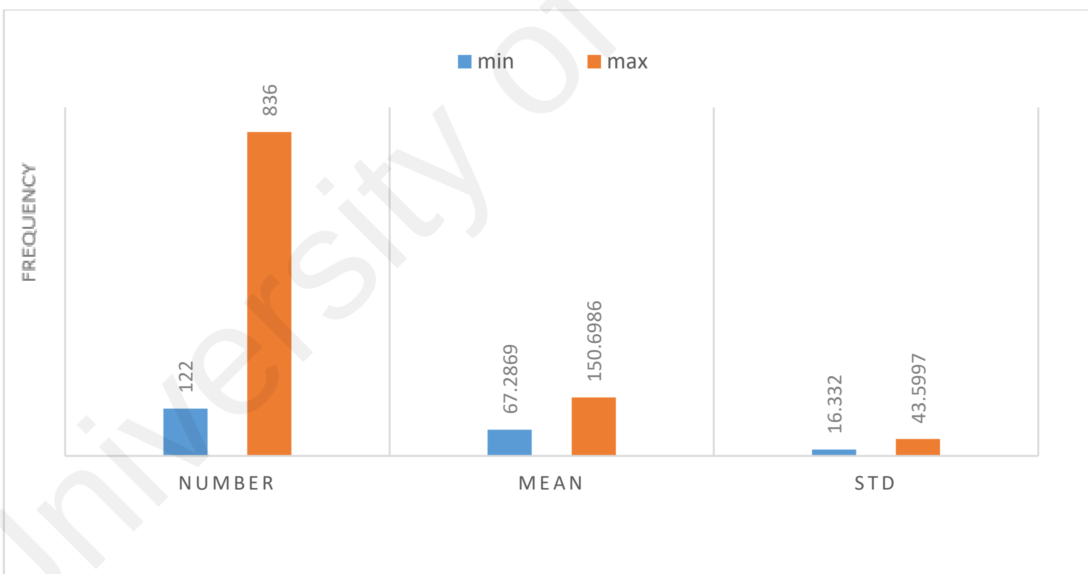


Figure 3.17: Number of Pixels, Mean and Standard Deviation for Min and Max Clusters of Foreground of Taxi Image

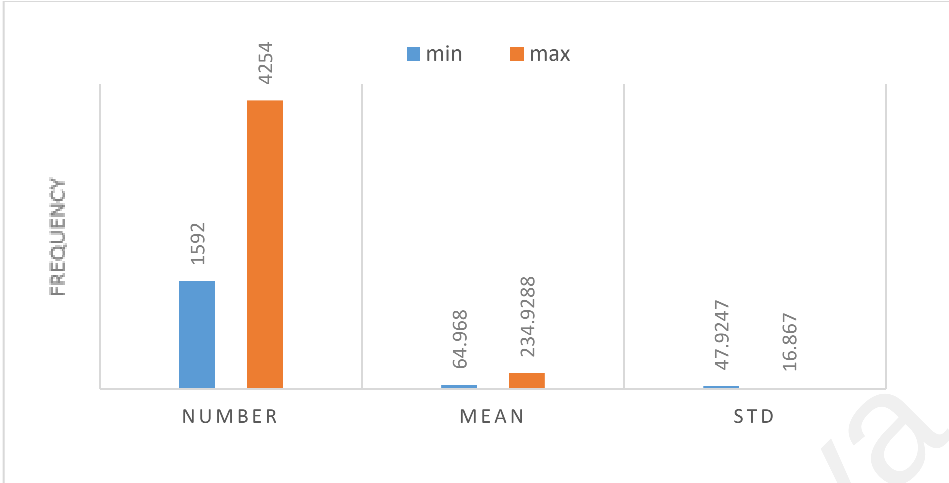


Figure 3.18: Number of Pixels, Mean and Standard Deviation for Min and Max Clusters of Background of Taxi Image

3.4 Experimental Results

In order to evaluate the proposed method, the experiment is run on the dataset. There is 1000 normal images and 1000 taxi images in the dataset, there are images which affected multiple adverse factors such as low resolution, blur and severe illumination effect, images with different background colours, images affected by head light, speed of vehicles, etc. Some of these plate numbers are collected from MIMOS (Research institute and funded by government) and other places like Universities, parks, streets and so on.

To evaluate the robustness of the proposed and the existing methods, the method considers classification rate with confusion matrix for experiments on classification, and recognition rate at character level for recognition experiments. Since there is no ground truth for the dataset, the method counts manually to calculate measures. For recognition experiments, there is consideration before and after classification to show the usefulness and effectiveness of the classification method. Before classification includes data of two classes for experimentation using different binarization methods. After classification includes data of individual class for experiments using the same binarization methods. Besides, the same experimentation set up is repeated for each existing classification method to show that the proposed classification is better than the existing classification methods.

In order to demonstrate that the proposed method is superior to the existing methods, there is adaptation of two latest classification methods. The first method is Xu et al.'s (2016), which explored the uniform colour of text components for classification of caption and scene text in video. The second method is Roy et al.'s (2016), which proposed tampered features for separating caption and scene texts in video. The main reason to choose these two existing methods for comparative study is that both the methods have the same objective as the proposed method. The methods consider scene texts are unpredictable, which suffer from distortions affected by multiple causes as taxi plates in this work. Similarly, the methods consider caption texts have good clarity and contrast, which is the same as normal license plates compared to taxi license plates. Therefore, caption and scene texts are the same as normal and taxi license plate images.

In addition, the method used the state of the art binarization methods for recognition experiments before and after classification, namely, Howe's method (2013) which based on handwritten and printed document images with colour bleeding effect. Another method by Su et al (2013), this focuses on degraded document images. Also Milyaev et al (2013), this focuses on natural scene images, and method of Roy et al (2015), this focuses on both natural scene and video images. The reason to consider these different methods for experiments before and after classification is that each method addresses its own challenge. Most importantly, the intention here is to show that recognition rate improves significantly if the classification of different types of images are performed.

3.4.1 Evaluating Classification Method

After the classification of the experiment has been done, the output shows that there are successful classification and unsuccessful classification, in the plate numbers. Fig. 3.19 and 3.20 show successful normal and taxi plate number, while Fig. 3.21 and 3.22 show unsuccessful normal and taxi plate numbers. The output of the result shows that the proposed method works well for images with blur, low contrast and illumination effects. However, the proposed method fails to classify images which have too many distortions and blur. Therefore, there is a scope for enhancement and extension of this proposed method. To show the proposed method is effective, there is comparison of the proposed method with two existing methods as discussed in the previous section. The results of the proposed and existing methods are reported in Table 3.1, where it is noticed that the proposed method gives better results than the existing methods. The reason for poor results of the existing methods is that the existing methods depend on character shapes while the proposed method depends on distribution of foreground and background pixels. For instance, tampered features proposed by Roy et al, (2016) exists only for caption text but not license plate images.

Figure 3.19: Sample of Successful Normal Plate Images

Figure 3.20: Sample of Successful Taxi Plate Images

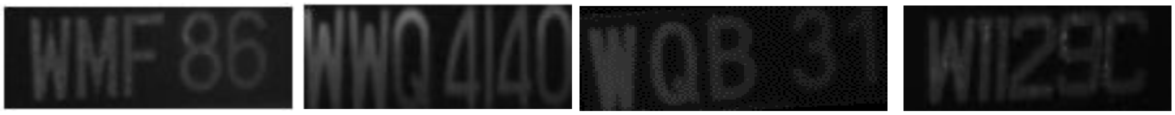


Figure 3.21: Sample of Unsuccessful Normal Plate Images

Figure 3.22: Sample of Unsuccessful Taxi Plate Images

Table 3.1: Confusion Matrix of the Proposed Method and Existing Methods

Plate Numbers	**Proposed Methodology**		**Xu et al. (2016)**		**Roy et al. (2016)**	
	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)
Normal	85.1	14.9	57.6	42.4	53.5	46.5
Taxi	11.3	88.7	33.69	66.31	31.98	68.02

The above table shows the recognition rates of proposed method on normal plate and taxi plate, and existing methods (Xu et al. (2016) and Roy et al. (2016)) that implemented on normal plate and taxi plate to compare them with proposed method in order to show the robustness of the algorithm of proposed method. In the above table, normal to normal is the normal plate number that the proposed method recognised as normal plate number, this is correct recognition (85.1 %), while normal to taxi is the normal plate number that the proposed method recognised as taxi plate number, this is wrong recognition (14.9 %). Taxi to taxi also is the taxi plate number that the proposed method recognised as taxi plate number, this is correct recognition (88.7 %), while taxi to normal is the taxi plate number that the proposed method recognised as normal plate number, and this is wrong recognition (11.3 %). The same thing goes to existing methods which are used to compare with proposed method. The existing methods recognition rates are very low compared to proposed method, the existing methods recognition rates also demonstrate in the above table, table 3.1.

3.4.2 Evaluating Usefulness of the Classification Method

For the validation of the usefulness of the proposed classification, we execute recognition experiments using different binarization methods before and after classification as shown in Table 3.2. In the Table 3.2, it shows that the binarization methods give better recognition rates after classification unlike before classification. This is valid because the method adjusts the parameters of binarization methods according to the complexity of input classes after classification. For instance, the method sets different window sizes for Milyaev et al (2013) and Roy et al (2015) methods to achieve better results after classification. This is the advantage of the classification method. When comparing recognition rates of binarization methods with classification methods, all the binarization methods score better recognition rates for the proposed classification compared to the other existing classification methods.

Experiments were executed on different rotations, scale and the images affected by different distortions to show that the proposed method is invariant to rotation, scaling and to some extent to distortion as shown in Fig. 3.25. Here it's clear that the hypotheses of normal images satisfy the voting condition for different rotations, scale and distortion respectively in Fig. 3.23 to 3.25. Overall, the objective of the work as mentioned in introduction, namely, developing a simple and effective license plate identification method to improve recognition rate, is satisfactorily achieved.

Table 3.2: Recognition Rate of the Binarization Methods for Before and After Classification on each Classification Methods

Binarization methods	Before classification	After classification					
	Normal + Taxi (%)	Proposed		Xu et al.(2016)		Roy et al. (2016)	
		Normal (%)	Taxi (%)	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)
Roy et al (2015)	14.8	22.3	20.7	19.9	17.3	20.8	19.5
Howe (2013)	22.07	31.6	24.2	25.1	21.4	29.6	23.4
Su et al (2013)	19.34	26.4	23.7	24.8	22.2	25.2	21.2
Milyaev et al (2013)	16.9	24.6	21.4	23.5	18.1	23.3	18.9

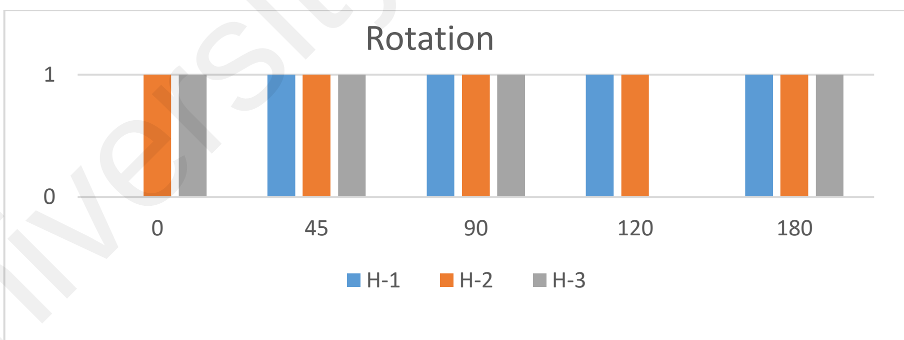


Figure 3.23: Hypotheses for Different Rotations of Plate Number Image

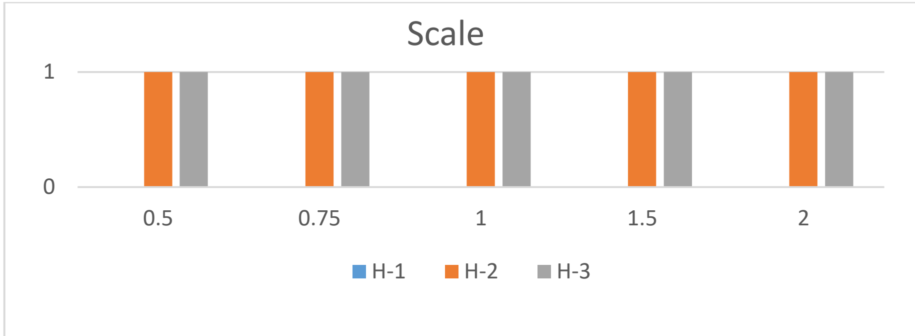


Figure 3.24: Hypotheses for Different Scaled of Plate Number Image

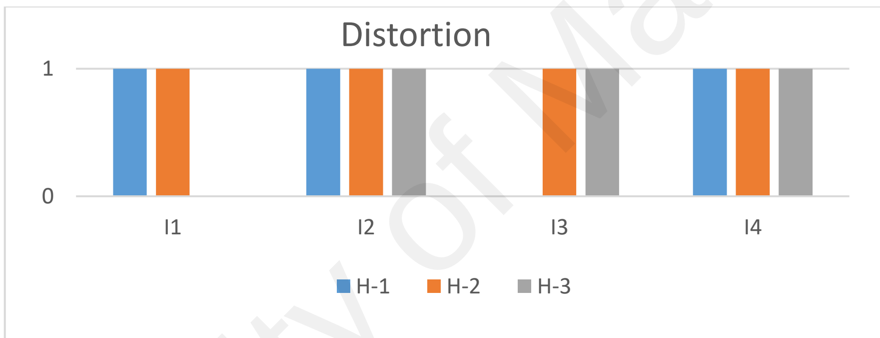


Figure 3.25: Hypothesis for Different Distortion such as Low Contrast, Poor Quality and Blur of Plate Number Images

3.5 Summary

In this chapter, there is proposition of dense cluster based voting for identifying normal and taxi license plate images. The proposed method separates foreground and background for an input image based edge information. The intensity values that correspond to foreground and background information was extracted and clustered into Max and Min cluster through the implementation of k-mean clustering. So therefore the process result in four clusters, namely, Max-Min for foreground and Max-Min for background of the same input image. The number of pixels in clusters (dense) and standard deviation of clusters are used to derive three hypotheses, which give three responses for the input image. The proposed method considers majority of responses for classifying normal and taxi plate images.

CHAPTER 4: MSER BASED METHOD FOR CHARACTER COMPONENT SEGMENTATION

4.1 Background

The previous chapter presents dense cluster based method for the classification of multi-type license plate images which is the method used for the classification of Malaysian Normal and Taxi plate number. As a result, this chapter chooses an appropriate method for recognition of Malaysian normal and taxi plates separately by taking advantage of classification. The chapter proposes modifications to existing Maximally Stable Extremal Regions (MSER) for recognizing license plate images by exploring the combination of Canny edge image and MSER concept.

The chapter is structured as follows. Section 4.2 introduces MSER for character components extraction, Section 4.3 presents OCR for character recognition in License plate images. Also, Section 4.4 demonstrate the experimental results of the proposed method, while Section 4.5 states the comparatives studies that were carried out between the existing method, and Section 4.6 summarize the whole task in the chapter.

4.2 MSER for Character Components Extraction

The method presented in previous chapter classifies a given input image as normal and taxi plate images as shown in Fig. 4.1. Unlike existing methods deploy MSER concept directly on gray image, the proposed method performs MSER operation over canny edge image of the input image in order to take advantage of canny edge image. It is true that Canny edge detector is good for both low and high contrast images which gives fine edge details while MSER is sensitive to low contrast which disconnect components into sub-components.

As a result, MSER over Canny edge image outputs character components which is nothing but character segmentation from the image. The segmented characters are passed to publicly available OCR for recognition. The logical steps of the proposed method is shown in Fig. 4.2.

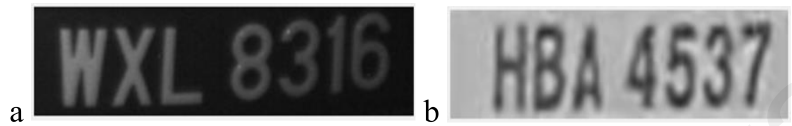


Figure 4.1: Grayscale Image of Input Image (a) Normal (b) Taxi

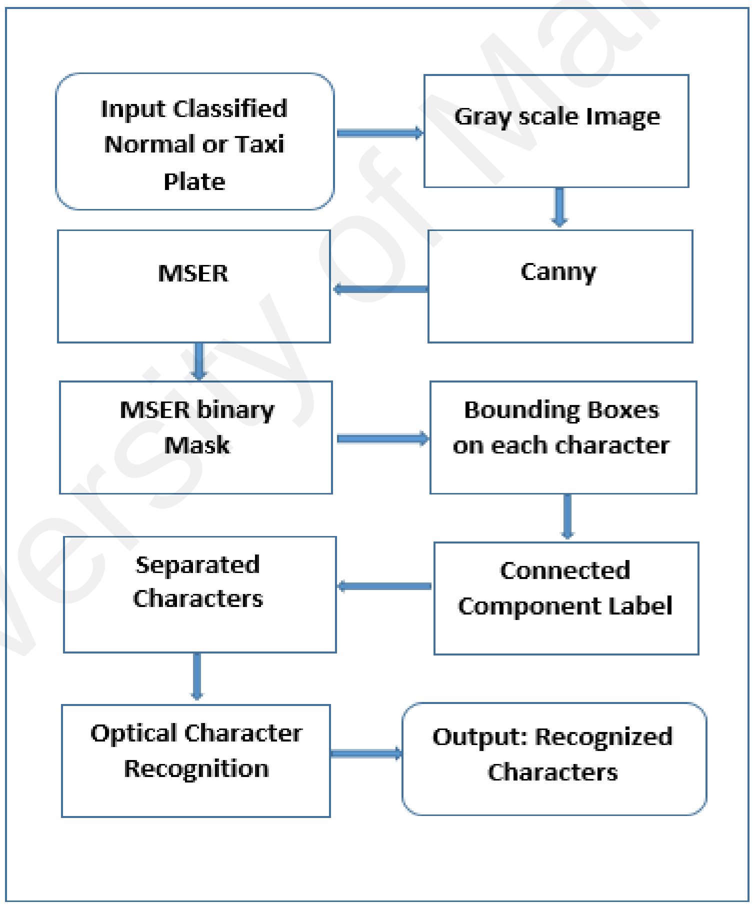


Figure 4.2: Block Diagram of the Flow of Proposed Method for Recognition

Edge Component Detection

For the gray image of the input, the proposed method obtains Canny edge image for the images in Fig. 4.1 as shown in Fig. 4.3 where one can see clear character shape and separation though the images shown in Fig. 4.1 suffer from blur, low contrast and bleeding colours. The reason for using canny edge is that canny edge detector applies Gaussian filter in order to smooth the input image so this will remove the noise, and it will find the intensity gradients of that image, it then apply non-maximum suppression to remove the spurious response to edge detection also apply double threshold to determine potential edges.

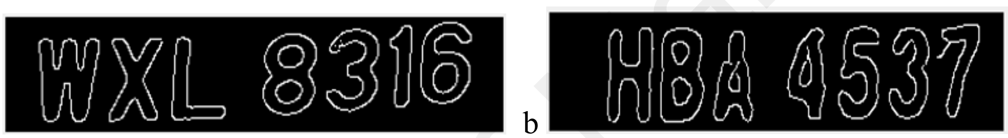
a  b

Figure 4.3: Canny Image of Input Image (a) Normal (b) Taxi

Implementation of MSER (Maximally Stable Experimal Region)

As proposed MSER by Matas et al (2004), it outputs the components which have same colour. These regions are defined by an extremal property of the intensity function in the region and on its outer boundary. The formal steps of MSER are as follows. Let ***Rt*** be the family of connected components representing an edge in the component tree. Matas et al. refer to such regions as to extremal, since either $I|\text{int}\,(Rt) < I|\partial Rt$ or $I|\text{int}\,(Rt) > I|\partial Rt$, i.e., all the pixel values in the regions are either strictly darker or strictly brighter than those on the boundary, where the intensity is exactly equal to ***t.***

The stability of a region ***Rt*** is defined as: $\Psi 1(Rt) = \frac{A(Rt)}{d/dt\ A(Rt)}$ (4.1)

Where **A(*Rt*)** denotes the area of *Rt*. A region is considered stable if its area changes only slightly with the change of the threshold ***t***. A region ***Rt*** is called maximally stable if **Ψ1*(Rt)*** has a local maximum at t. Such regions are image features detected by the MSER algorithm. Matas et al (2004) showed that MSER is affine covariant. This observation stems directly from the fact that area ratios are preserved under affine transformations, which implies that $\boldsymbol{\Psi 1(Rt)}$ is an affine-invariant property. This, in turn, implies that for an affine transformation T of the domain X, the corresponding regions R and R0 detected in images I and $I(T^{-1})$, respectively, will be related by $T\,R = R^{1}$.

The sample results of MSER operation on Canny edge images are shown in Fig. 4.4 where it can be seen that all the character component are separated by marking different colors. This is the advantage of the MSER over Canny edge image. Then the proposed method converts all colour values as white and non-colour values as dark, resulting in binary images with clear shape as shown in Fig. 4.5.

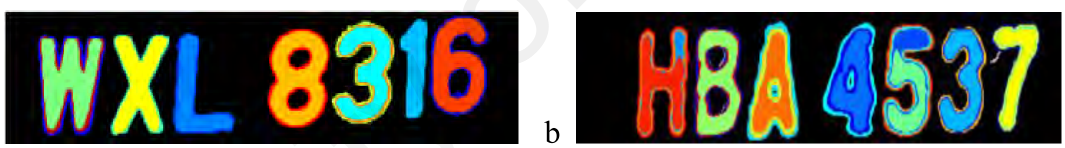
a b


Figure 4.4: MSER Image of Input Image (a) Normal (b) Taxi

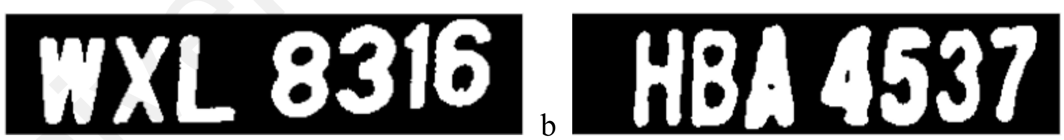
a b


Figure 4.5: Binary Mask MSER Image of Input Image (a) Normal (b) Taxi

4.3 OCR for Character Recognition in License Plate Images

For the above binary results given by MSER, the proposed method considers each component as connected component as shown in Fig. 4.6 bounding box for each connected component. Then the connected components are extracted as shown in Fig. 4.7 to feed to publicly available OCR for recognition. The sample results of recognition for the images are shown in Fig. 4.10. Fig. 4.10 shows that characters are recognized correctly.

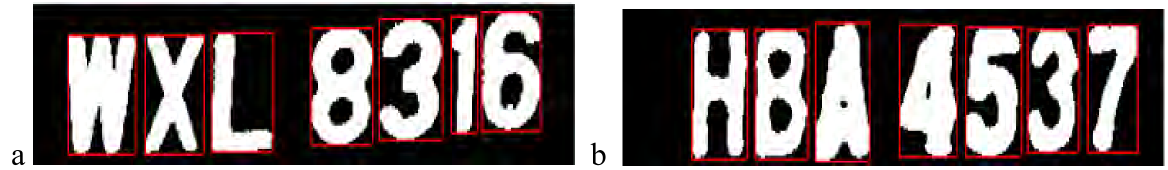


Figure 4.6: Bounding Boxes on MSER Binary Image of Input Image (a) Normal (b) Taxi

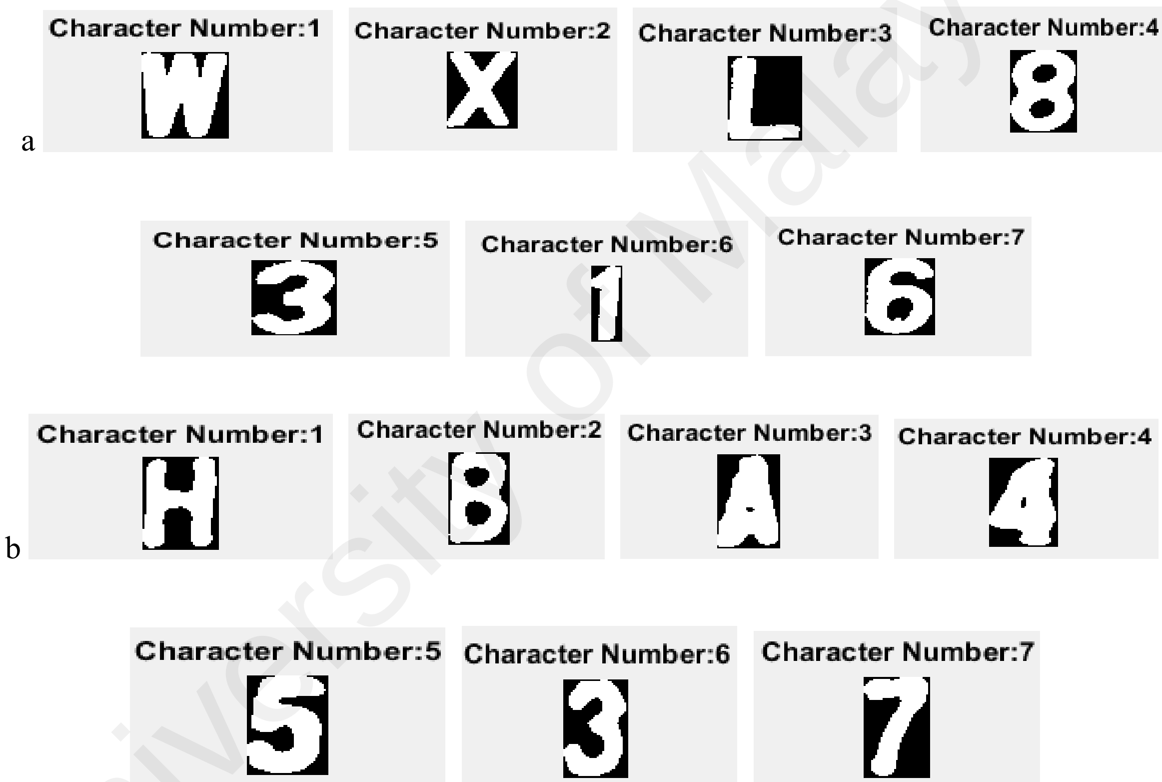


Figure 4.7: CCL on MSER Binary Image, the Area Captured by Bounding Boxes of Binary Image (a) Normal (b) Taxi.

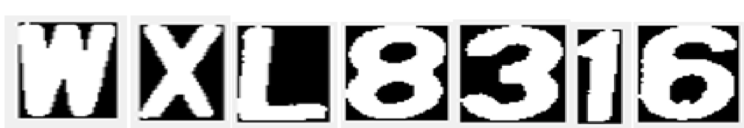
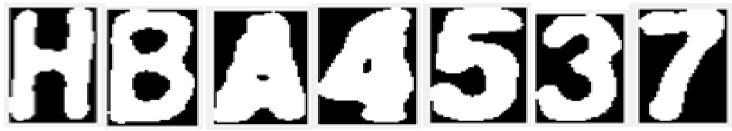
a  = WXL8316 b  = HBA4537

Figure 4.8: Recognized Characters of Input Image (a) Normal (b) Taxi.

4.4 Experimental Results

In order to evaluate proposed method, 1000 images of Malaysian normal plate numbers and 1000 images of Malaysian taxi plate numbers are considered in this work. This dataset includes different type of Malaysia plate number of both Normal and Taxi. For the measuring the performance of the proposed and the existing methods, recognition rate at character level is considered as metric in this work. Since there is no ground truth for the dataset, the measures are calculated manually. To show that the proposed method is effective, the results of the proposed method are compared with the existing methods on the same dataset. The existing methods considered for comparative study are Otsu, Niblack, Savuola which are state-of-the-art binarization methods for document analysis (He et al, 2005) and MSER (Maximally Stable Extremal Region) which uses gray information for obtaining components (Matas et al, 2004). In addition, the results of canny edge image are sent to OCR directly for recognition. This comparative is to show effectiveness of the proposed MSER.

Sample results of the proposed and existing methods are shown in Fig. 4.10 to Fig. 4.20 show that the existing methods, namely, Otsu, Niblack and Sauvola give poor results for the images which suffer from blur and distortion. This is due to thresholds fixed by the methods may not work well for the complex background images. The existing MSER give poor results for the images shown in Fig 4.10 to Fig. 4.14. This is because existing MSER is sensitive background complexity. The Canny edge operator reports poor results compared the proposed method. The reason for poor results is that Canny sometimes when background is complex which connect two components as one component. So therefore the existing methods threshold were tuned, to get better result and to compare their results with proposed method. On the other hand, the proposed modified MSER gives better results compared to existing methods. This is because the proposed method considers the advantages of Canny edge detector and MSER concept.

The quantitative results of the proposed and existing methods are reported in Table where one can notice that the proposed method give better results for both normal and taxi license plate images compared to the existing methods. This is because the proposed MSER combined canny with MSER, also defined new threshold and implement spatial bounding box to separate the character before OCR according to complexity of the normal and taxi license plate images by taking advantage of classification method. The reasons for poor results of the existing methods are same as discussed above.

Figure 4.9: Input Images of the Results and the Proposed Method Results

Below are poor results of existing methods before tuned threshold.

a 

b 

Figure 4.10: Sample of Poor Result for Otsu (a) Normal (b) Taxi

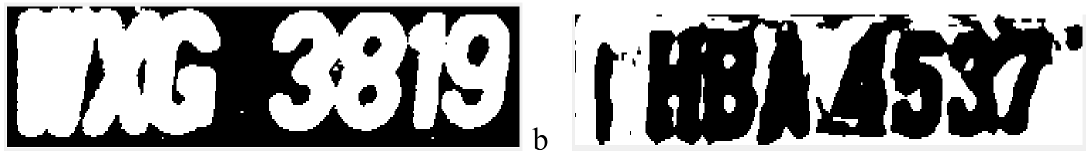
a b


Figure 4.11: Sample of Poor Result for Niblack (a) Normal (b) Taxi

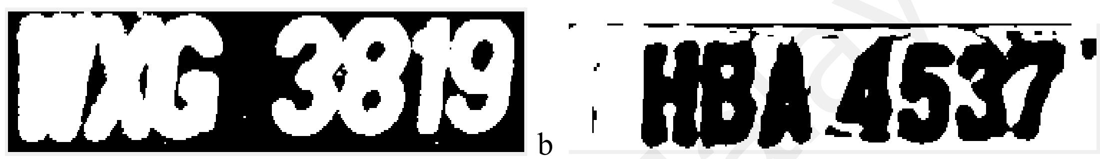
a b


Figure 4.12: Sample of Poor Result for Sauvola (a) Normal (b) Taxi

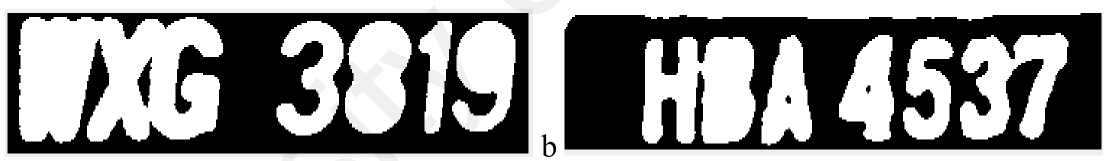
a b


Figure 4.13: Sample of Poor Result for MSER (a) Normal (b) Taxi

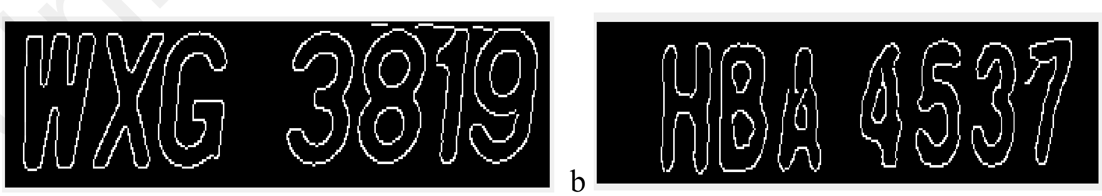
a b


Figure 4.14: Sample of Poor Result for Canny (a) Normal (b) Taxi

Below are correct results of existing methods after tuned threshold.

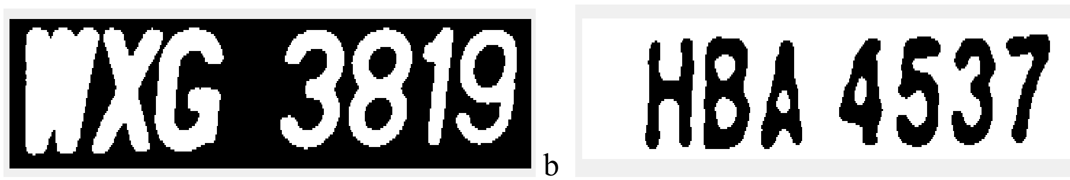


Figure 4.15: Sample of Correct Result for Otsu (a) Normal (b) Taxi

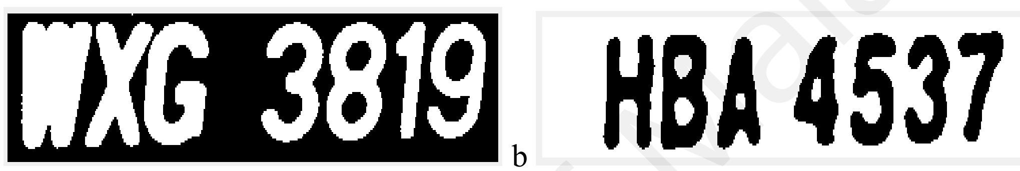


Figure 4.16: Sample of Correct Result for Niblack (a) Normal (b) Taxi

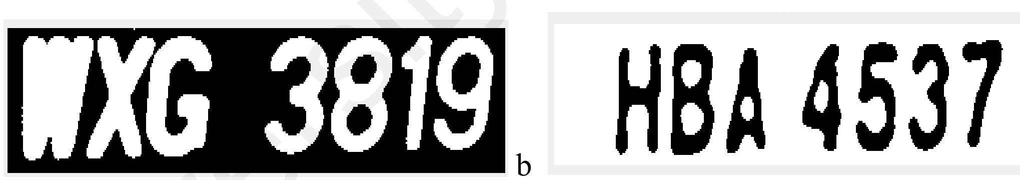


Figure 4.17: Sample of Correct Result for Sauvola (a) Normal (b) Taxi

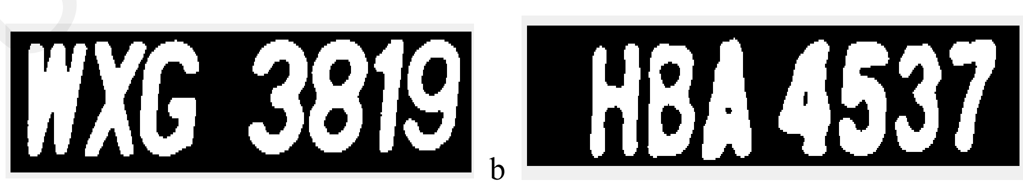
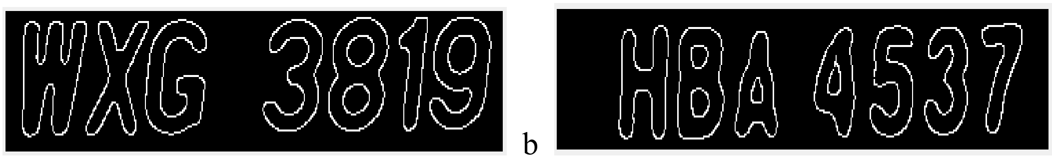
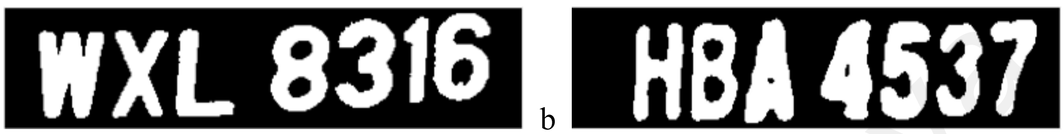


Figure 4.18: Sample of Correct Result for MSER (a) Normal (b) Taxi



a b

Figure 4.19: Sample of Correct Result for Canny (a) Normal (b) Taxi



a b

Figure 4.20: Sample Result of Proposed Method (a) Normal (b) Taxi

Table 4.1: Recognition Rate of the Proposed and Existing Methods for Normal and Taxi License Plate Images.

Recognition Methods	**Normal (%)**	**Taxi (%)**
Otsu (Zeng et al, 2012)	62.5	64.2
Niblack (Chandrakala, 2016)	74.1	76.6
Sauvola (Chandrakala, 2016)	72.4	78.5
Existing MSER (Saini et al, 2016)	82.6	84.8
Proposed Canny	45.7	38.9
Proposed Method	**91.35**	**93.3**

4.5 Summary

In this chapter, MSER concept for recognition of Malaysian normal and taxi plate number has been proposed. The method combines canny edge image and existing MSER concept to achieve better results for the complex license plate images. The results of modified MSER are labelled as connected component to feed to OCR for recognition. Experimental results of the proposed and existing method on normal, taxi license plate images show that the proposed method scores the best recognition rate compared to the existing methods.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 Summary

It is realized from review on license plate images that existing methods do not work well for the Malaysian license plate images. The main reason is that Malaysian license plate images have different colours to represent background and foreground (numbers) according to classification of normal (private) and taxi (public). To overcome this challenge, the proposed work introduces classification of normal and taxi plates such that one can choose an appropriate recognition methods to achieve better recognition rate. In this regard, the proposed work presents a new method called Dense Cluster based Voting for classifying normal and taxi license plate images. The proposed method first isolates the foreground from background using edge information given by canny edge detector. Then the proposed method extracts intensity values corresponding to foreground and background pixels from the input gray image. After that, the method propose to classify intensity values into a Max cluster which contains high values and a Min cluster which contains low values with the implementation of k-means clustering. This gives four clusters for the input image. The proposed method explores the number of pixels in the clusters (dense cluster) and the standard deviation of Max and Min clusters for deriving new hypotheses.

Since the above method classifies normal and taxi license plate images, the proposed work presents suitable modifications according to complexity of the normal and taxi license plate images. The recognition method explores Maximally Stable Extremal Regions (MSER) for recognizing Malaysian license plate images. The proposed method combines MSER with canny edge image detection, and it convert to MSER Mask, to segment character components from the license plate images it implemented the CCL. The segmented character components are passed to Optical Character Recognizer to recognize the license plate images at character level.

5.2 Future work

Though the proposed methods addresses the cause of distortion to some extent, when the images suffer from severe distortion, such as illumination, fog, snow, light, speed etc, the proposed method do not perform well. Sample failure cases of the proposed method are shown in Fig. 5.1 to 5.3 where it can be seen that images are severely damaged by the challenges. Therefore, there is a need for developing a method which can cope with the challenges. One way is to identify the distortion in the image for classification such that one can focus on particular cause to achieve good results. Other way is to figure out the feature which are invariant to distortion regardless of severity.

There is a plan to extend the same idea for other scripts of different country. In addition, there is a plan to develop a prototype or working model to fix in the real time environment.

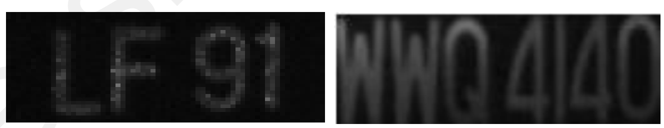


Figure 5.1: Sample of Misclassified Normal Plate Images

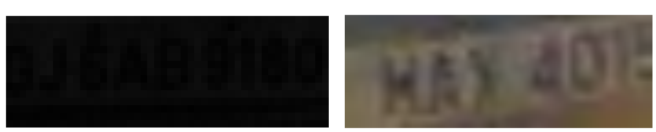


Figure 5.2: Sample of Misclassified Taxi Plate Images

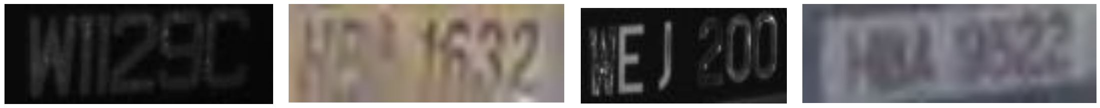


Figure 5.3: Sample of Plate Numbers That Characters Cannot Be Recognized

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