AN AUTOMATED VEHICULAR LICENSE PLATE RECOGNITION SYSTEM FOR SKEWED IMAGES

MD. YEASIR ARAFAT

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

AN AUTOMATED VEHICULAR LICENSE PLATE RECOGNITION SYSTEM FOR SKEWED IMAGES

MD. YEASIR ARAFAT

THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING SCIENCE

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

UNIVERSITY OF MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: Md. Yeasir Arafat

Matric No: KGA150020

Name of Degree: Master of Engineering Science

Title of Thesis: **An Automated Vehicular License Plate Recognition System for Skewed Images**

Field of Study: Signal and Systems

I do solemnly and sincerely declare that:

(1) I am the sole author/writer of this Work;
(2) This Work is original;
(3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
(4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
(5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya ("UM"), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
(6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature Date:

Subscribed and solemnly declared before,

Witness's Signature Date:

Name:

Designation:

AN AUTOMATEDVEHICULAR LICENSE PLATE RECOGNITION SYSTEM FOR SKEWED IMAGES

ABSTRACT

In recent years, automatic vehicular license plate recognition (AVLPR) framework has emerged as one of the most significant issues in intelligent transport systems (ITS) because of its magnificent contribution in real-life transportation applications. Restricted situations like stationary background, only one vehicle image, fixed illumination, no angular adjustment of the skewed images have been focused in most of the approaches. An innovative real time AVLPR technique has been proposed in this thesis for the skewed images where detection, segmentation and recognition of LP have been focused. A polar co-ordinate transformation procedure is implemented to adjust the skewed vehicular images. The image gets reorganized in accordance with the image inclined slope by utilizing polar co-ordinate transformation procedure by proper revolving. This includes in the pixel mapping of new image to the old image for getting this Euclidean entity under the projective distortion. Besides that, window scanning procedure is utilized for the candidate localization that is based on the texture characteristics of the image. Then, connected component analysis (CCA) is implemented to the binary image for character segmentation where the pixels get connected in an eight-point neighborhood process. Finally, optical character recognition is implemented for the recognition of the characters. For measuring the performance of this experiment, 300 skewed images of different illumination conditions with various tilt angles have been tested and the proposed method is able to achieve accuracy of 96.3% in localizing, 95.4% in segmenting and 94.2% in recognizing the LPs.

Keywords: license plates (LP); intelligent transport systems (ITS); character recognition; connected component analysis (CCA); skewed images.

PERGI KE SISTEMPENGIKTIRAFAN PLAT LESEN KENDERAAN AUTOMATIK UNTUK SKEWED IMEJ

ABSTRAK

Dalam tahun-tahun kebelakangan ini, rangka kerja pengiktirafan plat lesen kenderaan automatik (AVLPR) telah muncul sebagai salah satu isu yang paling penting dalam sistem pengangkutan pintar (ITS) kerana sumbangan yang luar biasa dalam aplikasi pengangkutan kehidupan sebenar. Keadaan terhad seperti latar belakang pegun, hanya satu imej kenderaan, pencahayaan tetap, tiada pelarasan sudut imej miring telah difokuskan pada kebanyakan pendekatan. Teknik AVLPR masa nyata yang inovatif telah dicadangkan dalam tesis ini untuk imej yang miring di mana pengesanan, segmentasi dan pengiktirafan LP telah difokuskan. Prosedur transformasi koordinat polar dilaksanakan untuk menyesuaikan imej kenderaan yang miring. Imej akan disusun semula mengikut cerun cenderung imej dengan menggunakan prosedur transformasi koordinat kutub dengan pusingan yang betul. Ini termasuk pemetaan pixel imej baru kepada imej lama untuk mendapatkan entiti Euclidean ini di bawah penyelewengan projektif. Selain itu, prosedur pengimbasan tingkap digunakan untuk penyetempatan calon yang berdasarkan kepada ciri-ciri tekstur imej. Kemudian, analisis komponen yang berkaitan (CCA) dilaksanakan kepada imej binari untuk segmentasi aksara di mana piksel disambungkan dalam proses kejiranan lapan titik. Akhirnya, pengecaman aksara optik dilaksanakan untuk pengiktirafan watak-watak. Untuk mengukur prestasi eksperimen ini, 300 imej kecondongan pelbagai keadaan pencahayaan dengan pelbagai sudut kecondongan telah diuji dan kaedah yang dicadangkan dapat mencapai ketepatan 96.3% dalam penyetempatan, 95.4% dalam segmen dan 94.2% dalam mengiktiraf LP.

Kata Kunci: plat lesen (LP); sistem pengangkutan pintar (ITS); pengiktirafan aksara; komponen yang berkaitan; imej yang miring.

ACKNOWLEDGEMENTS

First of all, I would like to express my gratitude to the Almighty Allah who has created the whole universe.

Foremost, I would like to thank my supervisors Dr. Anis Salwa binti Mohd Khairuddin and Prof. Dr. Raveendran A/L Paramesran for their continuous support, patience, motivation, enthusiasm, and immense inspiration. Their guidance has helped me in all the time of this work. I am proud that I have been their student.

I am especially grateful to my supervisor Dr. Anis Salwa binti Mohd Khairuddin for providing financial support from her research grant. I am greatly indebted to my parents and to my sister and brother-in-law for always being there beside me during the last 3 years of painstaking time.

Finally, I would like to acknowledge gratefully the University of Malaya for providing me the financial support to accomplish this work. Thanks also go to the staff of this institute as well as university who helped directly or indirectly to carry out this work.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ITS	:	Intelligent Transport System
VLP	:	Vehicular License Plate
AVLPR	:	Automatic Vehicular License Plate Recognition
LP	:	License Plate
LPD	:	License Plate Detection
CCA	:	Connected Component Analysis
LPR	:	License Plate Recognition
HOG	:	Histograms of Oriented Gradients
VEDA	:	Vertical Edge Detection Algorithm
HT	:	Hough Transform
HLS	:	Hue, Lightness, Saturation
HSI	:	Hue, Saturation, Intensity
HSV	:	Hue, Saturation, Value
RGB	:	Red, Green, Blue
TDNN	:	Time Delay Neural Network
DP	:	Dynamic Programming
HMC	:	Hidden Markov Chain
MAP	:	Maximum A Posteriori
MRF	:	Markov Random Field
GA	:	Genetic Algorithm
RMS	:	Root Mean Square
ANN	:	Artificial Neural Network
PNN	:	Probabilistic Neural Network
RNN	:	Recurrent Neural Network

CSV	:	Column Sum Vector
HMM	:	Hidden Markov Model
CNN	:	Convolutional Neural Network
LSTM	:	Long Short Term Memory
SVM	:	Support Vector Machine
WOS	:	Windows Operating System
RAM	:	Random Access Memory
OS	:	Operating System
VLPR	:	Vehicular License Plate Recognition
OCR	:	Optical Character Recognition
BLOB	:	Binary Large Object

CHAPTER 1: INTRODUCTION

1.1 Background

One of the very important topics which have emerged in recent years in intelligent transport systems (ITS) is the vehicular license plate (VLP) recognition system because of its magnificent contribution in real-life transportation applications enormously which apprises the coherent framework by aiming at the extraction of the region which possesses the information of license number of vehicle out of an image or frame sequence of a video. It has emerged as an important and complicated issue of research in recent times as explorations are carried on this issue with regard to the challenges and diversities of license plates (LP) including various illumination and hazardous situations. Automatic vehicular license plate recognition (AVLPR) system gets utilized for detecting vehicles. It provides a reference as well for further vehicle activity analysis and tracking. AVLPR system has become a core methodology because of its wide range of traffic applications along with security ranging from parking automation to vehicle surveillance, electrical tollgate management, restricted area security control, road traffic monitoring, analysis of vehicle activity, tracking for safety and calculating the traffic volume (Rajput, Som, & Kar, 2015; Türkyılmaz & Kaçan, 2017).

AVLPR systems should operate properly or attain real-time performance with relatively less processing time for fulfilling the requirements of ITS, where ‘real-time’ indicates the operational process throughout the image of identifying every desired single object with relatively faster processing. The AVLPR framework is generally comprised of four processing steps (Asif, Chun, Hussain, & Fareed, 2016) such as image acquisition, license plate detection (LPD), the character segmentation and the character recognition whilst LPD has emerged as the most important stage in the AVLPR system since the scheme’s accuracy gets influenced by it (Asif et al., 2016). In the acquisition stage the vehicle image is collected by utilizing cameras. For proper processing of this stage, some features associated with camera such as resolution, camera type, orientation, light, lens, and shutter-speed should be taken into account.

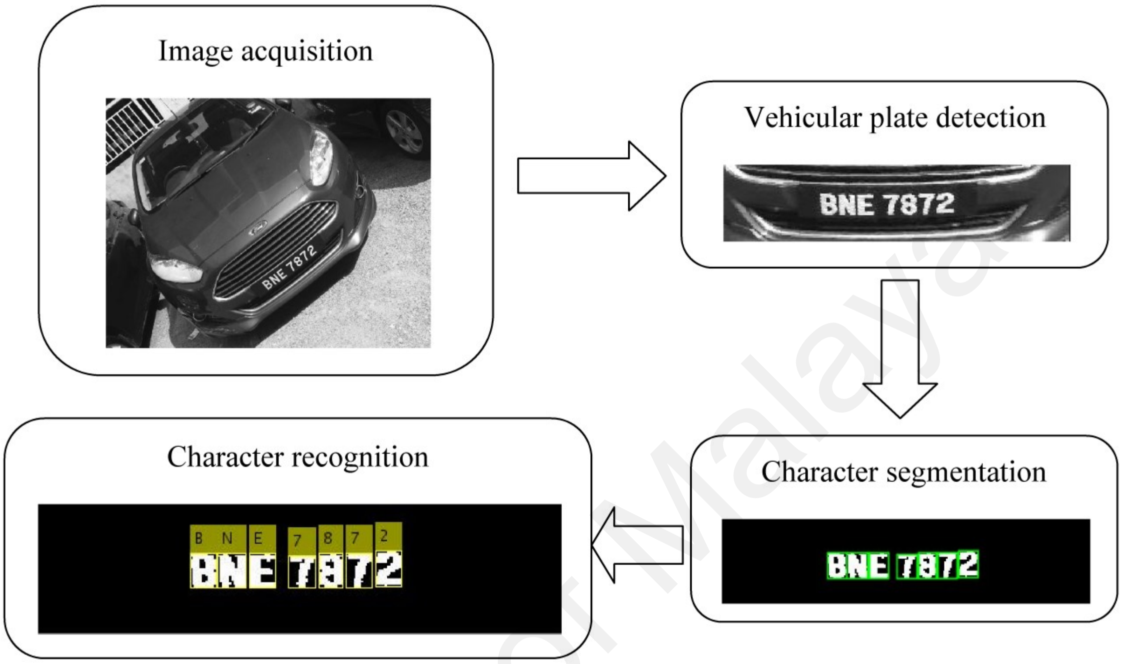


Figure 1.1: General four steps of AVLPR framework

The last three stages are the most crucial for determining the performance of the whole framework. Moreover, because of the parameter diversities involved in the vehicle images, LPD has become the most crucial stage among these steps (Abolghasemi & Ahmadyfard, 2009). There are many critical issues that hamper the stages of the AVLPR framework for which the overall performance of the system may fall. The system performance depends on the individual stage's robustness.

A lot of efforts have already been compiled in order to overcome the problems related with the extraction of potential area of license plate including neural networks (K. K. Kim, Kim, Kim, & Kim, 2000), fuzzy logic (Chang, Chen, Chung, & Chen, 2004), probabilistic approach (Al-Hmouz & Challa, 2010), sliding concentric windows (SCW) (C. N. E. Anagnostopoulos, Anagnostopoulos, Loumos, & Kayafas, 2006) and several other techniques such as Genetic algorithm, Gabor transform and wavelet transform. Normally the license plates possess rectangular shape with specific aspect ratio and edge detection techniques are generally used for detecting the possible rectangles from the image (Du, Ibrahim, Shehata, & Badawy, 2013). Major challenging issues in this field of research are the numerous varieties of vehicle license plates that change with respect to size, color, shape and pattern (Rajput et al., 2015) and skewed vehicular images. In this thesis, the center of attention lies on this issue. Some other important issues have also been taken into account. Various shaped i.e. rectangular, square and sized license plates of bus, truck, car, motor-bikes are taken to consideration. Moreover, crowded backgrounds where there may contain pattern with similarity to plate like other numbers that are stamped on the vehicle, low contrast images are some other obstacles to LPD which have also been taken into account. In many proposed intelligent transportation systems, the AVLPR is generally based on 640×480 resolution image (H.-H. P. Wu, Chen, Wu, & Shen, 2006) where at present the cameras are more sophisticated than previous and high definition license plate image processing (Du et al., 2013) has become another challenge in this research field. In this study, the algorithm can also detect license plates from high resolution (1280×720) images.

1.2 Problem Statement

For recognizing the vehicular license plates many approaches have been proposed by many researchers but the promising scenarios like tracking the number plates from speeding vehicles, skewed vehicle images, blurry and lower resolution images have been addressed in very few researches. Because of low contrast images, crowded background, skewed images and weak edge information the inefficiency in localizing the vehicle number plate area still exists despite the procedures proposed in previous works.

In most of the existing AVLPR systems the number plate text had been assumed to be lying in a plane and in that cases the angles with respect to the optical axis of the sensor are generally normal (Rajput, Som, & Kar, 2016). But in case of skewed images the angular adjustment is the precursor for proper recognition performance.

This thesis work is focused on restricted conditions such as using image of only one vehicle, stationary background, and no angular adjustment of the skewed images. Moreover all the three basic steps which are the license plate detection (LPD), character segmentation and recognition (Choi & Lee, 2017) have been focused in this work. In this work, a polar co-ordinate transformation based procedure has been proposed for the proper adjustment of the skewed vehicular images. A framework has been proposed in this study which consists of five stages (pre-processing, skew correction, candidate localization, character segmentation and recognition) for overcoming the challenges mentioned above. Besides that, window scanning procedure is utilized for the candidate localization that is based on the texture characteristics of the image. Then, connected component analysis (CCA) is implemented to the binary image for character segmentation where the pixels get connected in an eight-point neighborhood process.

1.3 Thesis Objectives

This research work is basically focused on investigating the three basic steps of the AVLPR framework which are:

a. Vehicular plate detection
b. Segmentation of vehicular LP
c. Recognition of the vehicle LP characters

In many existing works, vehicular plate recognition from skewed vehicular images had been ignored. For the case of skewed images; in order to acquire proper recognition performance, the angular adjustment is the precursor. The center of attention of this dissertation lies on this issue.

The objectives of this dissertation are listed as follows:

1. To develop a tilt correction technique for the skewed images within the automatic vehicular license plate recognition (AVLPR) framework.
2. To establish an effective method locating the region of interest (ROI) from various shaped vehicular plate images under various skewed conditions.
3. To develop an effective technique for segmentation of the license plate images for efficient character recognition.

1.4 Outline of the Thesis

This dissertation has been methodized by categorizing the contents into five major chapters. The first chapter introduces the overview of the research work. Second chapter overviews the existing AVLPR research works systematically and the existing procedures have also been categorized in accordance with the individually utilized attributes, convenience and inconveniences. The available recognition performances, platform for each procedure and processing time have also been reported. Some major challenging issues, procedures to cope with the issues including with available performance rates and some suggestions on the topics which should be taken into account have been addressed as well for future aspects. The proposed AVLPR approach for the skewed vehicular images is introduced and then explained in the third chapter. Chapter four shows the experimental results and a relative comparison between some existing methods and the proposed method. Finally, the dissertation has been concluded in chapter five with remarks and future aspects.

CHAPTER 2: LITERATURE REVIEW

AVLPR framework has become a very important methodology for ensuring the security and traffic applications ranging from parking lot access monitoring to vehicle surveillance, road traffic monitoring, vehicular law enforcement, automatic toll collection, calculating vehicle activity analysis, the traffic volume, and tracking for safety.

The existing AVLPR research works have been surveyed in this thesis systematically and the existing procedures have been categorized as well in accordance with the individually utilized attributes, convenience and inconveniences. The available recognition performances, platform for each procedure and processing time have also been reported. Some major challenging issues, procedures to cope with the issues including with available performance rates and some suggestions on the topics which should be taken into account have been addressed as well for future aspects.

2.1 Vehicular Plate Detection

The precision of the vehicular license plate recognition (VLPR) framework is largely influenced by the vehicular plate detection stage. Image acquisition is the basic initial part for this which works as the input data whereas the outcome of this stage involves in determining the region of input image data that attains the correct locus of vehicular license plate (VLP). Vehicular license plates color can be considered as another important attributes because there are some particular color codes for the license plate in accordance with jurisdictions under different states, provinces or countries i.e. according to the vehicular inspection and regulation rules in people's republic of China, the license plate attains rectangular shape consisting seven characters whereas yellow colored plates are maintained by the heavier vehicles and blue colored plates are allotted to the relatively lighter vehicles (Asif et al., 2016). Some other attributes such as texture, license plate region boundary, character existence, combined features etc can be considered in identifying the region of interest. The existing detection methods are categorized according to the utilized attributes as follows:

2.1.1 Texture Attributes

Texture is the changing of color taken place between the background and the consisting characters of the vehicular license plate. The methods based on texture attributes differentiate the momentous shift of grey level that occurs between the background and the consisting characters of the vehicular license plate. Because of this texture transition a region consisting of relatively higher edge density is observed. Various techniques have been implemented in (Parisi, Di Claudio, Lucarelli, &Orlandi, 1998; Seetharaman, Sathyakhala, Vidhya, & Sunder, 2004; Soh, Chun, & Yoon, 1994; H.-k. Xu, Yu, Jiao, & Song, 2005).Due to the shifting in the grey level there arises drastic peaks through the scanned line and this scan line procedure has been implemented in (Soh et al., 1994; H.-k. Xu et al., 2005).

An overall detection rate of 94% has been reported in (Azam& Islam, 2016) by utilizing frequency domain masking integrated with a better contrast enhancement procedure along with statistical process of binarization for vehicular images under various hazardous situations. Recently, a robust procedure of AdaBoost cascades integrated with a three layer local (3L-LBPs) binary pattern classifiers has been implemented in (Al-Shemarry, Li, & Abdulla, 2018) and a relatively higher detection accuracy of 98.56% has been reported. Another procedure of Daubechies wavelet transforms technique that utilizes a discrete single level two dimensional wavelet transform has been utilized in (Rajput, Som, &Kar, 2015) and reported a better detection accuracy of 97.33%.

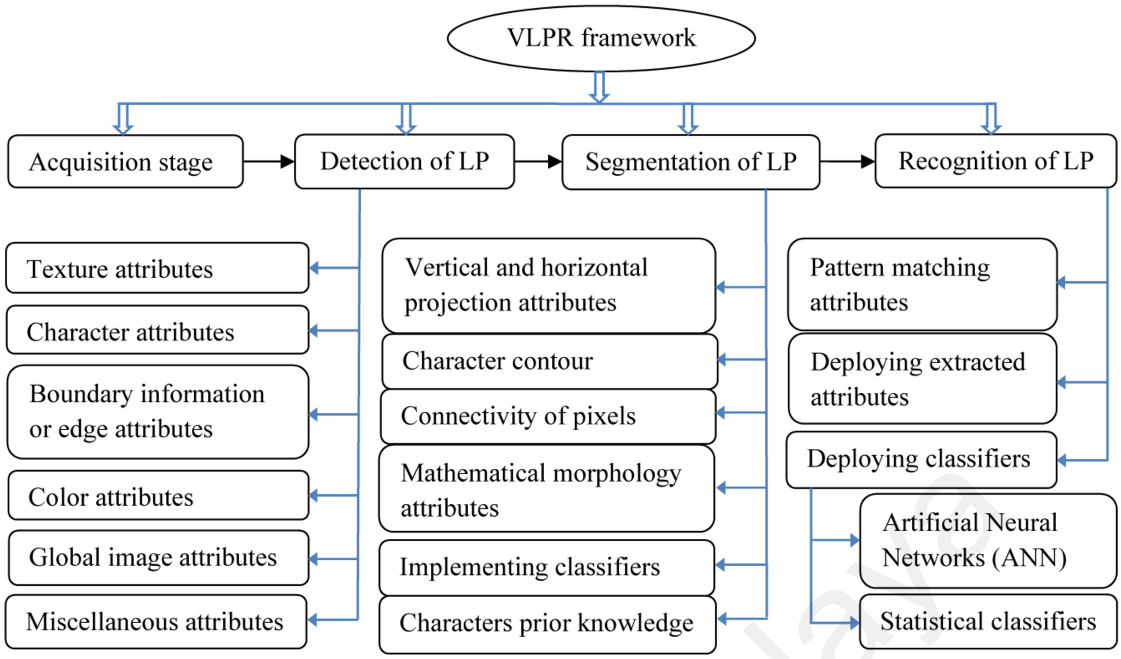


Figure 2.1: Categorization of AVLPR framework by utilized attributes

The procedures based on the texture attributes have an egregious characteristic of extracting the plate region of vehicular image although there is deformed boundary. But for the case of complex background images especially where exists a lot of edges or various illumination situations, these techniques can be found as relatively complex computationally.

2.1.2 Character Attributes

The procedures based on the character attributes have the characteristic of determining the probable plate region by localizing the character positions in the image by scanning the image for finding the character existence and when the character existence is found then the corresponding region gets detected for possessing the probable plate region.

The method of calculating the differences between background region and the character zone along with identification of character-width has been utilized in (Cho, Ryu, Shin, & Jung, 2011) in order to recognize the character region first. Finally the procedure yields a prominent detection rate which is 99.5% through enumerating the inter distances among the characters. The extraction of the characters by an analysis technique based on scale space has been implemented in (Hontani & Koga, 2001) resulting in extracting blob (Binary Large Object) shaped relatively larger sized figures which possess the relatively smaller line shaped figures as the candidate characters. A region based algorithm that involves in searching for the character shaped portions in the images has been used in (Matas & Zimmermann, 2005) in lieu of utilizing the license plate properties directly.

In order to identify the characters properly on the plate image, these techniques need to undergo through binarization process that happens by changing the gray-scale values of the image into binary. Furthermore, these techniques are non-robust for the case of existing extra text characters in the input image other than the desired characters. All the binary objects get processed here which results in much more processing time.

2.1.3 Boundary Information or Edge Attributes

Generally vehicular plates holding license information possess the shape of quadrangles along with particular aspect ratio. As a result the probable candidate region can be detected by scanning for the probable rectangular shapes that exist in the vehicular images. In order to locate this quadrangles or rectangular shapes this boundary information based techniques have been widely utilized in (R. Chen & Luo, 2012; Hongliang & Changping, 2004; Tarabek, 2012; S.-Z. Wang & Lee, 2003). The boundaries of these vehicular plates holding license information can be expressed through the edge density of the image because of the color alteration that take place between the vehicle body and the license plate. Sobel filters have been utilized in (Abolghasemi & Ahmadyfard, 2009; Kamat & Ganesan, 1995; Yang & Ma, 2005a; H. Zhang, Jia, He, & Wu, 2006a; D. Zheng, Zhao, & Wang, 2005) in order to extract this edge information. The process of detecting this edge horizontally results in identifying the dual horizontal lines whereas the detection technique of this edge vertically results in identifying the dual vertical lines. As a result the probable candidate quadrangles get detected after both of the edges had been detected simultaneously. A novel approach of VEDA (Vertical Edge detection Algorithm) has been proposed in (Al-Ghaili, Mashohor, Ramli, & Ismail, 2013) because of the extraction of this plate region. The procedure of implementing this VEDA has been noticed with a significant less processing time about 5 to 9 times less than the existing procedures that have implemented the Sobel operators. Another procedure of localizing the lines that forms quadrangles has been utilized implemented with geometrical attributes in order to detect the probable quadrangles of vehicular plate in (Babu & Nallaperumal, 2008).

Table 2.1: A relative comparison of the boundary information or edge-based procedures

Boundary information or edge detection algorithms	**References**	**Accuracy (%)**
Sobel vertical	(D. Zheng et al., 2005)	99.9
Robert and Rank	(M.-K. Wu, Wei, Shih, & Ho, 2009)	90.0
VEDA	(Al-Ghaili et al., 2013)	91.4
Sobel	(H. Zhang et al., 2006a)	96.4
Prewitt	(R. Chen & Luo, 2012)	96.75
Edge mapping & smoothing filter	(Bai, Zhu, & Liu, 2003)	96.0
Sobel vertical	(Yang & Ma, 2005a)	97.78
VEDA	(Dev, 2015)	96.0
Edge mapping & edge statistical analysis	(Hongliang & Changping, 2004)	99.6
Prewitt	(R.-C. Lee & Hung, 2013)	95.33

Another procedure based on boundary line integrated with the HT method with a contour algorithm has been introduced in (Duan, Du, Phuoc, & Hoang, 2005) results in a better accuracy of 98.8% detection rate. This edge based procedures are relatively simpler in accordance with other techniques to implement with faster processing time. A relative comparison of the edge-based algorithms has been depicted in the Table 2.1.

2.1.4 Color Attributes

Vehicular license plates color has been considered as one of the very important attributes because there are some particular color codes for the license plate in accordance with jurisdictions under different states, provinces or countries. Therefore, some methodologies which have been reported here involve in locating the color features in order to localize the probable plate region from image. The color combination between the characters and the vehicular plates is a unique feature whereas this color combination takes place especially in the candidate plate region. A detection technique has been implemented in (Shi, Zhao, & Shen, 2005) based on this basic concept. According to the vehicular inspection and regulation rules in People's Republic of China, the license plate attains rectangular shape consisting seven characters whereas yellow colored plates are maintained by the heavier vehicles and blue colored plates are allotted to the relatively lighter vehicles. In accordance with this plate format, a technique has been utilized here where the input image pixels get classified into thirteen categories through utilizing the HLS (Hue, Lightness, and Saturation) color model.

An HSV (hue, Saturation, and value) color space procedure integrated with fuzzy logic has been introduced in (F. Wang et al., 2008) in order to eliminate the difficulties associated with the images from different illumination situations. One of the remarkable conveniences of the vehicular plate detection procedures based on the color attributes lies in possessing the opportunity of detecting candidate plate regions notwithstanding the deformed and inclined positions including some difficulties although. In case of various illumination situations of the input images especially, the classification of the pixel color information utilizing the RGB basis becomes to be difficult. On the other hand, another method that is utilized to be the alternative color space technique, the HLS, has much sensitivity to the noise. Moreover, for some special cases whereas some part of input image possesses the exact color that of the candidate plate region, the procedures that are based on color projection become non-robust for wrong detection.

2.1.5 Global Image Attributes

CCA (Connected Component Analysis) is an image processing application in which the image is scanned first and the corresponding pixels are then labeled into components in accordance with the pixel connectivity(Wen et al., 2011). For the processing of the binary images this CCA integrated technique has been implemented as one of the significant methodologies (C.-N. E. Anagnostopoulos, Anagnostopoulos, Psoroulas, Loumos, & Kayafas, 2008; Qin, Shi, Xu, & Fu, 2006; B.-F. Wu, Lin, & Chiu, 2007).

For tracking out the connected objects, in (Chacon & Zimmerman, 2003) an algorithm has been implemented through utilizing the contour detection. The objects that get selected to be the desired candidate within these connected objects possess the identical geometrical attributes as that of the vehicular plate. On the other hand because of using images having bad qualities, this algorithm might end in distorted contours resulting in failure. Some other parameters like spatial measurements; for instance, aspect ratio and area are also widely utilized in (Bellas, Chai, Dwyer, & Linzmeier, 2006; H.-H. P. Wu et al., 2006) in case of tracking out this desired plate candidate.

Another procedure of connected component labeling integrated with Euler number computation has been introduced in (He & Chao, 2015). These two functions are simultaneously performed over the image in order to identify the position of hole first in binary image during the scanning of connected component labeling. From binary images, the connected component number, number of holes, the Euler number gets enumerated efficiently for different types of images and the outcome proves this algorithm to be much more proficient than conventional procedures for simultaneous labeling of connected components and the Euler number computation.

2.1.6 Miscellaneous Attributes

To strengthen the rate of detection of vehicular plates, miscellaneous attributes have been implemented by few procedures. These are the hybrid methods for the detection of vehicular license plates. A hybrid procedure with combined color information and edge attributes has been implemented in (M.-L. Wang, Liu, Liao, Lin, & Horng, 2010) for the desired plate candidate detection. The pixel values of those regions, having higher edge densities and which are identical to the plate get considered to be the probable candidate region. In order to detect the required edges from the image, a wavelet transform technique has been utilized here. For analyzing the correct structures and shapes of the image, the image morphology was utilized after the edges had been detected resulting in transforming the method to be more robust for localizing the desired candidate region. Another hybrid procedure with combined color information and texture attributes has been implemented in (K. K. Kim et al., 2000; Park, Kim, Jung, & Kim, 1999; Ter Brugge, Stevens, Nijhuis, & Spaanenburg, 1998; Xu, Li, & Yu, 2004). In (Z.-X. Chen, Liu, Chang, & Wang, 2009), the quadrangular shape attribute combined with color information and texture features has been implemented in order to track the plate region. A better rate of detection (97.3%) of images under different illumination situations has been reported for 1176 vehicular images captured from different scenes. For detecting both of the color attributes and the texture attributes, double neural networks integrated method has been utilized in (Ter Brugge et al., 1998). Through utilizing the edge numbers within the plate region, these two networks get trained in order to detect the color attribute and the texture as well. For detecting the desired candidate region, both of the neural networks outcomes are combined together.

Table 2.2: Relative comparison of existing detection methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy (%)
Texture attributes	Capable of detecting deformed boundaries for utilizing LP's frequent colour transitions.	Higher processing time and processing complexity for multiple edges.	(H. Zhang, Jia, He, & Wu, 2006b)(S.-Z. Wang & Lee, 2007)	93.5 99.0
Character attributes	Robustness even in rotation for utilizing LP characters.	Higher processing time as processes all binary objects. Error happens if image possesses other text.	(Cho et al., 2011) (Draghici, 1997)	99.5 99.0
Boundary information or edge attributes	Relatively faster and simpler for implementing the rectangular boundary attributes for LP.	Sensitivity to the unwanted edges. Error occurs for complex images.	(Duan, Du, Phuoc, & Hoang, 2005)(R. Chen & Luo, 2012)	98.8 96.75
Color attributes	Capable of detecting LPs containing deformities and skew	HLS model has noise sensitivity, limitation of RGB due to illumination situations.	(Chang et al., 2004) (Jia, Zhang, He, & Piccardi, 2005)	98.0 95.6
Global image attributes	Independent of LP position, Straightforward approach.	Sometimes broken objects might be generated.	(H.-H. P. Wu et al., 2006) (B.-F. Wu et al., 2007)	96.62 96.6
Miscellaneous attributes	Robust and reliable because combined implementation increases effectiveness.	Not cost effective as computationally complex approach.	(Z.-X. Chen et al., 2009)	97.3

2.1.7 Discussion

The most substantial stage of the total framework is the vehicular plate detection stage because without correct detection the identification of vehicular plate number is not possible (Asif et al., 2016). For this reason if each pixel of the input image are processed then it would be much more time consuming. Therefore, if the image is processed by utilizing few salient attributes then it would be easier to detect the correct locus of vehicular license plate resulting in decreasing the processing time as well. This attributes can be brought out by the constituting characters, vehicle plate's color, shape and format. Other attributes such as texture, license plate region boundary, character existence, combined features etc. might be considered in identifying the region of interest as well. Based on the utilized attributes the existing detection procedures have been classified here in chapter 2. The methodology, conveniences, inconveniences of the each class of attribute has been discussed in a nutshell in the Table 2.2.

2.2 Segmentation of Vehicular LP

Segmentation has become one of the very important topics recently in image processing field which involves in finding the meaningful, necessary information through processing an image properly whereas the meaningful desired region contains higher order of desired data. Because of extracting the desired characters from the detected vehicular plate for recognition, the isolated vehicular LP image needs to be segmented. But in the previous processes, the detected vehicular LP might possess some complications like non-uniform brightness, angular skew of the LP vertically or horizontally. Before stepping into this segmentation stage, all this complications need to be solved through implementing proper pre-processing techniques for better extraction of the desired characters.

Many researchers have proposed many techniques for tilt adjustment of the vehicular plate images for better character segmentation. For correcting the horizontal skew of the vehicular plate a line fitting procedure has been implemented in (Deb, Vavilin, Kim, Kim, & Jo, 2010) whereas this line fitting is integrated with orthogonal offsets including least square fitting. On the other hand for adjusting the vertical tilt, the variances of the projection point's co-ordinate values have been reduced. The character points have been projected after shear transform along with a vertically orientation and the segmentation of the desired characters have been accomplished after the horizontal tilt adjustment. Another procedure where the co-ordinates of the plate characters have been oriented in accordance with the Karhunen-Loeve transform into two dimensional covariance matrices, has been implemented in (M.-S. Pan, Xiong, & Yan, 2009). As a result the rotation angle α along with the eigenvector gets enumerated. After that skew adjustment in the horizontal direction gets accomplished. Finally for the skew adjustment in the vertical direction, another combined process is implemented. Because of enumerating the vertical skew angle θ, three procedures K-L transformation technique, based on the least squares a line fitting process and based on the K-means clustering another line fitting process gets combined.

Another procedure of tilt adjustment based on the Radon transformation, has been introduced in (Rajput et al., 2016) where the image intensities are projected along the radial line that is oriented at a particular rotation angle for plate recognition at the odd angles. According to a horizontal scale, the image gets rotated after the orientation angle had been determined through the algorithm. Finally the rotational noise is reduced by utilizing median filtering resulting in a relatively better performance including 98% accuracy rate for about 1110 vehicular plate images under different environmental situations.

Figure 2.2: Plate images of noisy, after global and adaptive thresholding from left to right (B. R. Lee, Park, Kang, Kim, & Kim, 2004)

A modified local binarization procedure of determining threshold values for individual character regions has been implemented in (B. R. Lee, Park, Kang, Kim, & Kim, 2004). For finding out the missing or split characters the pixel accumulating histogram analysis for individual character regions has been performed horizontally. For this reason, the region gets partitioned into two sub-regions and for these new regions the threshold values are re-designated. Comparing to the local binarization procedures, a 5% enhancement has been reported here. The binarization outcome after implementing global thresholds and adaptive thresholds are depicted in the Figure 2.2 as above.

There have been some more complicacies in case of segmenting the characters. In some cases the vehicular plate might possess frame that is surrounded with it which results in causing complexities for segmenting the candidate characters. As a result the frame gets attached to the candidate characters after binarizing the image. Before binarizing the image, the quality of the image should be improved. This will play as an important precursor for selecting an appropriate threshold value. There have been a number of popular procedures which had been implemented for improving the quality of the vehicular license plate images. Contrast enhancement procedures, histogram equalization, removal of noise have been utilized for the enhancement of the quality of the vehicular license plate image. Some other attributes such as projection profiles, utilizing character contours, the connectivity among the pixels, utilizing characters preceding conditions and assembled attributes have been considered in the segmentation of the meaningful desired region containing higher order of desired data. The existing segmentation methods are categorized according to the utilized attributes as follows.

2.2.1 Vertical and Horizontal Projection Attributes

After implementing binarization process, in the binary output image the binary values become inverse for the license plate characters and the plate backgrounds because the backgrounds and the characters possess different colors. In order to segment these characters, vertical and horizontal projection based techniques have been widely utilized in (Huang, Chen, Chang, & Sandnes, 2009; Rajput et al., 2015; L. Zheng, He, Samali, & Yang, 2010).In order to identify the opening points and the finishing points of the characters, the binary output of the extracted desired plate region gets projected vertically first. After that the detected vehicular license plate gets projected in the horizontal direction because of extracting the individual characters. Sometimes the binary output of the plate images are not utilized in case of segmentation, rather the color information of the characters is used. The color information of characters based projection procedure has been utilized in (E. R. Lee, Kim, & Kim, 1994; C. A. Rahman, W. M. Badawy, & A. Radmanesh, 2003b) rather than the binary plate images. Another character extraction procedure based on the vertical projection technique integrated with character sequence exploration and noise removal processes has been implemented in (S. Zhang, Ye, & Zhang, 2004). A relatively better performance including 99.2% accuracy rate along with processing time of ten to twenty milliseconds has been reported after processing above of thirty thousand images.

One of the important advantages of this projection attribute based method is that the character extraction process does not depend on the character positions and also functional for the little tilted vehicular license plate images. Overall, this procedure based on the exploitation of character pixels through horizontal and vertical projection scheme is relatively simpler and widely implemented.

2.2.2 Character Contour Attributes

For segmenting the characters of the license plate images this character contour feature is implemented as well. An active contour process integrated with shape driven feature has been utilized in (Capar & Gokmen, 2006) which implements alternative matching algorithm that is relatively faster. This procedure operates based on two stages. First of all, a relatively faster and simpler matching algorithm (Sethian, 1996) which is integrated with a speed function (Stec & Domanski, 2003) that is curvature dependent and gradient dependent has been implemented in order to track out the rough locations of the individual characters. After that a particular marching procedure which is relatively faster and dependent on the shape similarity, curvature and gradient information gets implemented resulting in the extraction of the exact boundaries. Figure 2.3 illustrates sample of broken characters initially and the merged segmented final outcomes as follows:

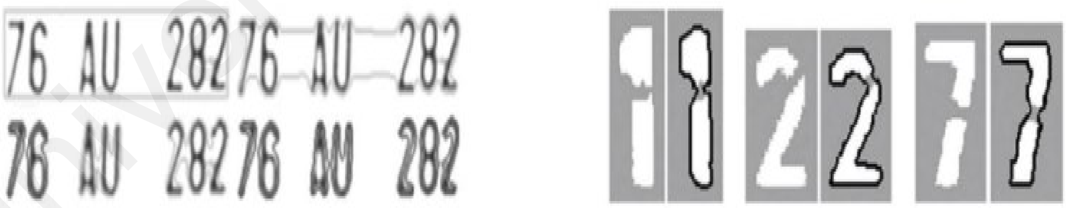


Figure 2.3: The sequence of segmentation & merging of the initially broken characters from left to right (C.-N. E. Anagnostopoulos et al., 2008)

2.2.3 Connectivity of Pixels

The attribute of connectivity of pixels has also been implemented for segmenting the characters of the license plate images. Vehicular plate images are processed through binarization process. After that from these binary vehicular plate images the connectivity of pixels gets explored and labeled. Based on this labeled connected pixels the segmentation procedure of characters has been carried through (Chang et al., 2004; Panahi & Gholampour, 2017; B.-F. Wu et al., 2007). After analyzing the labeled pixels, the aspect ratio and sizes of the characters are then explored. The characters possessing identical aspect ratio and size get finalized to be the expected vehicular license plate characters. These techniques based on connectivity of pixels have some conveniences such as straightforwardness, robustness to the rotation of the vehicular number plates and simplicity. But in case of the broken and joined characters, this procedure lapses in extracting all the characters.

2.2.4 Mathematical Morphology Attributes

For segmenting the characters of the license plate images proficiently, this mathematical morphology feature is implemented as well (Agarwal & Goswami, 2016). A thoroughly dedicated character segmentation procedure has been implemented in (Nomura, Yamanaka, Katai, Kawakami, & Shiose, 2005) which is based on an adaptive segmentation technique integrated with morphological processing. This technique emphasizes on the vehicular plate images with severe degradation. The fragments get detected by histogram projection based algorithm and after that the fragments get merged. Identification of noise gets accomplished by performing morphological thinning and morphological thickening operation on the binary image. The baseline is determined for the segmentation of connected characters through segmentation cost enumeration and morphological thinning algorithm. The overlapped characters get separated by locating the reference lines through the morphological thickening algorithm (Soille, 2013). The system results in segmenting the total character contents of 1005 degraded plate samples accurately out of a test sample of 1189 degraded vehicular plate images.

A novel dynamic programming (DP) based procedure has been introduced in (D.-J. Kang, 2009) for the segmentation of the main four (numeric) characters on the license plate image. The functionality of the procedure gets optimized through describing the threshold difference, the character alignments, and the interval distributions among the characters which has been utilized for extracting the character blobs. This DP algorithm based procedure operates relatively faster because of implementing the bottom-up approach. As a result by implementing the energy minimization scheme for the geometric configurations of the numeric characters that are located successively, this method can detect the plate numbers rapidly. The procedure has been reported as robust because this technique focuses on the minimization of utilizing the color and edge attributes which are environment dependent since by utilizing color features the system suffers failure for tracking the plate character location in case of the possession of similar colors between the vehicle body and the license plate. As a result the method has less impact of environmental situations, color and lighting variations on character extraction performance for utilizing gray-scaled images. A relatively better performance including 97.14% detection accuracy rate for the main four (numeric) characters has been reported.

2.2.5 Implementing Classifiers

In order to segment the characters of the vehicular license plate images proficiently, this classifiers are implemented as well. A character segmentation procedure for the low-resolution and noisy vehicular plate images based on the Hidden Markov Chains (HMC) integrated with estimation of the maximum a posteriori (MAP) has been implemented in (Franc & Hlavác, 2005). For modeling the stochastic pattern between the segmentation of characters and the input images HMC has been deployed. The segmentation problem has been revealed here as maximizing a posteriori calculation from an admissible segmentation set. The procedure has been reported to be capable of

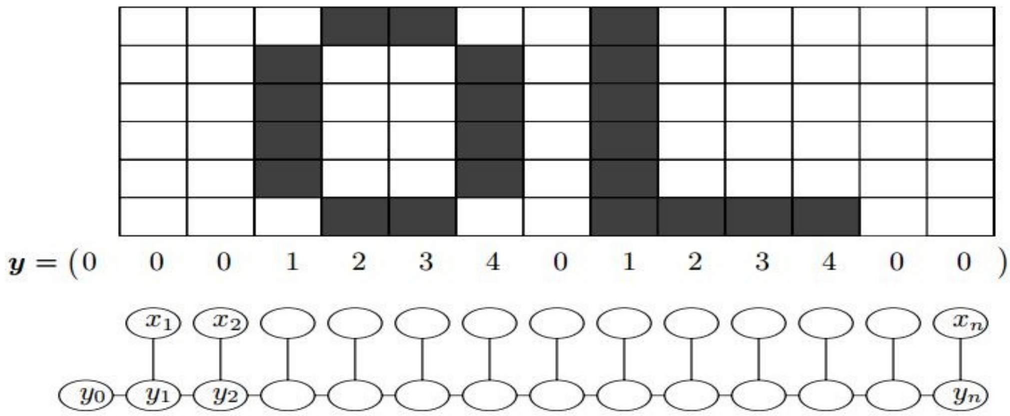


Figure 2.4: Hidden Markov Chain (HMC) model for license plate image alignment (Franc & Hlavác, 2005)

segmenting the characters of Czech Republic license plates correctly in spite of possessing very poor quality. The proposed algorithm has been executed on the set of 1000 image samples which were collected from an LPR system with real-life capture along with 3.3% error rate.

Apart from some existing single frame procedures, a simultaneous implementation of temporal and spatial information has been deployed by (Cui & Huang, 1998) integrated with the Markov random field (MRF) for segmenting the vehicular license plate characters from video sequences. MRF has been implemented for modeling the character extraction firstly and later for characterizing the uncertainty of pixel labeling the randomness attribute has been utilized. For incorporating the prior relevant constraints or information quantitatively the MRF modeling has been utilized. Finally, in order to enhance the convergence on the basis of (Rudolph, 1994) and for the optimization of the objective function a local greedy based mutation function integrated with Genetic Algorithm (GA) has been implemented.

2.2.6 Characters Prior Knowledge

The attribute of prior knowledge of the characters has been implemented as well for segmenting the characters of the license plate images. A procedure based on the color collocation scheme has been implemented in (Gao, Wang, & Xie, 2007) for locating the vehicular number plates from the images. This technique emphasizes on providing a solution for the vehicular plate images with severe degradation. For segmenting the characters, the dimensional prior knowledge of individual character has been utilized here. Finally for recognition of the characters a classifier has been constructed by utilizing the Chinese vehicular license plate layouts.

Another approach of segmenting the characters utilizing the information of known template sizes has been implemented in (Paliy, Turchenko, Koval, Sachenko, & Markowsky, 2004) where the extracted vehicular license plate gets resized according to this template size. All these character positions in this template are predetermined. The identical positions are then extracted to be finalized as the expected characters after resizing. This procedure possesses the convenience of relatively simpler implementation. The major drawback of this procedure occurs when the extracted vehicular license plates experience any shifting. This method fails in extracting the expected characters for this reason and the background gets extracted rather.

A hybrid binarization based procedure integrated with Hough transform method after horizontal scan line analysis on the vehicular license plate images has been implemented in (Guo & Liu, 2008) in order to cope with the dirt and rotation problems

Figure 2.5: HT method for skew correction from left to right (Guo & Liu, 2008)

because the character segmentation performance gets influenced basically by these two factors. For the corrective adjustment of the rotation problem of the vehicular plate images, the Hough transform technique has been utilized.

There are some particular color codes for the license plate in accordance with jurisdictions under different states, provinces or countries i.e. according to the vehicular inspection and regulation rules in Taiwan the background color of the license plate is white containing black characters. For solving the problems associated with dirty number plates, the hybrid binarization with feedback self-learning has been deployed.

For the 332 vehicular images with different illumination situations, an overall localization rate of 97.1% and character segmentation rate of 96.4% have been reported for this procedure. Another approach of segmenting the characters utilizing the horizontal scan line process has been deployed by (Busch, Domer, Freytag, & Ziegler, 1998) for searching the characters start point and end point. The property of pixel ratio between the characters and the background in this line is utilized for this purpose. The selection of the characters end point occurs when this ratio crosses a particular threshold value after being higher than this threshold and the start point occurs when this ratio crosses a particular threshold value after being smaller than this threshold.

2.2.7 Discussion

The proper segmentation rate has a great impact on the next stage i.e. recognition of the characters because majority of the recognition errors in vehicular license plate recognition (VLPR) framework happen due to the segmentation errors rather than because of the missing recognition power. As a result for ensuring the better segmentation performance some complications associated with the detected LP image like non-uniform brightness, angular skew of the LP vertically or horizontally, unpredictable shadows, physical damage, dirt problem need to be properly treated.

Based on the utilized attributes the existing segmentation procedures have been classified here. The methodology, conveniences, inconveniences of the each class of attribute has been discussed in a nutshell in the Table 2.3 as follows:

Table 2.3: Relative comparison of existing segmentation methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy (%)
Vertical & horizontal projection attributes	Character position independent and robust in slightly rotation.	Vertically & horizontally projected values might get affected by noise, character dimension related prior knowledge is required.	(S. Zhang et al., 2004) (Rajput et al., 2015)	99.2 95.93
Character contour attributes	Extraction of exact boundaries of the characters is possible.	Distorted, imperfect and partial contour dimensions might get produced and will slow down the performance.	(Kanayama, Fujikawa, Fujimoto, & Horino, 1991) (L. Zheng et al., 2010)	90.0 91.0
Connectivity of pixels	Robustness for the LPs having skew, relatively simple procedure.	In case of broken or mutually joined characters, the character extraction may lapse.	(Chang et al., 2004) (Yoon, Ban, Yoon, & Kim, 2011)	93.7 97.2
Mathematical morphology	More robust and reliable due to combined morphology.	Higher processing time for computational complexity.	(Kang, 2009) (Nomura et al., 2005)	97.14 84.5
Implementing classifiers	Real-time application, advanced and robust computational intelligence architecture.	Error might occur for broken or mutually joined characters, computational complexity.	(Franc & Hlavác, 2005) (Cui & Huang, 1998)	96.7 -
Characters prior knowledge	Relatively simpler and straightforward procedure.	Limited implementation depending on the prior knowledge and error might occur in case of any alteration.	(Guo & Liu, 2008) (Busch, Domer, Freytag, & Ziegler, 1998)	96.4 99.2

2.3 Recognition of Vehicular LP Characters

In the vehicular license plate recognition (VLPR) framework, in which stage the extracted characters get identified by means of showing the expected plate numbers of the input vehicular LP images as the output is called the character recognition stage. This stage plays a very significant role in VLPR framework in identifying the number of the LP.

In many cases the extracted vehicular plate characters differ from being uniform thickness(Miyamoto, Nagano, Tamagawa, Fujita, & Yamamoto, 1991) and size with regard to the zoom factor of the camera. In order to get over this hindrance before recognition the extracted characters needs to be resized into one identical size. Moreover, the font size of the characters varies from country to country because different countries have their own font sizes. As a result the characters' font does not remain identical all the time. On the other hand the extracted characters might possess some noise or the characters might be broken. These extracted characters might be tilted as well (Miyamoto et al., 1991). Sometimes the LP might possess unwanted information i.e. it might possess colors or pictures which never provide any meaningful information with regard to identify the number of the LP. This type of images needs to be processed for normalization and reduction of noise first (Jin et al., 2012).

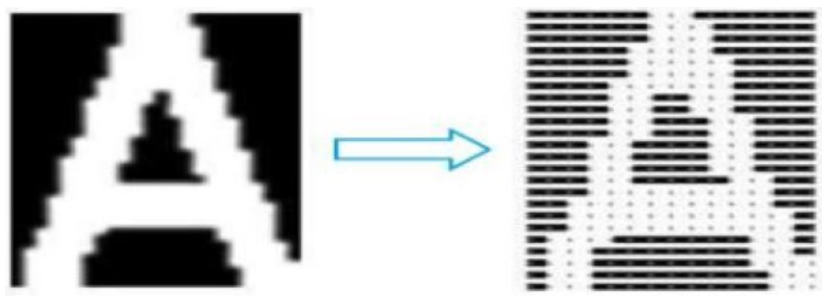


Figure 2.6: Digitization of image character (Ibrahim et al., 2014)

After that is the digitization procedure. In this image digitization procedure the individual characters get converted into a binary matrix according to specified dimensions whereas the similarity of dimensions between the saved patterns from the database and the input gets ensured through this procedure. For an instance, in the Figure 2.6, the alphabetical character ‘A’ gets digitized into 360 (=24×15) binary matrix, whereas each possesses either white or black colored pixel (Zakaria & Suandi, 2010). Converting the data into necessary meaningful information is very important. For this reason a binary function of image could be implemented whereas for every white pixels, the binary value 1 (foreground) gets assigned and for every black pixels, the binary value 0 gets assigned as the background as well (Asthana, Sharma, & Singh, 2011).

For recognizing the segmented vehicular LP characters various algorithms utilize pattern matching architectures using raw data, computational intelligence techniques, statistical or hybrid classifiers, extracted features. The existing methods on recognition of vehicular LP characters are categorized according to the utilized attributes as follows:

2.3.1 Pattern Matching Attributes

This pattern matching or template matching procedure is a straightforward and relatively simpler technique in this recognition of vehicular LP characters (C. A. Rahman, W. Badawy, & A. Radmanesh, 2003a; Sarfraz, Ahmed, & Ghazi, 2003). This template matching procedure is competent for recognizing the vehicular LP characters having non-rotating, fixed size, non-broken and single font characteristics. This template matching procedure generates incorrect output in case of any rotation, noise or font change and the characters differ from the templates (M.-S. Pan, Yan, & Xiao, 2008). The measurement of the uniformity between the template and a character gets analyzed in this procedure. In spite of being utilized in binary images preferably, this procedure can possess better performance for the grey-scaled images as well if the templates are built properly (C.-N. E. Anagnostopoulos et al., 2008). Majority of these pattern matching procedures utilize the binary images because if there is any alteration in the illumination situations, the grey-scaled images get changed as well (M.-S. Pan et al., 2008).

A pattern matching procedure based on the enumeration of the root mean square (RMS) error has been implemented successfully in (Huang, Lai, & Chuang, 2004) where the RMS error has been enumerated through every shift of template g over the $(M \times N)$ sized sub-image f. Sometimes there might some complications like tilted characters.

Another pattern matching procedure integrated with normalization of cross correlation has been incorporated in (Xiaobo, Xiaojing, & Wei, 2003) where the matching of the extracted characters along with the templates has been conducted through utilizing this cross correlation property. For calculating this normalized cross-correlation, the characters have been scanned column by column by each template. The most expected template is the one which possess the maximum value along with the most uniformity. In (Rajput et al., 2015), the template or pattern matching algorithm deploys the statistical correlation based procedure for calculating the correlation coefficient where a database of 36 alphanumeric templates having (38×20) block size has been utilized. The extracted characters got normalized first and the characters were refined into a block having no other additional white pixels (spaces) in the border after that.

2.3.2 Deploying Extracted Attributes

All of the pixels from a character do not possess the same significance in order to distinguish the character. As a result the feature extraction procedure in which some of the character attributes get extracted plays a relatively better role than the template matching technique for the grey-level images (Rahman et al., 2003b). It also requires less processing time than the template matching procedures since all the pixels are not being processed in this technique. For measuring the uniformity a feature vector gets formed by the extracted features where the pre-stored feature vectors get compared with this feature vector. This attribute can conquer the limitations of the template matching procedures if the extracted features are enough robust in distinguishing the characters in case of distortion (M.-S. Pan et al., 2008). A recognition procedure based on the feature vector integrated with normalization of the binary characters has been implemented in (Aghdasi & Ndungo, 2004) where a block sized (3×3) pixels has been deployed in order to divide the each binary character. After that the black pixels get enumerated for every character block. Another technique based on this feature vector has been implemented in (M.-K. Kim & Kwon, 1996) where the character contour has been sampled all around for generating the feature vector. The feature vector is extracted finally after quantizing the achieved waveform. There is no impact of character size or font change on this procedure because the character contour which has been implemented here is independent of font or size variation. As a result this procedure is capable of recognizing different sized and multi-font characters. Another technique based on this feature vector has been implemented in (Dia, Zheng, Zhang, & Xuan, 1988; Rahman et al., 2003a) where the binary character has been projected vertically and horizontally for generating the feature vector. The feature vector is extracted in (Dia et al., 1988) after quantizing the projection into four levels.

2.3.3 Deploying Classifiers

For recognizing the segmented characters of the license plate images proficiently classifiers are deployed after extracting the features. Artificial Neural Networks (ANN), statistical classifiers have been implemented in recognition procedure.

2.3.3.1 Artificial neural networks (ANN)

A single artificial neuron/node (shown in Figure 2.7) itself is capable of performing certain information processing. However, multiple nodes are required to be connected with each other in order to form a network of artificial neurons or nodes for performing more powerful computations and complex tasks. Among different architectures of ANN, the multi-layer feedforward network has been implemented in a number of researches (Broumandnia & Fathy, 2005; Oz & Ercal, 2005; Türkyılmaz & Kaçan, 2017) for the identification of the vehicular LP characters. For achieving good performances the network needs to be trained by several training cycles. After trial and error processing (Haykin, 2001) the respective neuron numbers along with the hidden layer numbers need to be defined.

For recognizing the alphanumeric 36 characters from Latin alphabet, a neural network architecture integrated with multi-layer perceptron has been implemented in (Nijhuis et al., 1995; TerBrugge et al., 1998) including with training set of 24 input neurons, 15 hidden neurons and 36 output neurons. For processing the classification in

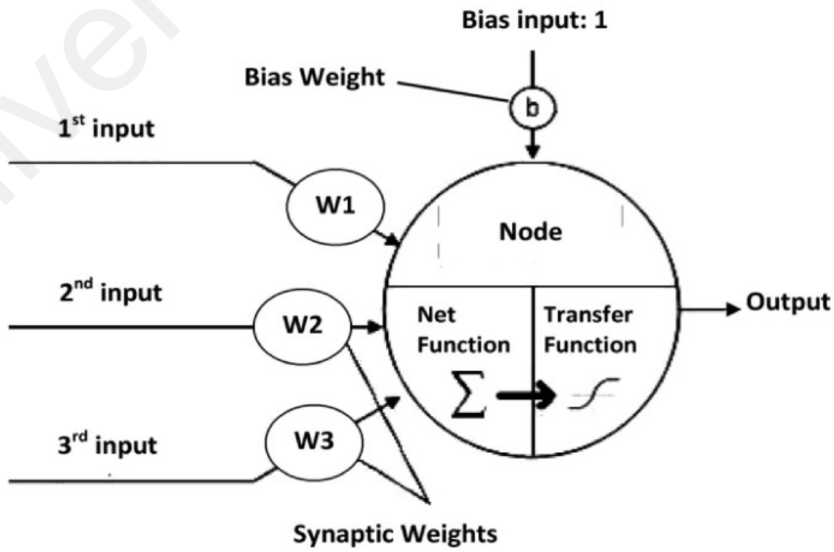


Figure 2.7: Illustration of a node or artificial neurons in ANN

(Nijhuis et al., 1995) the 24 input neurons had been fed with the previously extracted 24 features. For recognizing the segmented vehicular LP characters, the system had been applied to a large data set including 10,000 images and an excellent output of 98.5% recognition rate had been reported.

Another procedure utilizing the three layered feed-forward ANN integrated with the back-propagation learning algorithm has been implemented in (Türkyılmaz & Kaçan, 2017) for recognizing the segmented characters of the license plate images proficiently. Before this the segmented LP characters had been processed through the thinning procedure for better character recognition system. 600 neurons have been utilized in the input layer and 33 neurons have been utilized in the output layer.

For optimal performance, the neuron number in the hidden layer should be two third of the neuron number of input layer plus the neuron number in the output layer; had been reported. As a result 300 neurons have been utilized in the hidden layer. A relatively better recognition rate of 96.92% had been reported.

A new algorithm implementing PNN (Probabilistic Neural Network) for the VLPR framework had been introduced in (C Anagnostopoulos, Kayafas, & Loumos, 2000) where dual PNN systems had been utilized for recognizing the alphabets and the numbers separately. This PNN based architectures are relatively faster for getting trained and designed because the neurons of the hidden layer gets defined by the training pattern numbers and only once gets trained (Bishop, 1995).Another algorithm implementing PNN integrated with Column Sum Vector (CSV) enumerations has been developed in (Öztürk & Özen, 2012) for recognizing the vehicular plates under different illumination situations distance and tilt conditions where a relatively better recognition rate of 96.5% had been reported. Recently, deep learning based applications are being employed for solving computer vision problems. For solving VLPR problems, RNN

(Recurrent Neural Network) have been exploited. An LSTM (Long Short Term Memory) based RNN structure has been implemented in (Li & Shen, 2016) for the character identification in terms of sequence labeling after the LP's sequential features had been extracted by implementing a 37-class CNN (Convolutional Neural Network). Another RNN model integrated with CNN has been utilized in (Cheang, Chong, & Tay, 2017) overcoming the limitations associated with sliding window techniques. The end to end training on the labeled LP images is possible in CNN structure whereas a training data of the pre-segmented characters is required by sliding window approaches. Both of the methods have been reported as segmentation free and hence capable of avoiding segmentation associated errors.

2.3.3.2 Statistical classifiers

After the character segmentation stage the extracted region of interests are processed under a parameterization and preprocessing technique before implementing the Hidden Markov Model (HMM). It had been defined as one of dual stochastic process which is observable indirectly (hidden) whereas it can be observed only by some other set of stochastic systems which produce the observed character sequence (Aas, Eikvil, & Andersen, 1995; Blunsom, 2004). Generally, two major approaches are utilized for constructing the HMM for character recognition where one is implemented for every character and another is for every word (Aas et al., 1995). The convenience of this procedure is that this technique is capable of learning the differences and the uniformities between the LP image samples. The probabilities or the parameters in HMM process had been trained by utilizing the observation vector that had been extracted from the vehicular LP image samples(Daramola et al., 2011). Another procedure utilizing the HMM integrated with a complex parameterization and preprocessing technique has been implemented in (Llorens, Marzal, Palazón, & Vilar, 2005)for recognizing the characters of the LP images with a relatively better recognition result of 95.7%.

A character recognition technique based on the Support Vector Machine (SVM) has been implemented for Korean LP images in (K. K. Kim et al., 2000). Four character recognizers based on SVM had been implemented for recognizing the upper numerals and upper characters, lower numerals and lower characters on the LP. Another SVM based technique integrated with fuzzy logic has been implemented in (Samma, Lim, Saleh, & Suandi, 2016) for the Malaysian LPs. The feature selection, tuning and training of fuzzy SVM parameters had been performed by implementing an MPSO (Memetic Particle Swarm Optimization) algorithm. Another dual staged hybrid recognition method combined with structural and statistical recognition process for attaining higher recognition rate and robustness has been implemented in (X. Pan, Ye, & Zhang, 2005) where four statistical sub-classifiers had been utilized in the recognition process. The system had been applied to a large data set including more than 10,000 LP images and a better output of 95.41% recognition rate had been reported.

2.3.4 Discussion

Character recognition stage plays a very significant role in AVLPR framework in identifying the numbers of the LPs. But this recognition stage may suffer from some complications. Sometimes after the normalization step the produced characters may vary from the database samples because of the different shapes, styles and sizes of the characters which could end in identifying the false characters. This could enhance the complexity of the entire process and affect the performance of the whole framework. This is very significant for any of the processes to differentiate the extracted characters properly because there are some possibilities of the process being confused because of the uniformities among the forms of size and shape.

Based on the utilized attributes the existing character recognition procedures have been classified here. The methodology, conveniences, inconveniences of the each class of attribute has been discussed in a nutshell in the Table 2.4 as follows:

Table 2.4: Relative comparison of existing recognition methods with respect to the attributes

Class	Conveniences	Inconveniences	Reference	Accuracy (%)
Pattern matching attributes	More competent for recognizing non-broken, fixed size, single-font characters. Straightforward and relatively simpler technique.	Higher processing time because of processing inessential pixels, not robust for thickness change, rotation, noise, multi-font, broken characters.	(H.-J. Lee, Chen, & Wang, 2004) (Rajput et al., 2015)	95.7 95.6
Extracted attributes	Faster recognition, capable of extracting the salient attributes, robust in distinguishing the characters in case of distortion.	Performance might get degraded by the non-robust attributes, requires extra time for extracting the attributes.	(Wen et al., 2011) (S.-Z. Wang & Lee, 2003)	98.34 98.6
Classifiers:				
ANN	Relatively simpler implementation, higher recognition efficiency in case of huge amount of data.	Additional processing time for training the network, processing complexity.	(Nijhuis et al., 1995) (Türkyılmaz & Kaçan, 2017)	98.5 96.92
Statistical classifiers	Capable of learning the differences and the uniformities of the multiple characters.	Relatively complex, higher processing time.	(X. Pan et al., 2005) (Llorens et al., 2005)	95.41 95.7

CHAPTER 3: METHODOLOGY

The proposed automatic vehicular license plate recognition framework aims at overcoming the drawbacks of the existing methods. Proposed AVLPR approach consists of basic four phases: pre-processing, skew correction, candidate localization (region extraction & VLP detection), and character segmentation & recognition. Fig. 3.1 depicts the phases of the proposed AVLPR method sequentially.

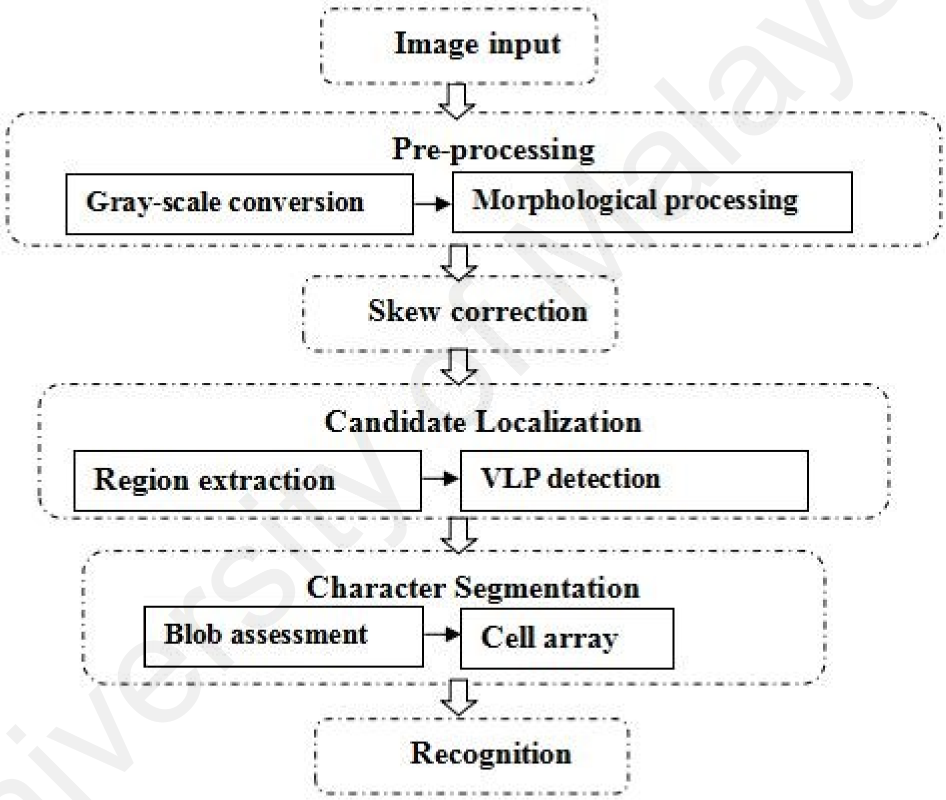


Figure 3.1: General four steps of proposed AVLPR framework

3.1 Pre-processing

Pre-processing is the preliminary phase in the digital image processing which improves the quality of the image data for both proper visual perception and computational processing. Pre-processing enhances the image data by removing both background noise, unwanted data, image reflections and normalising the intensities of the individual image particles. A major reason for the failure of vehicle license plate detection is the low quality of the vehicle image data (Abolghasemi & Ahmadyfard, 2009). In this work, the Pre-processing stage comprised of two major sub-processes such as conversion of the RGB color image into gray-scale and morphological processing which improves the contrast of the image data at such locations where there might be a possibility of holding the vehicle license candidate.

3.1.1 Gray-scale Conversion

The process of producing gray-scaled images from color (RGB) images is known as gray-scaling. The threshold of the image data is calculated in this procedure. When this value is smaller than the threshold value then to find out the proper gray-scale value, it is necessary to recalculate the image data. The intention of thresholding is for splitting the point of concern from the background. When an image was loaded into Matlab then, a matrix M (3 dimensional) of size (ZxYxX) with Z and Y being the number of pixels in z- and y-direction was obtained. Generally, this matrix is for the RGB images. The values for all the three colors are identical when it is a grayscale image; they generally range between 0 and 255. The threshold is applied to find out the proper gray-scale value. The threshold value is determined by the different intensity levels. The image data quality gets enhanced for further smooth computational processing by this gray-scaling procedure. Here,

Threshold = t;

Values below = (M < t);

Values above = (M >= t);

The values below then get set to black M (values below) = 0; and the values above then get set to white M(values above) = 255.

This technique has an important role by providing the necessary contrast of the image data. This helps in differentiating between the separate levels of intensities of the background and the object for smooth computational processing.

From the RGB (color) value (24-bit) of each corresponding pixel *(x, y)*; the Red, Green and Blue components are being separated and the (8-bit) gray level (converted) value is calculated by using this (Sarker, Yoon, & Park, 2014) following formula:

$$S(x,y) = 1/10\{3 \times R(x,y) + 6 \times G(x,y) + 1 \times B(x,y)\} \quad (3.1)$$

Here, R(x,y), G(x,y) and B(x,y) represents the spectrum of Red, Green and Blue components respectively and S(x,y) indicates the converted gray-scaled image of the input RGB image which has been depicted in Fig. 3.2 as follows:

Figure 3.2: Gray-scaled vehicular images

3.1.2 Morphological Processing

This image processing operation involves in morphological transformation by combining two sets through vector addition of the set elements (Haralick, Sternberg, & Zhuang, 1987). Here, input image data gets improvised through this operation by: joining the broken-lines, enhancing the brightness, sharpening the edges of objects and filling holes of the input image data.

Assuming that, E and F being the sets in Z-space (P^Z) including elements e and f, respectively, $e = (e_1, e_2, ..., e_Z)$ and $f = (f_1, f_2, ..., f_Z)$. As a result the subsets of P^Z is e and f. Hence, $E \oplus F$ indicates the dilation operation of E by F and is defined by using (Haralick et al., 1987) the equation as follows:

$$E \oplus F = \{j \in P^Z \mid j = e + f \text{ for some } e \in E \text{ and } f \in F\} \quad (3.2)$$

Here, the dilation operation gets along by both the close & open arithmetic operations(Yang & Ma, 2005b).

For close: Set F close aggregate set E as follows:

$$E \bullet F = (E \oplus F) \Theta F \quad (3.3)$$

For open: Set F open aggregate set E as follows:

$$E \circ F = (E \; \Theta \; F) \oplus F \quad (3.4)$$

There are several important tasks both for close and open arithmetic operations.The close arithmetic is involved in filling the smaller holes of the objects, sharpening the edges, smoothing the boundary of the objects, connecting the neighbourhood objects whereas open arithmetic is involved in eliminating relatively smaller objects, smoothing of the boundary of the relatively large objects, separating the objects at the fine places.

Figure 3.3: Vehicular images after morphological processing

In this research, Malaysian vehicle images have been utilized. Here, close arithmetic operation has been performed in this research resulting in smoothing the boundary of the objects. After morphological processing, the edges get sharper. As a result the gray value difference between the two neighboring pixels gets enhanced specially at the edges of the object. Figure 3.3 depicts the vehicular images after morphological processing.

3.2 Skew Correction

Regarding the vehicle license plate images which are inclined, the characters including the image, also become inevitably inclined. As a result, the tilting adjustment of the characters becomes necessary precursor in order to get the characters in identical horizontally adjusted position. Not only for improving the accuracy of the character recognition step but also to facilitate character segmentation this tilting adjustment is very advantageous. This adjustment process works on the basis of average-height of image pixels. In general, for several images, which includes various characters, from both left and right parts of the character the pixel height needs to be horizontally placed at a nearer position. The image entity gets inclined in case of the relatively high fluctuations and then corrective adjustment is required (Zhai, Gao, Hu, & Tian, 2011).

For the tilt adjustment, the pixels average heights from both left and right parts of the image need to be enumerated firstly and afterwards the slope is determined because when the pixel height of the character from the right and left sides shows relatively high fluctuations, the image existence shows to be inclined. The image gets reorganized in accordance with the image inclined slope by utilizing polar co-ordinate transformation procedure by proper revolving. This includes in the pixel mapping of new image to the old image for getting this Euclidean entity under the projective distortion.

The procedure is described briefly in three steps as follows:

- Progressive in accordance with scanning the image through column from the left part first and afterwards counts aggregates the height; then the image pixels average height from the left part is enumerated.
- Repeat step 1 replacing the left part by the right part.
- The slope is now calculated in accordance with the pixels average heights from both left and right parts of the image.

In general, images consisting of numerous characters have possibilities of possessing the pixel height of the character from the right and left sides at a close horizontal position. In case of the relatively high fluctuations, the image existence shows to be inclined. For this tilt adjustment, the pixels average heights from both left and right parts of the image need to be enumerated firstly and afterwards the slope is determined.

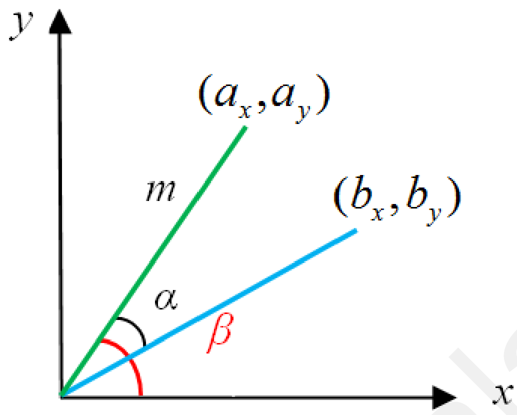


Figure 3.4: Pixel revolving diagram

The image is readjusted then in accordance with the skewed slope of the image by utilizing polar co-ordinate transformation procedure by proper revolving. The co-ordinates (a_x, a_y) of the image pixel are set α degrees rotation clockwise yielding the co-ordinate (b_x, b_y). Before rotation, the pixels polar co-ordinate can be expressed by the following equations:

$$a_x = m\cos(\beta) \tag{3.5}$$

$$a_y = m\sin(\beta) \tag{3.6}$$

Here, m is the slope and β is the angle between x-axis and the co-ordinates (a_x, a_y).

This relationship is illustrated at the Figure3.4.

After revolving α :

$$b_x = m\cos(\beta - \alpha)$$

$$= m\{\cos(\beta)\cos(\alpha) + \sin(\beta)\sin(\alpha)\}$$

$$= m\cos(\beta)\cos(\alpha) + m\sin(\beta)\sin(\alpha)$$

$$= a_x \cos(\alpha) + a_y \sin(\alpha) \tag{3.7}$$

$$b_y = m\sin(\beta - \alpha)$$

$$= m\{\sin(\beta)\cos(\alpha) - \cos(\beta)\sin(\alpha)\}$$

$$= m\sin(\beta)\cos(\alpha) - m\cos(\beta)\sin(\alpha)$$

$$= a_y \cos(\alpha) - a_x \sin(\alpha)$$

$$= -a_x \sin(\alpha) + a_y \cos(\alpha) \tag{3.8}$$

The inclined image gets reorganized in accordance with the inclined slope by utilizing polar co-ordinate transformation procedure by proper revolving. This includes in the pixel mapping of new image to the old image for getting this projective distortion.

This experiment focuses on the skewed vehicle images and tilt adjustment has been performed on the entire vehicle image as the image gets reorganized in accordance with the tilted slope. The adjustment of the tilted slope takes place where the pixel heights fluctuations are relatively high. The car detection process is performed after tilt adjustment.

Equation (3.7) & (3.8) can be expressed as matrix as follows:

$$\begin{bmatrix} b_x \\ b_y \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha & 0 \\ -\sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_x \\ a_y \\ 1 \end{bmatrix}$$

In accordance with the above formula, the introduced matrix expression is as follows:

$$\begin{bmatrix} a_x \\ a_y \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} b_x \\ b_y \\ 1 \end{bmatrix} \tag{3.9}$$

In conformity with equation (3.9), after revolving the image, for every point, the corresponding image can be obtained as follows:

Figure 3.5: Vehicle images after skew correction

3.3 Candidate Localization

In most cases, candidate localization has become one of the significant precursors for the AVLPR recognition framework. This stage has been comprised of two basic sub-processes i.e. region extraction and VLP (Vehicular License Plate) detection for the proper recognition framework as follows:

3.3.1 Region Extraction

Here, in this region extraction stage, the candidates probable set of quadrangles that contain the highest possibilities of possessing the LP are investigated. This candidature region extraction has been methodized on the basis of the texture characteristics of the images by considering the fact of frequent transient differences or rapid spatial variation of image in the probable candidate region that are much more than other areas of the vehicle image. Here, for the extraction of the probable set of quadrangles that possess the larger possibilities of attaining the LP, window scanning procedure has been utilized.

The procedure is explained here briefly with the basic stages:

Stage 1: Initially for an input image $g(a,b)$ with size of $(x \times y)$, the aggregate of the transient differences for each of the windows are being enumerated.

For $q = 1 : y - 1$

For $p = 1 : x - X_W - 1$

$$S_T = \sum_{i=p}^{p+X_W} g(i,q) - g(i+1,q)$$

Here, the window starts with the coordinate (p,q) where X_W denotes the width of the window.

Stage 2: Secondly, the aggregate of the transient differences for each of the windows are stored in the variable, S_T as the window traverses.

If $(S_T \rangle T)$

Set $R^p = 1$

Else set $R^p = 0$

Here, T is used for the threshold value. The threshold T is utilized for adjusting the aggregate of the transient differences for each of the windows. This threshold is automatically adjusted by the algorithm for selecting the consecutive rows to be summed up for each of the windows. The spatial variance curves have been depicted in experimental result section (Fig. 4.2).

Stage 3: Thirdly, the consecutive rows are summed up, labelled *R* to one line after line. Then the aggregated amount of the consecutive rows is stored into *L*.

For $p = 1 : y - 1$

If $R^p = 1, (p = r, r+1, r+2, \ldots, n)$

Set $L = \sum_{p=r}^{n} R^p$

Stage 4: If $(L \rangle T_T)$

$$\text{Set, } A_{end}^{z} = p$$

$$A_{initial}^{z} = p - L \; (z = 1,2,3,.....)$$

where T_T indicates an adequate threshold value, z denotes the probable regions for the candidate. These regions are being extracted as the probable candidate in accordance with the arrays $A_{initial}$ and A_{end} .There are some candidate-regions which have been achieved after applying the stages above.

The threshold value in this stage T_T is used after the consecutive rows get aggregated. This threshold is selected as half of the total consecutive rows that are summed up. The probable regions are that areas which possess the highest transient differences or spatial variations. Above this threshold value T_T , the candidate regions are extracted as probable region possessing the LP. These probable regions are shown in Figure 3.6.

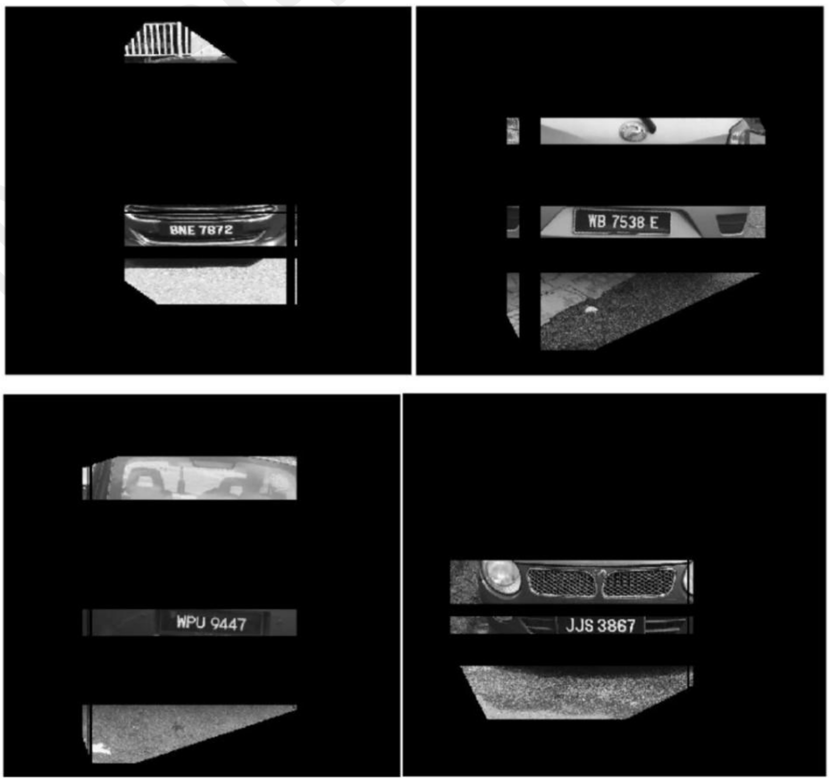


Figure 3.6: Extracted candidate plate images

Then finally the exact location of the vehicular LP gets detected after using the dynamic threshold which is the highest value of the transient differences. The corresponding regions having transient difference values lower than the threshold are then separated and the exact locus gets detected.

3.3.2 VLP Detection

The final stage of determining the correct location of vehicular license plate (VLP) is the VLP detection. The output from the region extraction step attains the highest possibility of containing the exact locus of the vehicular LP. Here, the final output of the region extraction step contains some other portions along with this VLP of the input image data. Among these parts of the probable candidate region, the part possessing the highest transient differences comprises the highest possibility of containing the exact locus of the vehicular LP. In order to find out the region attaining the highest transient differences, a dynamic threshold value is to be implemented and the transient differences of the linear windows for the probable candidates are being processed by this value of threshold.

Figure 3.7: Detected vehicular LPs

The outcome from this process yields the portion comprising the maximum probability of possessing the exact locus of the VLP finally. Figure 3.7 depicts the detected vehicular LPs.

3.4 Character Segmentation and Recognition

This character segmentation stage performs a very important role in this vehicular license plate recognition framework for the proper recognition of the vehicular LP. Here, in order to perform character segmentation properly on the plate image, it needs to undergo through binarization process by changing the grey-scale values of the image into binary. Therefore the pixels at the background get suppressed and the pixels that are for interest get highlighted. Then the connected component analysis (CCA) is implemented (Wen et al., 2011) which is an image processing application in which the image is scanned first and the corresponding pixels are then labeled into components in accordance with the pixel connectivity. For this case identical pixel intensity-values are shared by all of the pixels in a specified connected component. These pixels then get connected among themselves in some way (either get four-connected or get eight-connected). Each of the pixels is then labeled with a value in accordance with the component with which it got assigned after all groups had been determined. CCA works on the grey-level or the binary images with different forms of connectivity. Here, for this experiment CCA has been implemented on the binary image in order to search for an eight-connected component situation.

Let, δv be an eight-point neighborhood process where $c(v)$ denotes the neighbor set which is connected to point *v*. The set $c(v)$ ought to acquire the following properties for all *v* and *l*:

$$c(v) \subset \delta v$$

$$l \in c(v) \Leftrightarrow v \in c(l)$$

The domain $D \subset V$ will get connected under $c(v)$ if there for all $v, l \in D$, exists an order of N pixels: $v_1, v_2, ..., v_N$ such that:

$$v_1 \in c(v), v_2 \in c(v_1), ..., v_N \in c(v_{N-1}), l \in c(v_N)$$

The connected components get extracted by the following algorithm:

Algorithm (Region extraction):

Label counter =1

Initialize $M_l = 0$ *for* $l \in V$

for each $v \in V$

if $(M_v = 0)$

Connected Set (v, M, Label counter)

Label counter $\leftarrow$ *Label counter +1*

end

end

Then the blob (binary large object) (Kocer & Cevik, 2011) assessment technique is implemented which belongs the strong architecture for determining the contactless and closed regions in the binary image.

The procedure is described briefly in five steps as follows:

Step 1: First of all the label counter which is initiated to one is created. Then the binary image gets scanned.

Step 2: For the selected region-criterion, every pixel is checked for the eight-connectivity. When a neighbor matches due to the criterion, the pixel is then assigned to that region.

Step 3: For the case of multiple neighbors that fit result in all the numbers are of the equivalent region and the pixels are assigned to their region.

Step 4: For case of no neighbors fitting the criteria, the region counter value is assigned and then the region counter is increased by one. Afterwards for assigning the same region value to all the equivalent regions, the image is scanned again.

Figure 3.8: Character extracted plate images (Blob assessment output)

Step 5: The procedure continues in the image as soon as there left no unlabeled pixels.

Here, the extracted characters have been depicted in Figure 3.8 in the green boxes.

After that the cell array is created in order to store the segmented characters individually. The indexed characters are then returned according to the corresponding element numbers and then saved in the cell array.

The procedure is described briefly in three steps as follows:

Step 1: Loop over through every blob that already has been detected.

Step 2: The blob of pixels is then to be extracted in order to acquire each of the characters.

Step 3: Placing the characters into the cell array by defining a cell array: cell *(x,y)* which is the empty matrices of x by y cell array where y is according to the number of elements in the array.

The final part of this Automatic Vehicular License Plate Recognition (AVLPR) framework is the character recognition. After all of these procedures in character segmentation stage are carried out through the image, the characters become much more proficient for the optical character recognition (OCR) system in order to perfect recognition in this AVLPR framework. Template matching technique has been implemented in Matlab for the optical character recognition.

Segmented characters get compared with the ones that are stored in the database by this pattern matching algorithm in order to achieve the perfect match. The created templates (A-Z), (0-9) are of size (38×20). All the created templates must be of identical window size. The characters extracted from the segmentation process need to be normalized and need to be resized with similarity to the template window.

For this pattern matching algorithm, the correlation coefficient concept has been utilized. The linear relationship or the strength of straight line between two variables is measured by the correlation coefficient. For computing the correlation coefficient the equation is defined as follows:

$$X(p,q) = \frac{\sum_{q'=0}^{j-1}\sum_{p'=0}^{i-1}\widetilde{Z}(p',q')\widetilde{Y}(p+p',q+q')}{\sqrt{\sum_{q'=0}^{j-1}\sum_{p'=0}^{i-1}\widetilde{Z}(p',q')^2\sum_{q'=0}^{j-1}\sum_{p'=0}^{i-1}\widetilde{Y}(p+p',q+q')^2}} \quad (3.10)$$

Where $\widetilde{Z}(p',q') = Z(p',q') - \overline{Z}$, $\widetilde{Y}(p+p',q+q') = Y(p+p',q+q') - \overline{Y}(p,q)$, $\overline{Z}$ denotes the average pixel values in the template and $\overline{Y}(p,q)$ denotes the average image pixel value in the image location*(p,q)*.

After template matching, the recognized characters have been depicted in Fig. 4.6 and some unsuccessful samples have been depicted as well in Fig. 4.9(b).

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Experimental Setup

For this experiment, the utilized systems in which the proposed algorithm has been evaluated are listed as follows:

a) Matlab (2016 a)
b) WOS (Windows Operating System): 8
c) Processor: Intel® Core™ i3
d) Clock speed: 3.70 GHz
e) Operating system (OS): 64 bit
f) RAM: 4.00 GB

In this work, Malaysian vehicle images have been utilized. The vehicular images had been captured from the University premises and the nearby roads at a distance of 6-12 feet. The sample images had been collected originally by utilizing a digital camera of 13 Mega-pixel. For measuring the performance of this experiment 300 skewed images of different illumination conditions with various tilt angles have been tested.

Some samples of the utilized skewed vehicular image data for this work are depicted as follows:

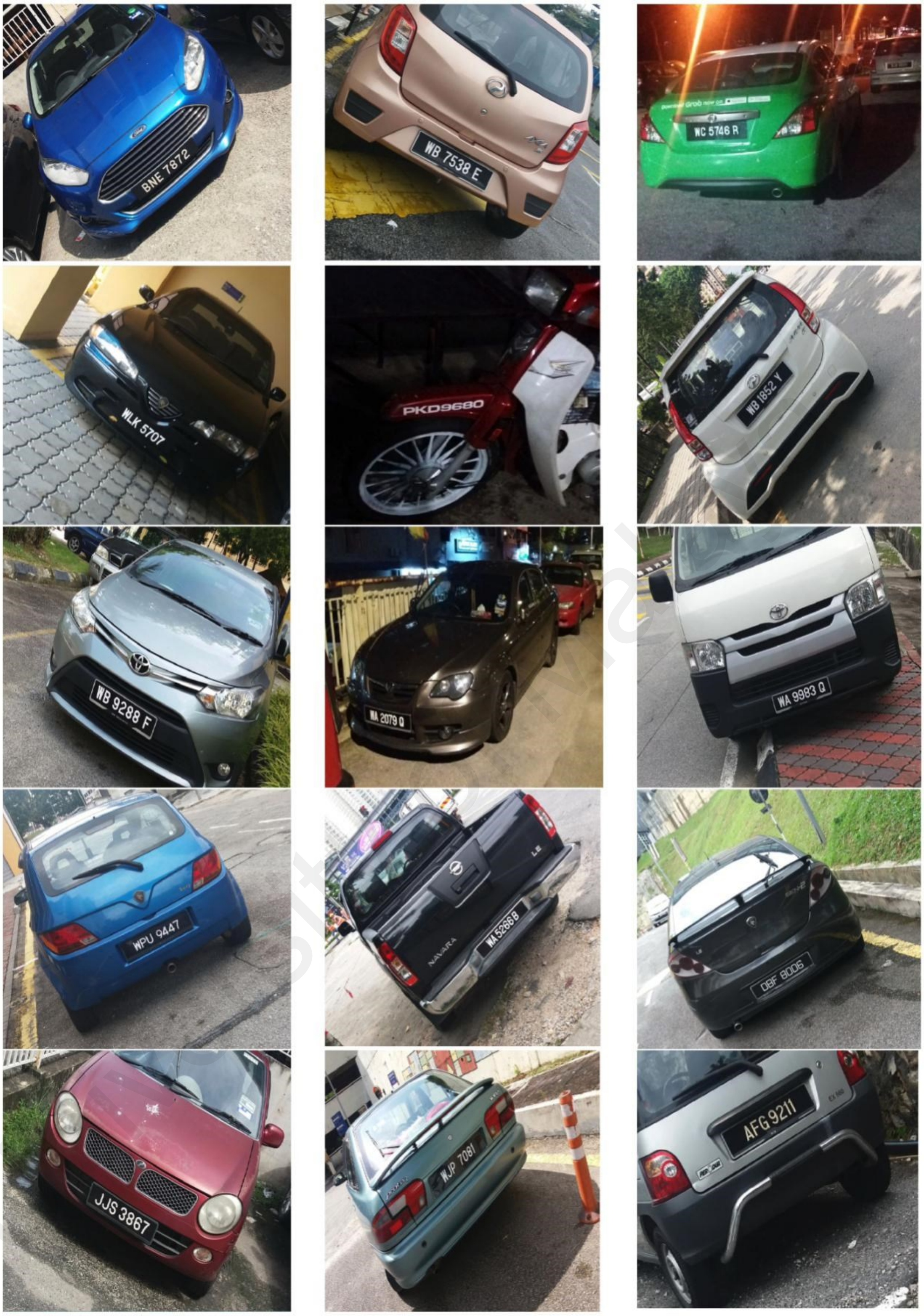


Figure 4.1: Sample of skewed vehicular images

4.2 Experimental Results

In the candidate localization stage, the candidate regions having larger frequent transient differences or rapid spatial variation possess the highest probability of possessing the license number. The rapid spatial variance curves of few sample images have been depicted here in Figure 4.2 as follows:

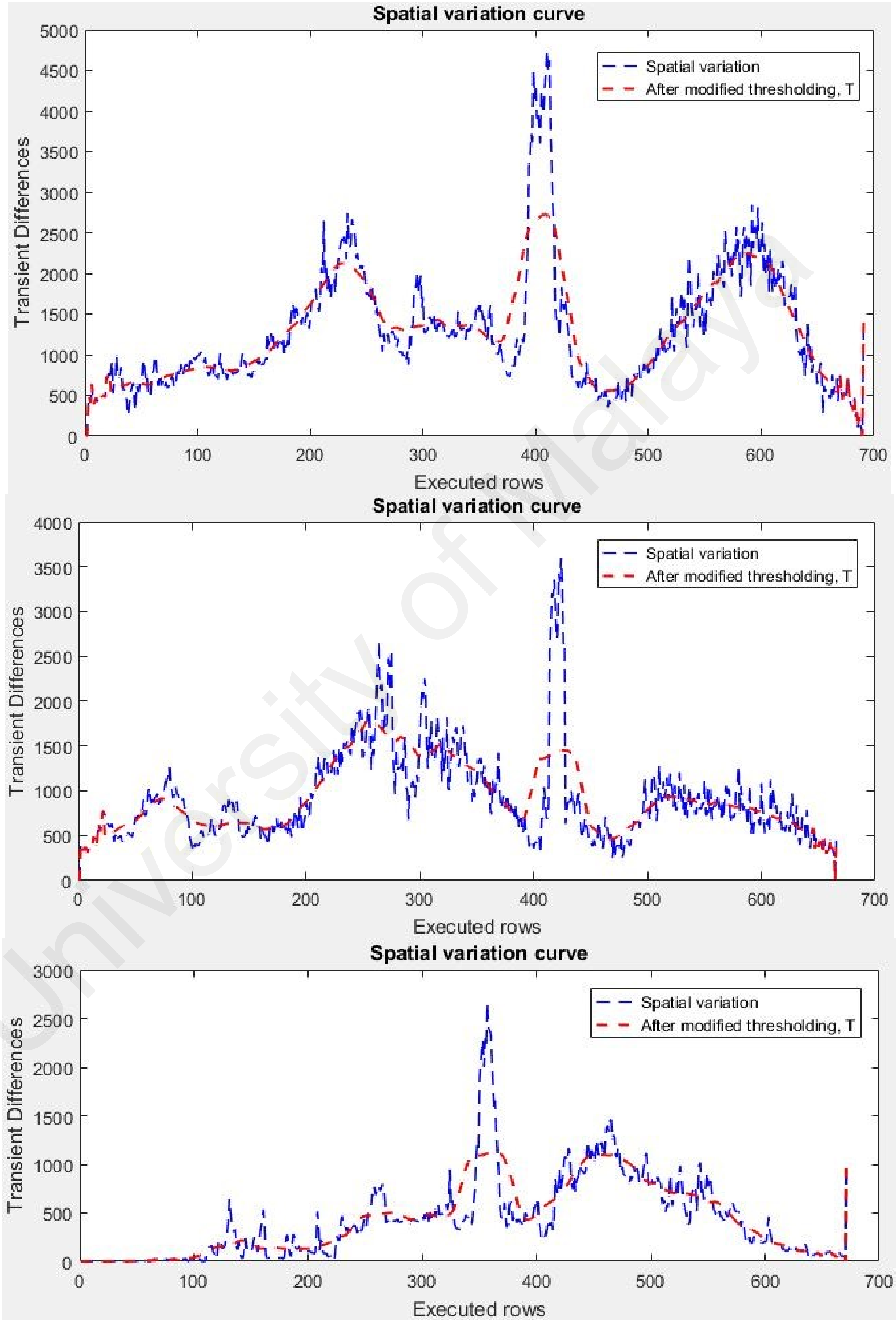


Figure 4.2: Spatial variation curve for candidate localization

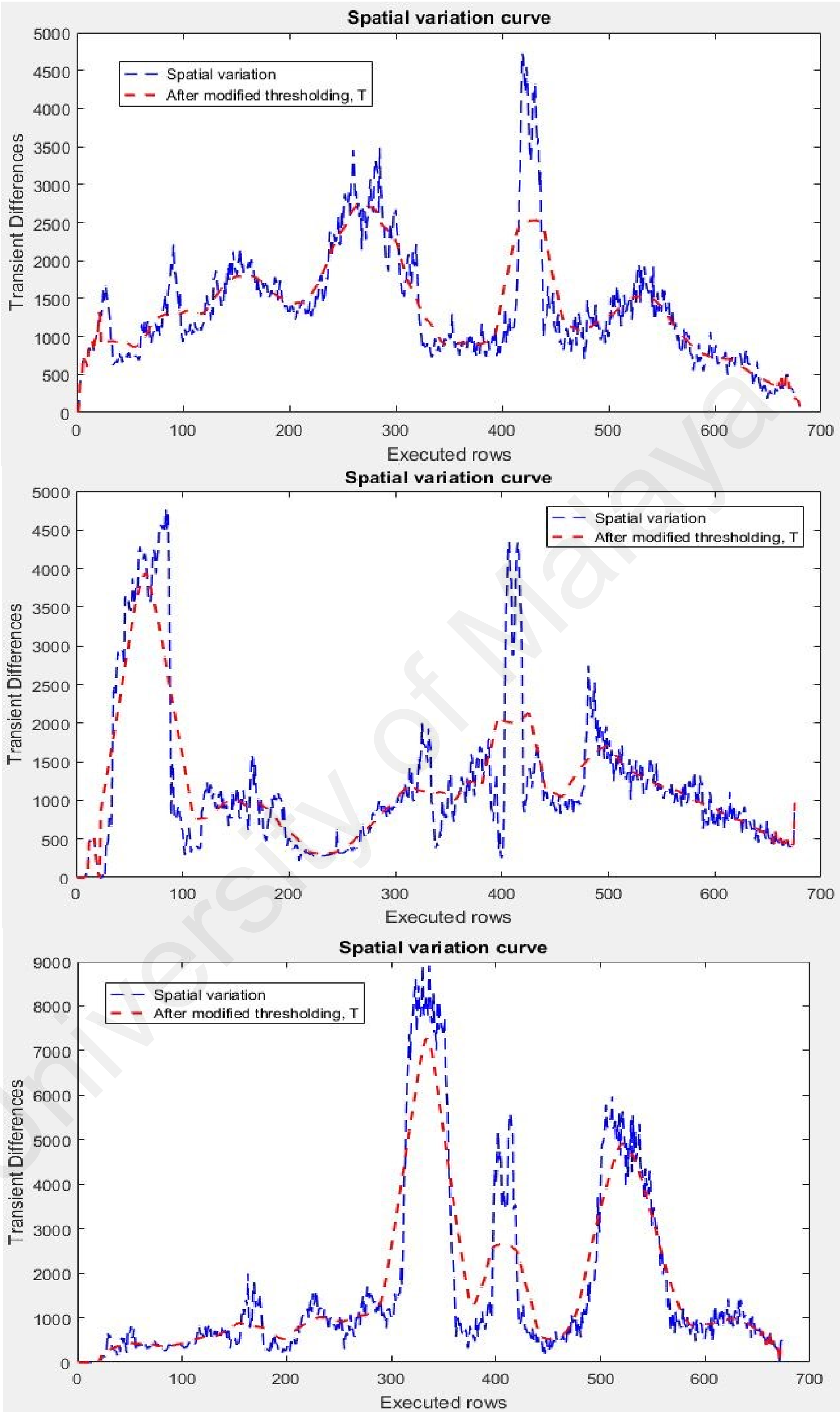


Figure 4.2, continued

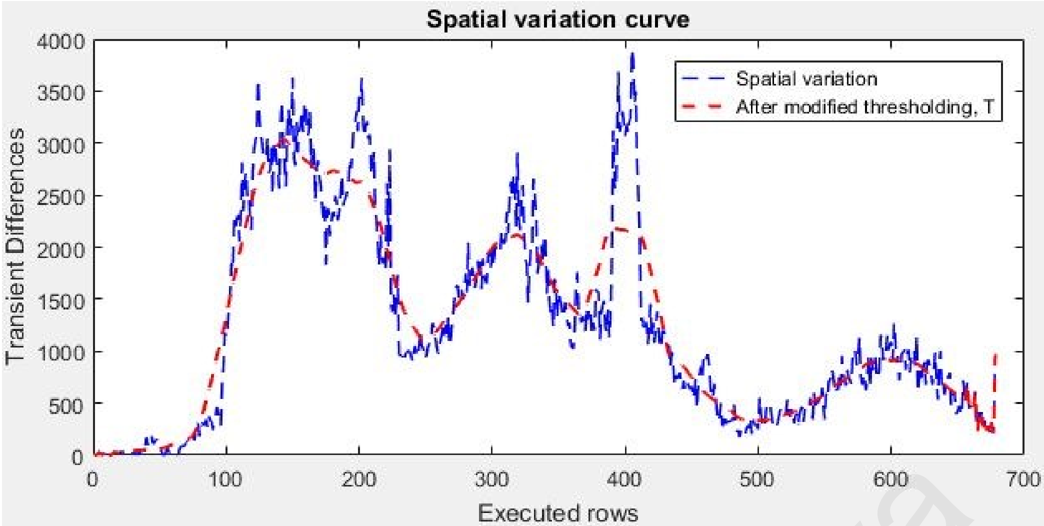
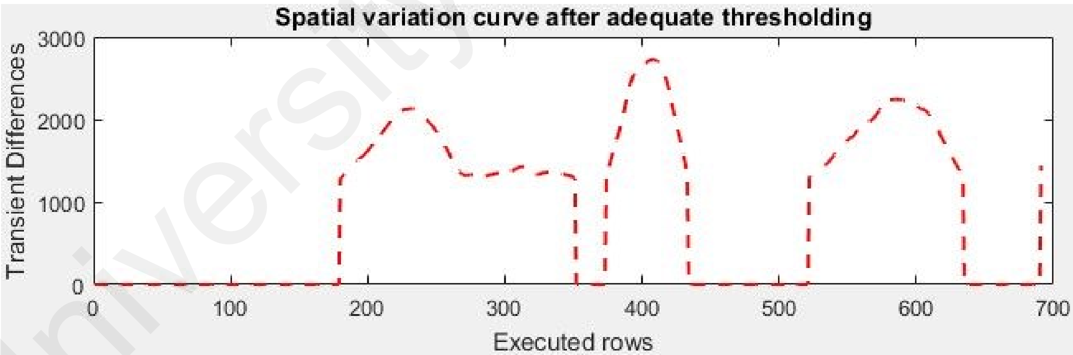


Figure 4.2, continued

The probable regions are that areas which possess the highest transient differences or spatial variations. An adequate threshold value T_T has been used after the consecutive rows get aggregated. The rapid spatial variance curves of few sample images after adequate thresholding have been depicted here in Figure 4.3 as follows:



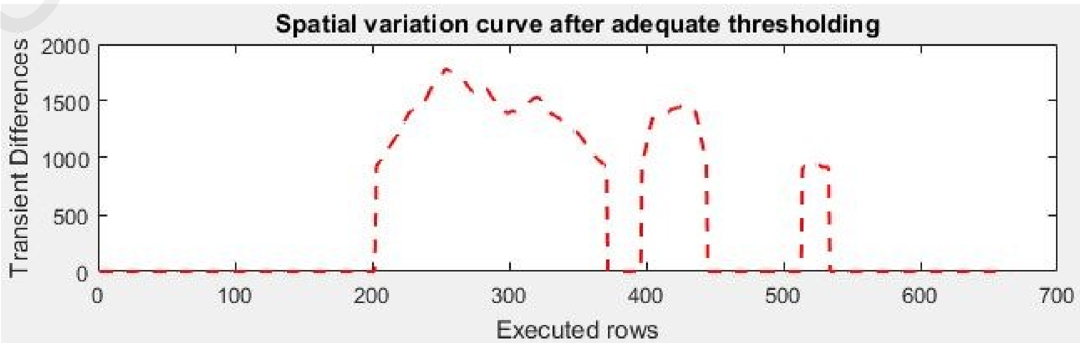


Figure 4.3: Spatial variation curve after adequate thresholding

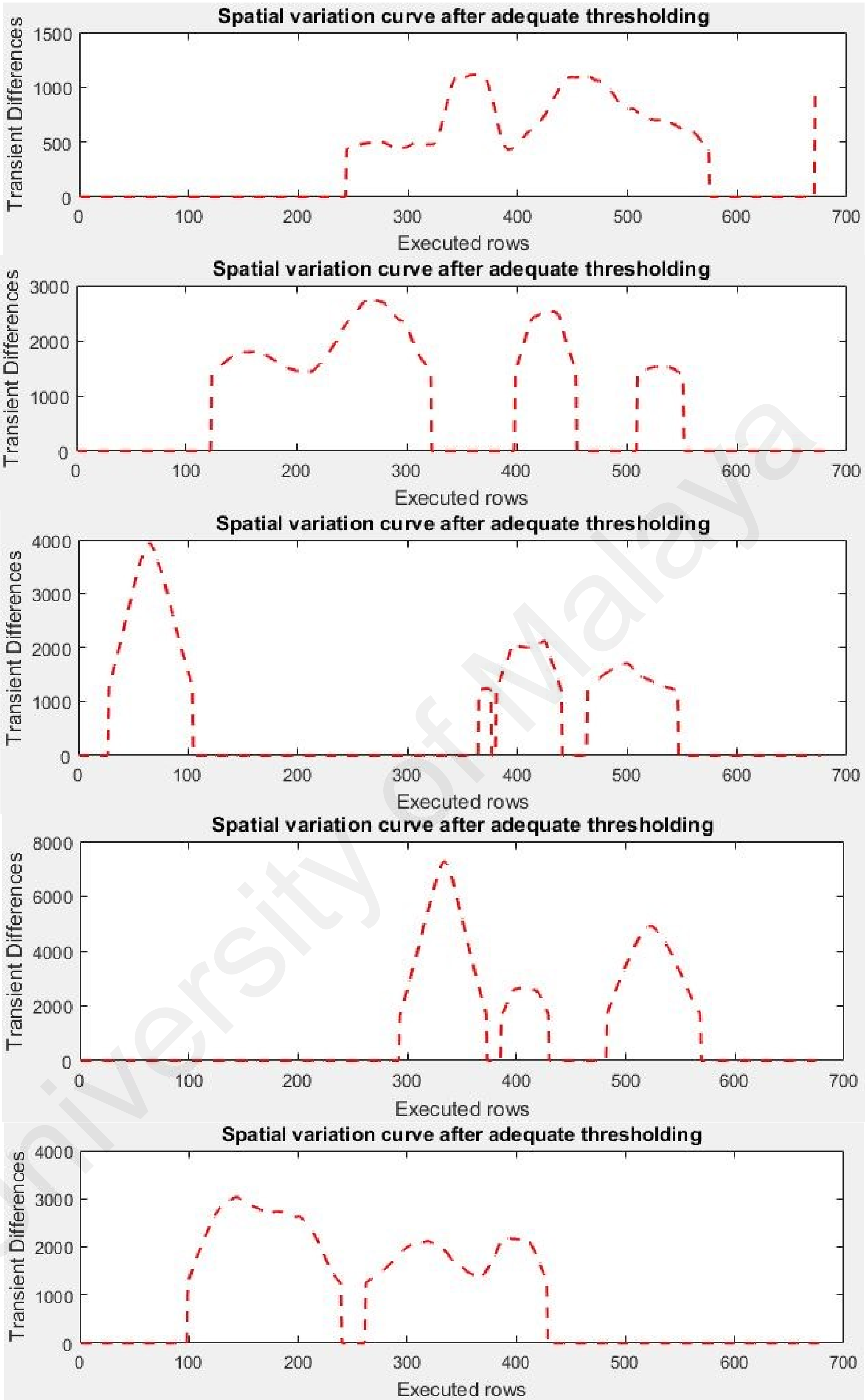


Figure 4.3, continued

After the blob assessment, Figure 4.4 here depicts all the segmented characters of the vehicular license plate individually according to the cell arrays as follows:

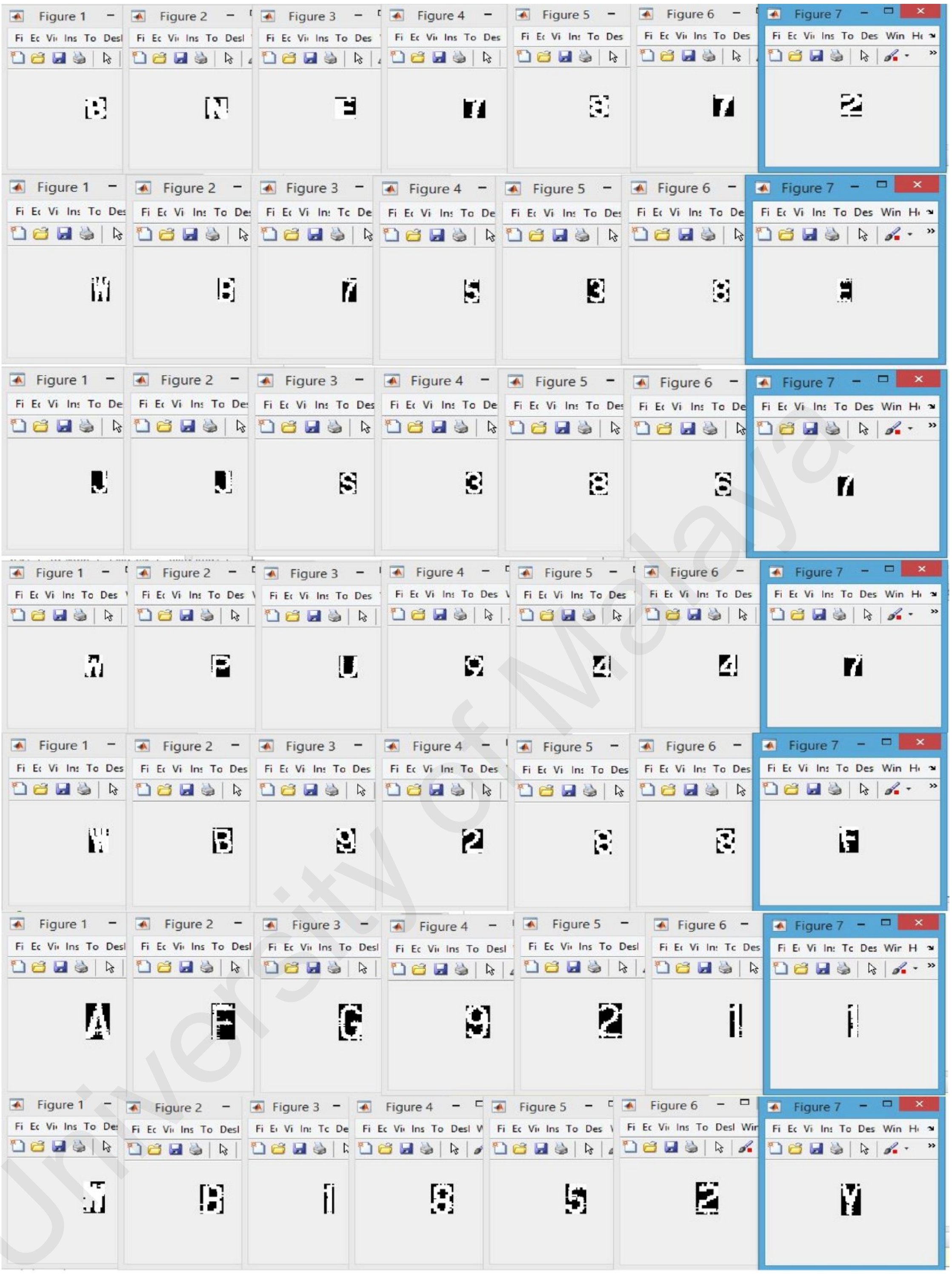


Figure 4.4: Segmented characters of the vehicular LP individually

The LP localization, character segmentation and recognition results have been summarized in the Table 4.1 as follows:

Table 4.1: Results for LP localization, character segmentation and recognition systems

LP localization stage	Quantity	Percentage
The number of total tested vehicle images	300	100
Correctly detected LP images	289	96.3
Images with unsuccessful detection	11	3.7
Character segmentation stage		
Total character numbers	2100	100
Successful character segmentation	2004	95.4
Unsuccessful character segmentation	96	4.6
Character recognition stage		
Total character numbers	2100	100
Successful character recognition	1978	94.2
Unsuccessful character recognition	122	5.8

This procedure has achieved a noteworthy performance. The results have been depicted in the graph in Figure 4.5 as follows:

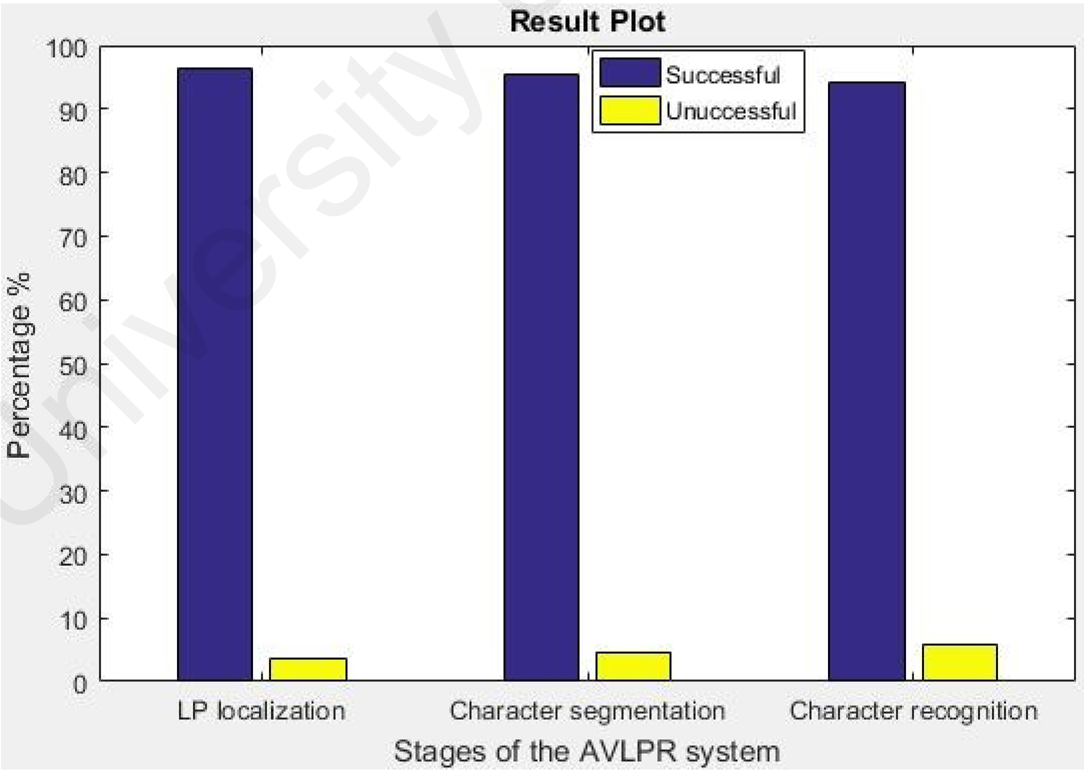


Figure 4.5: Result graph of the proposed system

The LP localization rate has achieved an accuracy of 96.3%, character segmentation attained a success rate of 95.4% and the character recognition achieved an accuracy of 94.2% which satisfies the procedure to be helpful for the real time applications.

The recognized characters of the vehicular license plate have been depicted in Figure 4.6 individually after the pattern matching as follows:

Figure 4.6: Character recognition of the vehicular LP

The performance of the proposed system has been compared with respect to some existing procedures in the Table 4.2 as follows:

Table 4.2: Performance comparison with respect to some other existing systems

References	LP localization	Character segmentation	Character recognition	Skew correction
(Deb, Chae, & Jo, 2009)	82.5%	-	-	-
(Rajput et al., 2016)	98%	-	-	yes
(Kang, 2009)	-	84.5%	-	-
(M.-L. Wang et al., 2010)	96.8%	91.1%	87.5%	-
(Asif et al., 2016)	93.86%	-	-	-
(Al-Hmouz & Aboura, 2014)	97.27%	-	-	-
This work	96.3%	95.4%	94.2%	yes

The performance graph of the proposed system including LP localization, character segmentation and recognition compared with respect to some existing procedures has been depicted in Figure4.7 as follows:

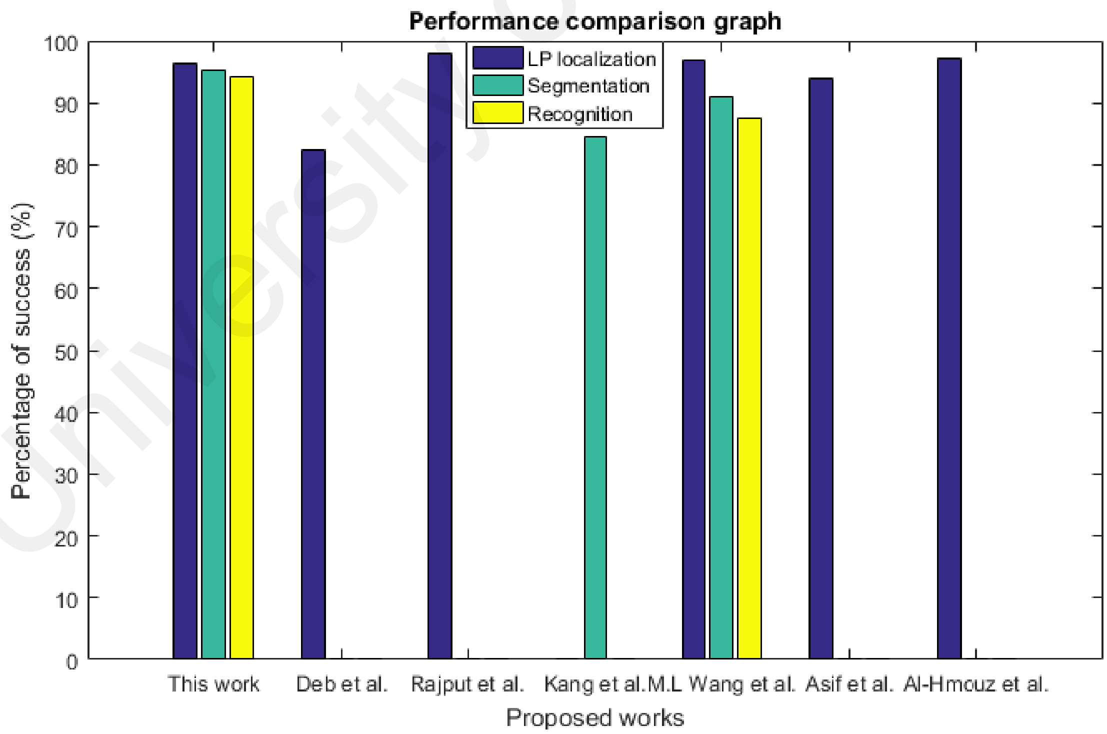


Figure 4.7: Performance comparison plot

4.3 Unsuccessful Samples and Analysis

VLP detection was not successful for several samples. This might be of their being white in color for samples. As a result, under the sunshine, the images get over exposed and the extraction of exact locus of VLP gets seriously hindered by this factor. On the other hand, for several samples, in case of the mesh thing appearing in front of the VLPs, the morphological processing functions get hindered by this to search for the VLP. Other samples contained dirty plates and were not capable of removing the dirty of the plates completely by the pre-processing algorithm. As a result wrong detection occurred as well. Meanwhile for several cases the skew corrected images contained some noises from the polar transformation based angular rotation. This might be another obstacle for the extraction of exact locus of VLP. A better and efficient noise removing algorithm will be developed in the future study for further efficiency and robustness.

There are specific significant factors as well which cause the hindrances for the segmentation stages. There have been more complicacies in case of segmenting the characters. In some cases the vehicular plate might possess frame that is surrounded with it which results in causing complexities for segmenting the candidate characters. As a result the frame gets attached to the candidate characters after binarizing the image. In many cases, the most significant hindrance that leads to wrong recognition outcome might be the noise and interferences that remained at the surrounding of the VLP number areas. Moreover, another complications associated with the detected LP image such as non-uniform brightness, unpredictable shadows, physical damage, and dirt problem resulted in complicacies on the segmentation performance as well which has reflected on the recognition performance too. Unsuccessful image samples of VLP localization have been depicted in Figure 4.8 as follows:

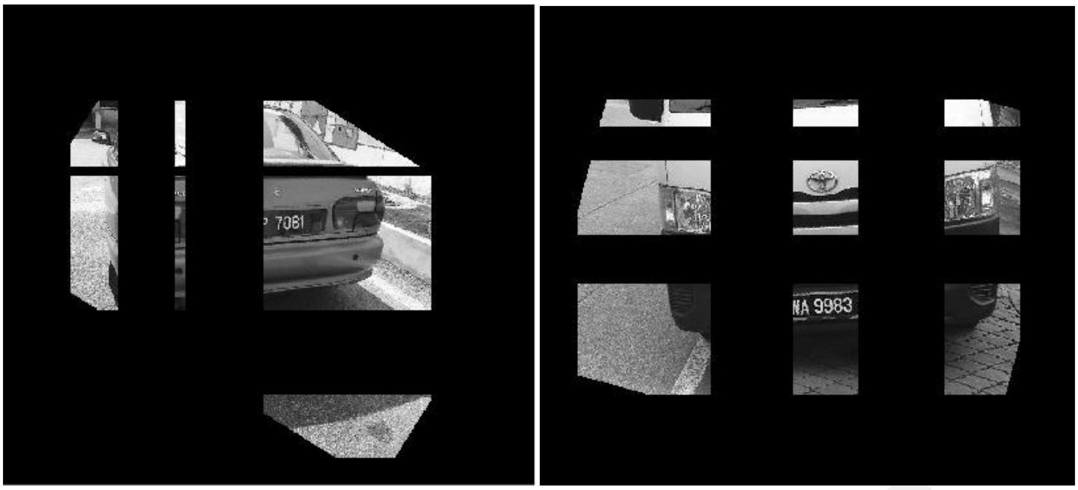


Figure 4.8: Unsuccessful sample of VLP localization

In recognition stage, there were complications as well. After the normalization step the produced characters may vary from the database samples because of the different shapes, styles and sizes of the characters which ended in identifying the false characters.

For this reason, several specific characters were wrongly recognized. Such as character ‘8’ got identified wrongly as ‘B’, in several samples this happened because of the identical font diversity. In another samples number ‘0’ recognized wrongly as character alphabet ‘O’, character ‘D’ recognized mistakenly as character alphabet ‘O’, ‘G’ recognized wrongly as character ‘C’, number ‘4’ recognized mistakenly as character alphabet ‘A’ because of having pretty much noise, blurriness and font similarity. An efficient algorithm will be developed in the future study for further efficiency and robustness in recognizing these characters which possess font similarity problems.

Unsuccessful character segmentation and recognition samples are depicted as well in Figure 4.9 as follows:

(a)

(b)

Figure 4.9: Unsuccessful sample: (a) character segmentation (b) character recognition

CHAPTER 5: CONCLUSION

5.1 Conclusion

In this work, a skew correction technique where the image gets reorganized in accordance with the image inclined slope by utilizing polar co-ordinate transformation procedure has been presented here along with an AVLPR recognition framework. Experiments were done in 3 stages: LP localization stage, character segmentation stage and character recognition stage. The results tabulated that unsuccessful detected images is 3.7%, unsuccessful character segmentation is 4.6% while unsuccessful character recognition is 5.8% for LP localization stage, character segmentation stage and character recognition stage respectively. Hence, the proposed system possesses a noteworthy performance which proves the approach to be helpful for the real time applications.

Besides, a comprehensive investigation on existing AVLPR techniques has been presented here where an analytical review has been carried as well in this work on the basis of the utilized attributes and the procedures have been categorized as well. An analytical comparison has also been presented according to each categorized attributes including with conveniences, inconveniences and recognition results. The AVLPR framework on the basis of existing techniques has been focused here by the aspects of detecting, segmenting and recognizing the plates. AVLPR based future forecast including with some potential challenges in this field has been addressed in this work.

5.2 Contribution of the Present Research

This work focuses on restricted conditions such as using image of only one vehicle, stationary background, and no angular adjustment of the skewed images. Moreover all the three basic steps which are the license plate detection (LPD), character segmentation and recognition have been focused in this work. Followings are the specific contribution rendered in the present research.

1. A polar co-ordinate transformation based procedure has been developed for the proper adjustment of the skewed image of the entire vehicle as the image gets reorganized in accordance with the tilted slope.
2. A rapid spatial variation of skewed vehicular image in the probable candidate region has been introduced to achieve better detection rate.
3. Connected component analysis (CCA) integrated with blob assessment and cell array has been implemented for character segmentation.

5.3 Future Aspects

A wide number of research works on AVLPR have been proposed by the researchers in the past several decades and many significant improvements have also been made. But still there are many factors that need to be taken into account for designing a robust AVLPR system capable of functioning properly under various illumination and environmental situations, different styled plate conditions. In the AVLPR system the multi-styled VLPs possessing various syntax and fonts should be dealt with for more efficiency and robustness. This issue has been taken into account in few existing works whereas the constraints regarding to this issue haven't been overcome thoroughly. For overcoming the problems associated with the multi-style number plate, based on four critical parameters, such as the rotation angle of the plate, the utilized alphanumeric character types, the line number of the characters and the character formats, a procedure has been proposed in (Jiao, Ye, & Huang, 2009).The system has been applied to a large data set including 16,800 images and a relatively better overall success rate of 90% has been reported where a processing speed of 8 f/s has been utilized for the images with lower resolution. Thermal image processing has been implemented in (Sangnoree &

Chamnongthai, 2017) which brings a better result for night-time traffic surveillance. In order to cope with this poor visibility problem which appears in night time particularly, some supplemental lighting instruments for focusing the visible portions, for example the tail-light or the head-light, could be implemented additionally with camera (W. Wang, Shen, Zhang, & Paisitkriangkrai, 2009). So, vehicular plate recognition during night time could be a field of interest to the researchers.

Still images or few frames from the image sequence get captured and analyzed in most cases of the AVLPR system. For improving the system performance significantly the temporal information of video could be exploited. Implementation of temporal information enhances the efficiency of the recognition stage by tracking vehicles with respect to time for estimating the LP motions. For this reason a procedure based on the reconstruction of super resolution has been implemented in (Suresh, Kumar, & Rajagopalan, 2007) where sub-pixel shifted images, multiple lower resolution images get combined for constructing higher resolution images. Besides, for the video based AVLPR systems another challenge is the motion detection by extracting the frame of the moving vehicles. Furthermore, there are uniformities among the ambiguous characters. Recognition error may happen for identifying these characters (O/0, I/1, Z/2, C/G, D/O, K/X, A/4, S/5, B/8). These ambiguity issues should be given importance for future research in optical character recognition. To cope with this problem, finding the aspect ratio (horizontal to vertical length) of the character might help. Vehicle recognition from the blurred image is another challenge in this field.

For future study, license plate recognition from speeding vehicles, blurry and darker images will be investigated. Besides that, recognition of LP for images with multi-vehicles will be explored.

REFERENCES

Aas, K., Eikvil, L., & Andersen, T. (1995). *Text recognition from grey level images using hidden Markov models.* Paper presented at the International Conference on Computer Analysis of Images and Patterns.

Abolghasemi, V., & Ahmadyfard, A. (2009). An edge-based color-aided method for license plate detection. *Image and Vision Computing, 27*(8), 1134-1142.

Agarwal, A., & Goswami, S. (2016). *An Efficient Algorithm for Automatic Car Plate Detection & Recognition.* Paper presented at the Computational Intelligence & Communication Technology (CICT), 2016 Second International Conference on.

Aghdasi, F., & Ndungo, H. (2004). *Automatic licence plate recognition system.* Paper presented at the AFRICON, 2004. 7th AFRICON Conference in Africa.

Al-Ghaili, A. M., Mashohor, S., Ramli, A. R., & Ismail, A. (2013). Vertical-edge-based car-license-plate detection method. *IEEE transactions on vehicular technology, 62*(1), 26-38.

Al-Hmouz, R., & Aboura, K. (2014). License plate localization using a statistical analysis of Discrete Fourier Transform signal. *Computers & Electrical Engineering, 40*(3), 982-992.

Al-Hmouz, R., & Challa, S. (2010). License plate localization based on a probabilistic model. *Machine Vision and Applications, 21*(3), 319-330.

Anagnostopoulos, C.-N. E., Anagnostopoulos, I. E., Psoroulas, I. D., Loumos, V., & Kayafas, E. (2008). License plate recognition from still images and video sequences: A survey. *IEEE Transactions on intelligent transportation systems, 9*(3), 377-391.

Anagnostopoulos, C. N. E., Anagnostopoulos, I. E., Loumos, V., & Kayafas, E. (2006). A license plate-recognition algorithm for intelligent transportation system applications. *IEEE Transactions on intelligent transportation systems, 7*(3), 377-392.

Asif, M. R., Chun, Q., Hussain, S., & Fareed, M. S. (2016). Multiple licence plate detection for Chinese vehicles in dense traffic scenarios. *IET Intelligent Transport Systems, 10*(8), 535-544.

Asthana, S., Sharma, N., & Singh, R. (2011). Vehicle number plate recognition using multiple layer back propagation neural networks. *International Journal of Computer Technology and Electronics Engineering (IJCTEE), 1*(1).

Babu, C. N. K., & Nallaperumal, K. (2008). An efficient geometric feature based license plate localization and recognition. *Int. J. Imaging Sci. Eng, 2*(2), 189-194.

Bai, H., Zhu, J., & Liu, C. (2003). *A fast license plate extraction method on complex background.* Paper presented at the Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE.

Bellas, N., Chai, S. M., Dwyer, M., & Linzmeier, D. (2006). *FPGA implementation of a license plate recognition SoC using automatically generated streaming accelerators.* Paper presented at the Parallel and Distributed Processing Symposium, 2006. IPDPS 2006. 20th International.

Blunsom, P. (2004). Hidden markov models. *Lecture notes, August, 15*, 18-19.

Busch, C., Domer, R., Freytag, C., & Ziegler, H. (1998). *Feature based recognition of traffic video streams for online route tracing.* Paper presented at the Vehicular Technology Conference, 1998. VTC 98. 48th IEEE.

Capar, A., & Gokmen, M. (2006). *Concurrent segmentation and recognition with shape-driven fast marching methods.* Paper presented at the Pattern Recognition, 2006. ICPR 2006. 18th International Conference on.

Chacon, M. I., & Zimmerman, A. (2003). *License plate location based on a dynamic PCNN scheme.* Paper presented at the Proc. Int. Joint Conf. Neural Netw.

Chang, S.-L., Chen, L.-S., Chung, Y.-C., & Chen, S.-W. (2004). Automatic license plate recognition. *IEEE Transactions on intelligent transportation systems, 5*(1), 42-53.

Chen, R., & Luo, Y. (2012). An improved license plate location method based on edge detection. *Physics Procedia, 24*, 1350-1356.

Chen, Z.-X., Liu, C.-Y., Chang, F.-L., & Wang, G.-Y. (2009). Automatic license-plate location and recognition based on feature salience. *IEEE transactions on vehicular technology, 58*(7), 3781-3785.

Cho, B., Ryu, S., Shin, D., & Jung, J. (2011). License plate extraction method for identification of vehicle violations at a railway level crossing. *International Journal of Automotive Technology, 12*(2), 281-289.

Choi, M.-R., & Lee, S.-S. (2017). An image enhancement Method for extracting multi-license plate region. *KSII Transactions on Internet & Information Systems, 11*(6).

Cui, Y., & Huang, Q. (1998). Extracting characters of license plates from video sequences. *Machine Vision and Applications, 10*(5-6), 308-320.

Daramola, S. A., Adetiba, E., Adoghe, A., Badejo, J., Samuel, I., & Fagorusi, T. (2011). Automaticvehicle identification system using license plate. *International Journal of Engineering Science and Technology (IJEST), 3*(2), 1712-1719.

Deb, K., Chae, H.-U., & Jo, K.-H. (2009). Vehicle License Plate Detection Method Based on Sliding Concentric Windows and Histogram. *JCP, 4*(8), 771-777.

Deb, K., Vavilin, A., Kim, J.-W., Kim, T., & Jo, K.-H. (2010). *Projection and least square fitting with perpendicular offsets based vehicle license plate tilt correction.* Paper presented at the SICE Annual Conference 2010, Proceedings of.

Dev, A. (2015). *A Novel Approach for Car License Plate Detection Based on Vertical Edges.* Paper presented at the Advances in Computing and Communications (ICACC), 2015 Fifth International Conference on.

Dia, Y., Zheng, N., Zhang, X., & Xuan, G. (1988). *Automatic recognition of province name on the license plate of moving vehicle.* Paper presented at the Pattern Recognition, 1988., 9th International Conference on.

Draghici, S. (1997). A neural network based artificial vision system for licence plate recognition. *International Journal of Neural Systems, 8*(01), 113-126.

Du, S., Ibrahim, M., Shehata, M., & Badawy, W. (2013). Automatic license plate recognition (ALPR): A state-of-the-art review. *IEEE Transactions on circuits and systems for video technology, 23*(2), 311-325.

Duan, T. D., Du, T. H., Phuoc, T. V., & Hoang, N. V. (2005). *Building an automatic vehicle license plate recognition system.* Paper presented at the Proc. Int. Conf. Comput. Sci. RIVF.

Franc, V., & Hlavác, V. (2005). *License plate character segmentation using hidden markov chains.* Paper presented at the DAGM-Symposium.

Gao, Q., Wang, X., & Xie, G. (2007). *License plate recognition based on prior knowledge.* Paper presented at the Automation and Logistics, 2007 IEEE International Conference on.

Guo, J.-M., & Liu, Y.-F. (2008). License plate localization and character segmentation with feedback self-learning and hybrid binarization techniques. *IEEE transactions on vehicular technology, 57*(3), 1417-1424.

Haralick, R. M., Sternberg, S. R., & Zhuang, X. (1987). Image analysis using mathematical morphology. *IEEE transactions on pattern analysis and machine intelligence*(4), 532-550.

He, L., & Chao, Y. (2015). A very fast algorithm for simultaneously performing connected-component labeling and euler number computing. *IEEE Transactions on Image Processing, 24*(9), 2725-2735.

Hongliang, B., & Changping, L. (2004). *A hybrid license plate extraction method based on edge statistics and morphology.* Paper presented at the Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on.

Hontani, H., & Koga, T. (2001). *Character extraction method without prior knowledge on size and position information.* Paper presented at the Vehicle Electronics Conference, 2001. IVEC 2001. Proceedings of the IEEE International.

Huang, Y.-P., Chen, C.-H., Chang, Y.-T., & Sandnes, F. E. (2009). An intelligent strategy for checking the annual inspection status of motorcycles based on license plate recognition. *Expert Systems with Applications, 36*(5), 9260-9267.

Huang, Y.-P., Lai, S.-Y., & Chuang, W.-P. (2004). *A template-based model for license plate recognition.* Paper presented at the Networking, Sensing and Control, 2004 IEEE International Conference on.

Ibrahim, N. K., Kasmuri, E., Jalil, N. A., Norasikin, M. A., Salam, S., & Nawawi, M. R. M. (2014). License plate recognition (LPR): a review with experiments for Malaysia case study. *arXiv preprint arXiv:1401.5559*.

Jia, W., Zhang, H., He, X., & Piccardi, M. (2005). *Mean shift for accurate license plate localization.* Paper presented at the Intelligent Transportation Systems, 2005. Proceedings. 2005 IEEE.

Jiao, J., Ye, Q., & Huang, Q. (2009). A configurable method for multi-style license plate recognition. *Pattern Recognition, 42*(3), 358-369.

Jin, L., Xian, H., Bie, J., Sun, Y., Hou, H., & Niu, Q. (2012). License plate recognition algorithm for passenger cars in Chinese residential areas. *Sensors, 12*(6), 8355-8370.

Kamat, V., & Ganesan, S. (1995). *An efficient implementation of the Hough transform for detecting vehicle license plates using DSP'S.* Paper presented at the Real-Time Technology and Applications Symposium, 1995. Proceedings.

Kanayama, K., Fujikawa, Y., Fujimoto, K., & Horino, M. (1991). *Development of vehicle-license number recognition system using real-time image processing and its application to travel-time measurement.* Paper presented at the Vehicular Technology Conference, 1991. Gateway to the Future Technology in Motion., 41st IEEE.

Kang, D.-J. (2009). Dynamic programming-based method for extraction of license plate numbers of speeding vehicles on the highway. *International Journal of Automotive Technology, 10*(2), 205-210.

Kim, K. K., Kim, K., Kim, J., & Kim, H. J. (2000). *Learning-based approach for license plate recognition.* Paper presented at the Neural Networks for Signal Processing X, 2000. Proceedings of the 2000 IEEE Signal Processing Society Workshop.

Kim, M.-K., & Kwon, Y.-B. (1996). *Multi-font and multi-size character recognition based on the sampling and quantization of an unwrapped contour.* Paper presented at the Pattern Recognition, 1996., Proceedings of the 13th International Conference on.

Kocer, H. E., & Cevik, K. K. (2011). Artificial neural networks based vehicle license plate recognition. *Procedia Computer Science, 3*, 1033-1037.

Lee, E. R., Kim, P. K., & Kim, H. J. (1994). *Automatic recognition of a car license plate using color image processing.* Paper presented at the Image Processing, 1994. Proceedings. ICIP-94., IEEE International Conference.

Lee, H.-J., Chen, S.-Y., & Wang, S.-Z. (2004). *Extraction and recognition of license plates of motorcycles and vehicles on highways.* Paper presented at the Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on.

Lee, R.-C., & Hung, K.-C. (2013). An Automatic Vehicle License Plate Recognition Based on Prewitt Edge Detection and Artificial Neural Network. *International Journal Of Scientific Research And Education, 1*(5), 79-90.

Llorens, D., Marzal, A., Palazón, V., & Vilar, J. M. (2005). *Car license plates extraction and recognition based on connected components analysis and HMM decoding.* Paper presented at the Iberian Conference on Pattern Recognition and Image Analysis.

Matas, J., & Zimmermann, K. (2005). *Unconstrained licence plate and text localization and recognition.* Paper presented at the Intelligent Transportation Systems, 2005. Proceedings. 2005 IEEE.

Miyamoto, K., Nagano, K., Tamagawa, M., Fujita, I., & Yamamoto, M. (1991). *Vehicle license-plate recognition by image analysis.* Paper presented at the Industrial Electronics, Control and Instrumentation, 1991. Proceedings. IECON'91., 1991 International Conference on.

Nijhuis, J., Ter Brugge, M., Helmholt, K., Pluim, J., Spaanenburg, L., Venema, R., & Westenberg, M. (1995). *Car license plate recognition with neural networks and fuzzy logic.* Paper presented at the Neural Networks, 1995. Proceedings., IEEE International Conference on.

Nomura, S., Yamanaka, K., Katai, O., Kawakami, H., & Shiose, T. (2005). A novel adaptive morphological approach for degraded character image segmentation. *Pattern Recognition, 38*(11), 1961-1975.

Paliy, I., Turchenko, V., Koval, V., Sachenko, A., & Markowsky, G. (2004). *Approach to recognition of license plate numbers using neural networks.* Paper presented at the Neural Networks, 2004. Proceedings. 2004 IEEE International Joint Conference on.

Pan, M.-S., Xiong, Q., & Yan, J.-B. (2009). A new method for correcting vehicle license plate tilt. *International Journal of Automation and Computing, 6*(2), 210-216.

Pan, M.-S., Yan, J.-B., & Xiao, Z.-H. (2008). Vehicle license plate character segmentation. *International Journal of Automation and Computing, 5*(4), 425-432.

Pan, X., Ye, X., & Zhang, S. (2005). A hybrid method for robust car plate character recognition. *Engineering Applications of Artificial Intelligence, 18*(8), 963-972.

Panahi, R., & Gholampour, I. (2017). Accurate detection and recognition of dirty vehicle plate numbers for high-speed applications. *IEEE Transactions on intelligent transportation systems, 18*(4), 767-779.

Park, S. H., Kim, K. I., Jung, K., & Kim, H. J. (1999). Locating car license plates using neural networks. *Electronics Letters, 35*(17), 1475-1477.

Qin, Z., Shi, S., Xu, J., & Fu, H. (2006). *Method of license plate location based on corner feature.* Paper presented at the Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on.

Rahman, C. A., Badawy, W., & Radmanesh, A. (2003a). *A real time vehicle's license plate recognition system.* Paper presented at the Advanced Video and Signal Based Surveillance, 2003. Proceedings. IEEE Conference on.

Rahman, C. A., Badawy, W. M., & Radmanesh, A. (2003b). *A Real Time Vehicle's License Plate Recognition System.* Paper presented at the AVSS.

Rajput, H., Som, T., & Kar, S. (2015). An Automated Vehicle License Plate Recognition System. *Computer, 8*, 56-61.

Rajput, H., Som, T., & Kar, S. (2016). Using Radon Transform to Recognize Skewed Images of Vehicular License Plates. *Computer, 49*(1), 59-65.

Samma, H., Lim, C. P., Saleh, J. M., & Suandi, S. A. (2016). A memetic-based fuzzy support vector machine model and its application to license plate recognition. *Memetic computing, 8*(3), 235-251.

Sangnoree, A., & Chamnongthai, K. (2017). Thermal-Image Processing and Statistical Analysis for Vehicle Category in Nighttime Traffic. *Journal of Visual Communication and Image Representation*.

Sarfraz, M., Ahmed, M. J., & Ghazi, S. A. (2003). *Saudi Arabian license plate recognition system.* Paper presented at the Geometric Modeling and Graphics, 2003. Proceedings. 2003 International Conference on.

Sarker, M. K., Yoon, S., & Park, D. S. (2014). A Fast and Robust License Plate Detection Algorithm Based on Two-stage Cascade AdaBoost. *KSII Transactions on Internet & Information Systems, 8*(10).

Sethian, J. A. (1996). A fast marching level set method for monotonically advancing fronts. *Proceedings of the National Academy of Sciences, 93*(4), 1591-1595.

Soille, P. (2013). *Morphological image analysis: principles and applications*: Springer Science & Business Media.

Stec, P., & Domanski, M. (2003). *Efficient unassisted video segmentation using enhanced fast marching.* Paper presented at the Image Processing, 2003. ICIP 2003. Proceedings. 2003 International Conference on.

Suresh, K. V., Kumar, G. M., & Rajagopalan, A. (2007). Superresolution of license plates in real traffic videos. *IEEE Transactions on intelligent transportation systems, 8*(2), 321-331.

Tarabek, P. (2012). *Fast license plate detection based on edge density and integral edge image.* Paper presented at the Applied Machine Intelligence and Informatics (SAMI), 2012 IEEE 10th International Symposium on.

Ter Brugge, M., Stevens, J., Nijhuis, J., & Spaanenburg, L. (1998). *License plate recognition using DTCNNs.* Paper presented at the Cellular Neural Networks and Their Applications Proceedings, 1998 Fifth IEEE International Workshop on.

Türkyılmaz, İ., & Kaçan, K. (2017). License Plate Recognition System Using Artificial Neural Networks. *ETRI Journal, 39*(2), 163-172.

Wang, M.-L., Liu, Y.-H., Liao, B.-Y., Lin, Y.-S., & Horng, M.-F. (2010). *A vehicle license plate recognition system based on spatial/frequency domain filtering and neural networks.* Paper presented at the International Conference on Computational Collective Intelligence.

Wang, S.-Z., & Lee, H.-J. (2003). *Detection and recognition of license plate characters with different appearances.* Paper presented at the Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE.

Wang, S.-Z., & Lee, H.-J. (2007). A cascade framework for a real-time statistical plate recognition system. *IEEE Transactions on Information Forensics and Security, 2*(2), 267-282.

Wang, W., Shen, C., Zhang, J., & Paisitkriangkrai, S. (2009). *A two-layer night-time vehicle detector.* Paper presented at the Digital Image Computing: Techniques and Applications, 2009. DICTA'09.

Wen, Y., Lu, Y., Yan, J., Zhou, Z., von Deneen, K. M., & Shi, P. (2011). An algorithm for license plate recognition applied to intelligent transportation system. *IEEE Transactions on intelligent transportation systems, 12*(3), 830-845.

Wu, B.-F., Lin, S.-P., & Chiu, C.-C. (2007). Extracting characters from real vehicle licence plates out-of-doors. *IET Computer Vision, 1*(1), 2-10.

Wu, H.-H. P., Chen, H.-H., Wu, R.-J., & Shen, D.-F. (2006). *License plate extraction in low resolution video.* Paper presented at the Pattern Recognition, 2006. ICPR 2006. 18th International Conference on.

Wu, M.-K., Wei, J.-S., Shih, H.-C., & Ho, C. C. (2009). *2-level-wavelet-based license plate edge detection.* Paper presented at the Information Assurance and Security, 2009. IAS'09. Fifth International Conference on.

Xu, J.-F., Li, S.-F., & Yu, M.-S. (2004). *Car license plate extraction using color and edge information.* Paper presented at the Machine Learning and Cybernetics, 2004. Proceedings of 2004 International Conference on.

Yang, F., & Ma, Z. (2005a). *Vehicle license plate location based on histogramming and mathematical morphology.* Paper presented at the Automatic Identification Advanced Technologies, 2005. Fourth IEEE Workshop on.

Yang, F., & Ma, Z. (2005b). *Vehicle license plate location based on histogramming and mathematical morphology.* Paper presented at the Fourth IEEE Workshop on Automatic Identification Advanced Technologies (AutoID'05).

Yoon, Y., Ban, K.-D., Yoon, H., & Kim, J. (2011). *Blob extraction based character segmentation method for automatic license plate recognition system.* Paper presented at the Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on.

Zakaria, M. F., & Suandi, S. A. (2010). Malaysian car number plate detection system based on template matching and colour information. *IJCSE) International Journal on Computer Science and Engineering, 2*, 1159-1164.

Zhai, W., Gao, T., Hu, Y., & Tian, Y. (2011). Research and Implementation of License Plate Character Segmentation Based on Tilt Correction. *Information and Automation*, 92-97.

Zhang, H., Jia, W., He, X., & Wu, Q. (2006a). *A fast algorithm for license plate detection in various conditions.* Paper presented at the Systems, Man and Cybernetics, 2006. SMC'06. IEEE International Conference on.

Zhang, H., Jia, W., He, X., & Wu, Q. (2006b). *Learning-based license plate detection using global and local features.* Paper presented at the 18th International Conference on Pattern Recognition (ICPR'06).

Zhang, S., Ye, X., & Zhang, M. (2004). *Car plate character extraction under complicated environment.* Paper presented at the IEEE INTERNATIONAL CONFERENCE ON SYSTEMS MAN AND CYBERNETICS.

Zheng, D., Zhao, Y., & Wang, J. (2005). An efficient method of license plate location. *Pattern Recognition Letters, 26*(15), 2431-2438.

Zheng, L., He, X., Samali, B., & Yang, L. T. (2010). *Accuracy enhancement for license plate recognition.* Paper presented at the Computer and Information Technology (CIT), 2010 IEEE 10th International Conference on.

LIST OF PUBLICATIONS

Publication in ISI Indexed Journals:

1. **M. Y. Arafat**, A.S.M. Khairuddin, R. Paramesran (2018); "A Vehicular License Plate Recognition Framework for skewed images" in *KSII Transactions on Internet and Information Systems*, volume-12, Issue-11, 2018 **(Published).**
2. **M. Y. Arafat**, Anis Salwa Mohd Khairuddin, Raveendran Paramesran (2018); "A Systematic Review on Vehicular License Plate Recognition Framework" in *IET Intelligent Transport Systems* **(Published in 2019).**
3. **M. Y. Arafat**, Anis Salwa Mohd Khairuddin, Raveendran Paramesran (2018); "A CCA integrated edge based technique for automatic vehicular license plate recognition framework" in *IET Intelligent Transport Systems* (**Under Review**).