

Development of a License Plate Recognition System for a Non-ideal Environment

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Abstract — A new algorithm for license plate character recognition system is proposed on the basis of Signature analysis properties and features extraction. Signature analysis has been used to locate license plate region and its properties can be further utilised in supporting and affirming the license plate character recognition. This paper presents the implementation of Signature Analysis combined with Features Extraction to form feature vector for each character with a length of 56. Implementation of these two methods is used in tracking of vehicle's automatic license plate recognition system (ALPR). The developed ALPR comprises of three phase. The recognition stage utilised the vector to be trained in a simple multi-layer feed-forward back-propagation Neural Network with 56 inputs and 34 neurons in its output layer. The network is trained with both ideal and noisy characters. The results obtained show that the proposed system is capable to recognise both ideal and non-ideal license plate characters. The system also capable to tackle the common character misclassification problems due to similarity in characters.

Keywords – ALPR, Signature Analysis, Features Extraction, Character Recognition, License Plate, Artificial Neural Network

I. INTRODUCTION

A rapid technical growth in the area of computer image processing has increased the need for an efficient and affordable security, thus resulted in the evolution of different kinds of solution based on computer image analysis. One type of these solutions is automatic license plate character recognition (ALPR). ALPR is a crucial subject of research due to its wide market applications to meet specific demands such as automatic system steering to access protected area, route traffic monitoring system, electronic payment system (toll fee, parking fee payment) and etc. Therefore, image processing based algorithm is feasible to develop a vehicle license plate recognition system. The aim of this project is to design a system to detect and recognise a vehicle's license plate.

The rest of the paper is organised as follows. The next section comprises of a review of other related researches that have been addressed in the literature. Section III presents the overall system and its three phases. Phase one and phase two of license plate localisation and segmentation are presented in [1]. Phase three of the system which is the license plate character recognition system and its main methods are discussed thoroughly here. Experimental results, restrictions and discussions will be delivered in Section IV to manifest feasibility of the system. Overall project and future extensions are presented in Section V.

II. REVIEW OF OTHER RELATED WORK

Recognition algorithm covered in existing research are basically comprised of several processing steps, such as tracking and localisation of vehicle, detecting license plate, extraction of license plate region, character segmentation and recognition of each character. The main intention of this section is to provide a brief reference source for the researchers regarded in character recognition, despite of any

specific application fields (i.e. optical character recognition (OCR), handwriting recognition, printed character and etc.).

Gabor filter is a linear filter used for edge detection. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Gabor filter has been one of the major tools for texture analysis. This method has the privilege of analyzing texture in a limitless number of directions and scales. This filter has been applied to various applications such as, texture analysis [2], tracking object in motion [3] and face recognition [4]. Gabor Transform has been used to locate license plate as presented in [5]. This method is time consuming, although the results were encouraging [6]. Conventional Gabor filter also has been enhanced based on features extraction to tackle recognition of low resolution grey character [7]. The authors indicate that the test results are very effective in character recognition.

Multi layer perceptron Neural Networks were used for character recognition as in [8] and [9]. Generally, error backpropagation is used to train this kind of networks. The network needs to be trained for many training cycles in order to reach a good performance. This method has its advantage as the network can be trained with both noise or without noise. Although in some papers shows that the training is rather time consuming.

In [9] an automatic recognition of Arabic printed text is developed using Neural Networks. The authors points out the advantages of the network architecture such as it combines both rule-based (structural) and classification tests, feature extraction is inexpensive and the execution time is independent of character font and size. A three layer Artificial Neural Network (ANN) was used for Arabic words classification. In spite of the enormous research done on this paper, the authors claim that the recognition of Arabic characters is still in its infancy.

Genetic Algorithm (GA) is a search heuristic that imitates the process of natural evolution. Basically, this heuristic is used to render practicable solutions for optimization and search problems. A conventional genetic algorithm requires two elements; a genetic representation of the solution domain and a fitness function to evaluate the particular solution domain. In [10], a genetic algorithm in the pattern of cellular automata and through Conway’s rules of the game of life is applied to generate a system of printed Thai character recognition. The system proposed consisted of two main parts; recognition training and recognition testing. With sample data as large as 1015 printed Thai character tested, the authors found out that the system could recognise 986 characters, which is 97.14% success. The system rejected 6 characters which is 0.59% and the misrecognised 23 characters, 2.27%. As for the average execution time was 85 seconds per character.

A simple and fast recognition method is pattern matching. The idea behind the execution of a correlation based on the identification scheme is simple. Two template pools are used to construct a template consisting of all the possible values for the letters, and one of all the values of the digits. Once the character is segmented, the normalized correlation coefficient between the image of the character and the appropriate template pool is computed. This method can be used to evaluate the correlation coefficient between a number of known images with the same size unknown images or parts of an image with the highest coefficient between the images and producing the best match [11]. Pattern matching or also known as template matching is also implemented successfully in [12], [13] and [14].

In this paper, an algorithm implementing Signature Analysis properties and features extraction is considered for license plate character recognition. Signature Analysis has been used in [15] for license plate region localisation and further extends here to enhance the recognition process.

III. METHODOLOGY

The license plate detection and recognition system comprises of three phases. TABLE I outlined the overall system and its approaches.

TABLE I. OVERALL SYSTEM AND ITS APPROACHES

| License Plate Character Recognition System for Non-ideal Environment | | |
|--|---------|---|
| 1 | Phase 1 | Vehicle license plate localisation Signature Analysis combined with Improved Connected Component Analysis (SAICCA) |
| 2 | Phase 2 | License plate segmentation Connected Component Analysis (CCA) |
| 3 | Phase 3 | License plate character recognition Signature analysis, thinning algorithm, features extraction, neural network |

Phase one is the vehicle’s license plate localisation as presented in [1]. Phase two is license plate segmentation and follows by phase three which is the license plate character recognition. The license plate character recognition sequence, which is proposed in this paper, consists of three distinct parts. The first one deals with the further usage of properties obtained from Signature Analysis as presented in [15]. The second part includes operations of thinning algorithm on the signature. Finally, the third part deals with the thinned character, where its features will be extracted to be trained in a simple ANN. Methods used in both phase 1 and phase 2 of the system are described thoroughly as in [1]. Hence, this section is focus on phase three of the developed system. Signature Analysis, the main algorithm that has been used extensively as in phase one is briefly discussed here, and its contribution in phase three is highlighted in this section.

A. Signature Analysis

The fundamental idea of Signature Analysis as presented in [15] and [16] comes from the general assumptions such as; the license plate is in a rectangular region mostly filled with characters. Additionally, the plate is set near the vertical axis of the vehicle and the characters should have higher distinctive intensities from its background.

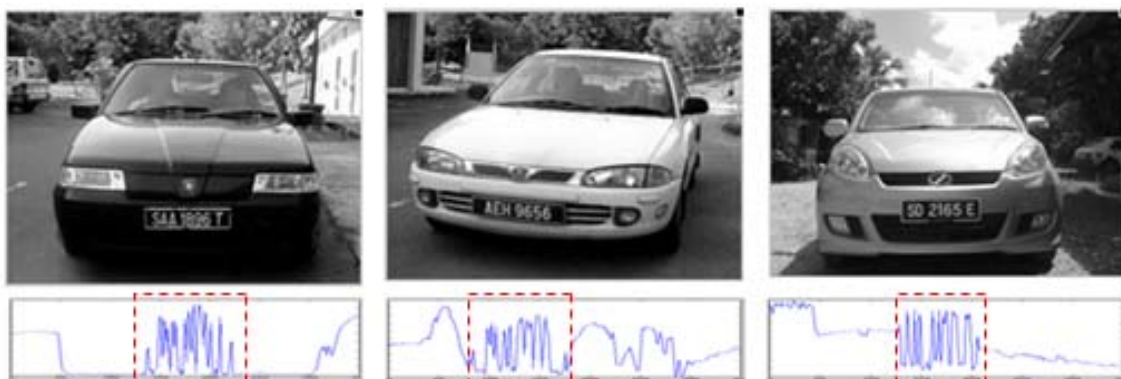


Figure 1. Example of Signature Analysis.

Hence, the license plate text forms a dense region of vertical strokes and this unique pattern is identified as the signature of a license plate.

Hypothetically, license plate also can be viewed as irregularities in the texture of the image and therefore abrupt changes in the local characteristics of the image, manifest probably the presence of a license plate [5]. Based on the above, this paper proposes recognition technique by means of Signature Analysis properties as obtained in [15].

The bounding box is referring to the minimum rectangular box that is capable to encapsulate the whole character image. The properties obtained in Signature Analysis are used to form the width-to-height (WH) ratio and later on to be trained in a simple ANN for recognition purpose.

Fig. 1 shows examples of ‘signature’. Input image frame is extracted to perform background subtraction and converted to grayscale. Next, the intensity of each pixel value is projected. As depicted from the examples, darker region in the image would produce lower intensity and vice versa. Thus, the license plate region would be able to locate by searching for the dense region of vertical strokes.

Fig. 2 shows how the properties obtained in Signature Analysis are used to form the WH ratio and later on to be trained in a simple ANN for recognition purpose. The size of this bounding box is crucial as only a certain WH ratio of the bounding box as shown in (1) will be considered in thinning and recognition stage. WH ratio is defined as ratio of bounding box width, w , to bounding box height, h , of that object. This approach can be beneficial since size of each character may vary at each iteration as the vehicle moving forward approaching the camera or driving away leaving the camera sight of view.

Therefore, having the ratio of the character can assure and prevent false recognition by taking the advantage of Signature Analysis approach that has been used in vehicle localisation. Moreover, the properties ready in the computation memory may speed up the recognition procedure

$$W = \frac{w}{h} \tag{1}$$

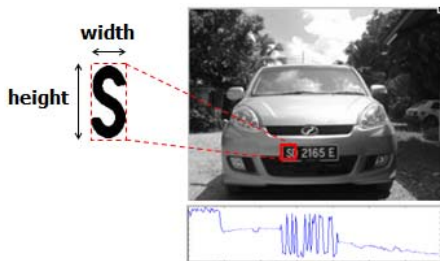


Figure 2. Finding WH ratio. Character ‘S’ is set so that the region points would have value ‘1’ and background ‘0’.

B. Thinning Algorithm

Thinning algorithm is performed on the segmented character before it is fed to the ANN for training. This morphological operation successively removes the pixels so that an object without holes shrinks to a minimally connected stroke erodes away the foreground pixels until they are one pixel width ‘skeleton’. On the other hand, an object with holes shrinks to a connected ring halfway between each hole and the outer boundary.

In this algorithm, region points are assumed to have value ‘1’ and background ‘0’. The iterative method consists of successive passes, where certain conditions have to be met in order for the point to be deleted (inverted). The definition of a contour point is any pixel with value ‘1’, that has at least one pixel in the 8-neighbour valued ‘0’. Fig. 3 shows a pixel p is examined for deletion, and the 8-neighbours pixels in its 3x3 windows.

The result has several advantages; it preserves the Euler number, retains the topology of the original object, and forces the ‘skeleton’ being in the middle of the segmented character.

Moreover, thin-line images of elongated forms would be more amenable to extraction of critical features such as end points, junction points and connection among the pixels. In detecting and tracking a moving vehicle’s license plate, angles and distance from the camera influenced the quality of the extracted license plate; as the width of the characters may be differ from one and another.

Firstly, the image is divided into two distinct subfields in a checkerboard pattern. If one or more conditions are violated, the value of the point in question is unchanged. If all of the three conditions as defined in (2), (4) and (7) are satisfied then the point is flagged for deletion. However the point is not deleted until all border points have been processed [17].

Fig. 4 shows iterations of thinning algorithm performed on character ‘S’ by using the derived equations. The iterations are repeated until the image stops changing. It is perceivable that from the 4th iteration and onwards, the image stops changing. Once all border points are processed, results from first sub-iteration is applied, then follow processing the conditions in second sub-iteration. This routine covers one iteration of the algorithm, which is then repeated for each point.

| | | |
|-------|-------|-------|
| x_4 | x_3 | x_2 |
| x_5 | p | x_1 |
| x_6 | x_7 | x_8 |

Figure 3. 8-neighbours relationship.

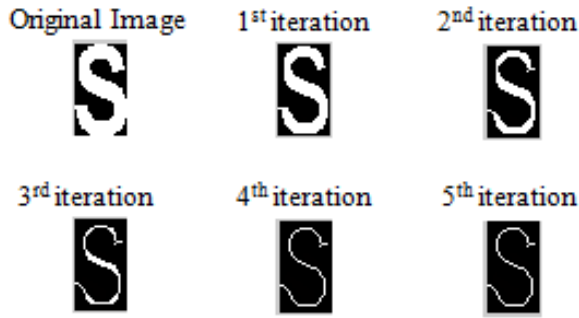


Figure 4. Thinning of character 'S'.

The first condition G1, defined the crossing number as the number of times one crosses over from a white point to black point when the points in the 8-neighbours are traversed in order. Therefore,

Condition G1:

$$X_H(p) = \sum_{i=1}^4 b_i X_H(p) \quad (2)$$

where,

$$b_i = \begin{cases} 1, & \text{if } x_{2i-1} = 0 \text{ and } (x_{2i} = 1 \text{ or } x_{2i+1} = 1) \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Here $x_1, x_2, x_3, \dots, x_8$ are the values of the eight neighbours of p , starting with the east neighbour and numbered in counter-clockwise order.

Condition G2:

$$2 \leq \min \{n_1(p), n_2(p)\} \leq 3 \quad (4)$$

where,

$$n_1(p) = \sum_{k=1}^4 x_{2k-1} \vee x_{2k} \quad (5)$$

$$n_2(p) = \sum_{k=1}^4 x_{2k} \vee x_{2k+1} \quad (6)$$

Condition G3:

$$(x_6 \vee x_7 \vee \overline{x_4}) \wedge x_5 = 0 \quad (7)$$

C. Features Extraction

Features extraction is an approach used to extract geometric features of the character contour. After the shortest matrix for the character skeleton is found, the image is zoned into 9 equal size windows. Features extraction is applied on the individual zones rather than the whole image. This approach also concentrates on the positional features of the character skeleton which gives more information about the fine detail.

For instance, Fig. 5 shows that the horizontal line segment occurs in the upper zones, central zones and lower zones of character 'T', 'H' and 'L' respectively. On the other hand, a diagonal line segment may occur in character such as '2' and '7'.

To extract different line segments in a particular zone, the entire skeleton in that zone should be traversed. A technique as proposed in [18] is applied in this paper in order to find the line segment. The segmented line segment is further classified into four different line types; horizontal line, vertical line, right diagonal line and left diagonal line. Hence, a direction vector is extracted from each line segment which will aid in defining each line type. A rule is required to specify the position of neighbouring pixel with respect to the centre pixel under consideration.

Fig. 6 illustrates the line segment analysis, with 'C' represents the centre pixel and the neighbouring pixels are numbered in a clockwise manner starting from pixel below the central pixel. The algorithm is programmed to traverse through the entire pixels in the line segments in the order they form the line segment. Evaluation of line type and its direction is analyzed by using (8). The first pixel to be analysed is from column_zone1 of character 'S', (5, 11).

$$line_direction = next_pixel - current_pixel \quad (8)$$

Line type for each segment is classified based on maximum of occurrence of the direction type. As for example in Fig. 6, maximum occurring direction type is 6 and 2, then the line type will be classified as right diagonal. After the line type for each segment in each zone is determined, a feature vector is formed based on this information.

To enhance the recognition purpose, certain features such as Euler Number were extracted for the entire image based on the regional properties. Euler Number is defined as the difference of number of objects and number of holes in a particular image.

TABLE II shows examples of input characters and its Euler Number



Figure 5. Character zoning.

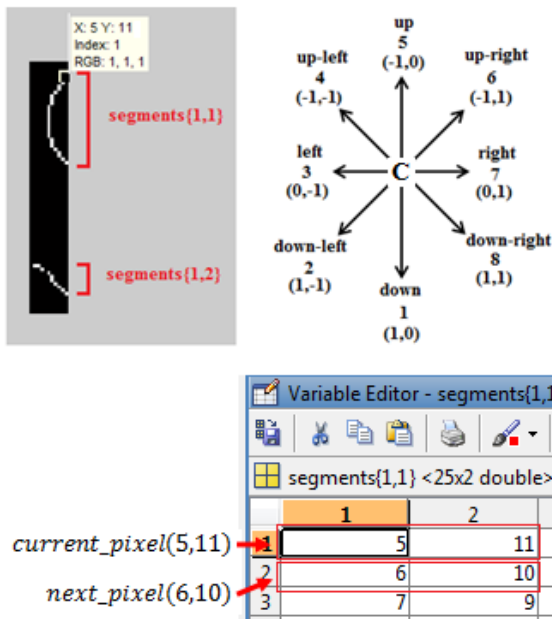


Figure 6. Line type evaluation.

TABLE II. CHARACTER EULER NUMBER EVALUATION

| Character | Number of objects in the image | Number of holes in the image | Euler number |
|-----------|--------------------------------|------------------------------|--------------|
| A | 1 | 1 | $1 - 1 = 0$ |
| B | 1 | 2 | $1 - 2 = -1$ |
| C | 1 | 0 | $1 - 0 = 1$ |
| S | 1 | 0 | $1 - 0 = 1$ |

With all the information gathered based on Signature Analysis, and the characters' features, now the data is ready to be trained in a simple ANN. Every character has a feature vector corresponding to it with a length of 56.

D. Neural Network Architecture

In this paper, a simple multi-layer feed-forward back-propagation Neural Network with 56 input and 34 neurons in its output layer is used to identify the letters. The log-sigmoid transfer function at the output layer was picked because its output range (0 to 1) is perfect for learning to output Boolean values. The hidden layer has 10 neurons. The numbers of hidden layers as well as the respective neurons were defined after a trial and error procedure. The network is trained to output 1 in the correct position of the output vector and to fill the rest of the output vector with 0's.

The network is trained with both ideal and noisy vectors (characters). Firstly, the network is trained on ideal vectors until it has a low sum-squared error. Then the network is trained on 136 of both ideal and noisy vectors.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system has been prototyped using Matlab 7.10 (R2010a) running in 32 bit and MySQL Community Server Version 5.1.29. The architectures of this simulation test include CPU Intel Core 2 Duo and 2GB of server memory. The sample of data is taken by using Canon PowerShot S90 and adjusted to acquire 640 x 480 pixels video with 30 fps. The camera is set to record the moving vehicle, while the angle of view is changed according to the observational setup. The distance between the camera setup and the vehicle varied from 2 to 10 meters at a height of 1.5-1.8 meters from the ground.

TABLE III demonstrates the overview of analysis and tests to be performed. Test 1, Test 2 and Test 3 are applied in phase one, used to justify the performance in vehicle license plate localisation.

The fourth test is applied to evaluate the performance of the character recognition system with variety of test inputs given to it. Test 4-A, Test 4-B and Test 4-C evaluate the performance of phase three, a neural network with input of 56-elements vector (obtained from Signature Analysis properties and features extraction) in recognising non-ideal characters.

Fig. 7 shows the results of Test 1. The results show that the proposed system was successfully tracking and locating the license plate.

However, it is noticeable that in the first iteration, the license plate cannot be localised because of several factors such as: distance from the camera, camera's illumination self-adjustment, deficiency of perceptual information etc.

As a vehicle driving away from the system's field of vision, the proposed system started to fail in detecting license plate correctly. This is due to a weak signature generated from the image.

In a case of a vehicle making a turn as shown in Fig.7, the side view of the license plate prevents the system from detecting and generating a strong signature or in this case no signature is generated at all.

A signature can be generated as soon as the front part of the vehicle moving towards the system's field of vision thus granting the system to gain a full view of the license plate.

TABLE III. OVERVIEW OF ANALYSIS AND TESTS

| Test and Analysis Performed on the Developed System | |
|---|---|
| Test 1 | Test input under variety driving motion |
| Test 2 | Distinguishing two moving vehicles |
| Test 3 | Distinguishing overlapping vehicles |
| Test 4-A | Test of effectiveness of character recognition for ideal character. |
| Test 4-B | Test of effectiveness of character recognition for non-ideal character. |
| Test 4-C | Test of effectiveness of character recognition for 'similar' characters such as 'B' and '8', '2' and 'Z'. |

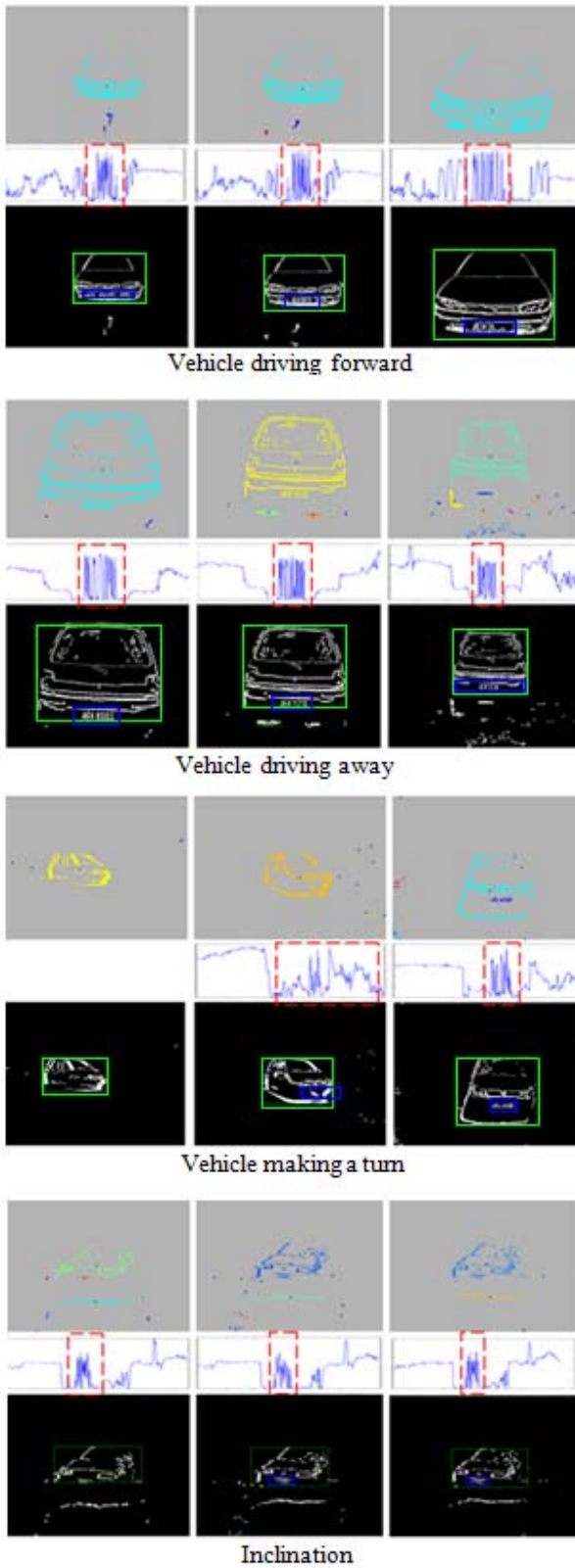


Figure 7. Test 1 - Test input under variety driving motion.

Fig. 8 shows the test results of Test 2. The Improved Connected Component Analysis (ICCA) that has been developed by combining isotropic dilation approach and the conventional Connected Component Analysis (CCA) is used to identify the two moving vehicles.

After the improvement, the non-unique components are detected as part of the same vehicle. However, the system is failed to locate the license plate of vehicle 2 due to deficiency of perceptual information.

Another issue need to be considered in this field of research is when the two vehicles positioned in a way that overlapped with each other.

Fig. 9 shows the analysis and outcomes of Test 3. Frame 35th shows that the two vehicles are not overlapped with each other thus the enhanced labelling analysis labelled both the vehicles with cyan (vehicle 1) and yellow (vehicle 2) colour. Started from frame 55th and above, the two vehicles started to overlapped and labelled with cyan colour. Therefore, a procedure is performed to check for overlapping of the bounding box edges. In frame 115th, the added procedure successfully distinguished vehicle 2 which is totally overlapped behind vehicle 1.

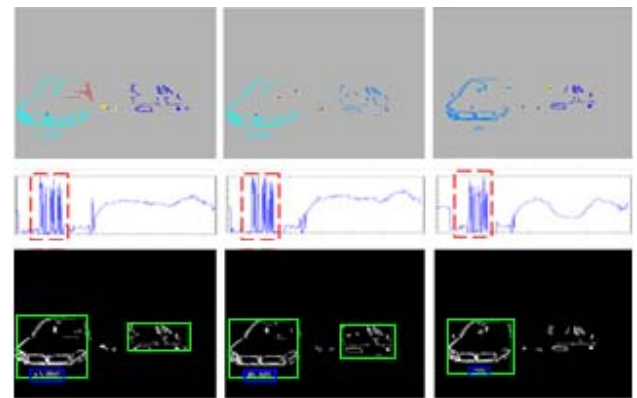


Figure 8. Test 2 - Distinguishing two moving vehicles.



Figure 9. Test 3 - Distinguishing overlapping vehicles.

Fig. 10 shows character recognition experimental results based on the proposed algorithms. Sample of license plate characters were thinned before they were fed to the neural network for training. All tests were performed on the same data set.

Test 4-A shows successful recognition for ideal character input. Test 4-B shows an example of unsuccessful result, where character ‘8’ was misidentified as ‘D’ due to reflection from the surrounding light. Whereas, Test 4-C shows that the algorithm is capable to differentiate character ‘2’ correctly although it can be easily misclassified as ‘Z’. Features extracted from each zone gave more details on all the lines and points that form a particular character, and thus leads to more reliable character recognition.

It is noticeable that the restrictions of the proposed algorithm in phase three are strongly related to the environmental conditions during the acquisition setup. As execution time for character recognition is still a crucial criterion that needs to be improved, thus this paper has proposed several steps to decrease the execution time to a minimum value.

The developed system is tested on 50 samples of data taken around the campus area. TABLE IV demonstrates the analysis of the conventional CCA and the ICCA. The analysis shows an improvement of 32% in license plate localisation by using adaptive searching of Signature Analysis - Improved CCA (SAICCA) [1].

TABLE V shows the performance analysis of the overall license plate recognition system. The SAICCA approach used in phase one of the system yields a good result without compromising too much of the overall execution time.

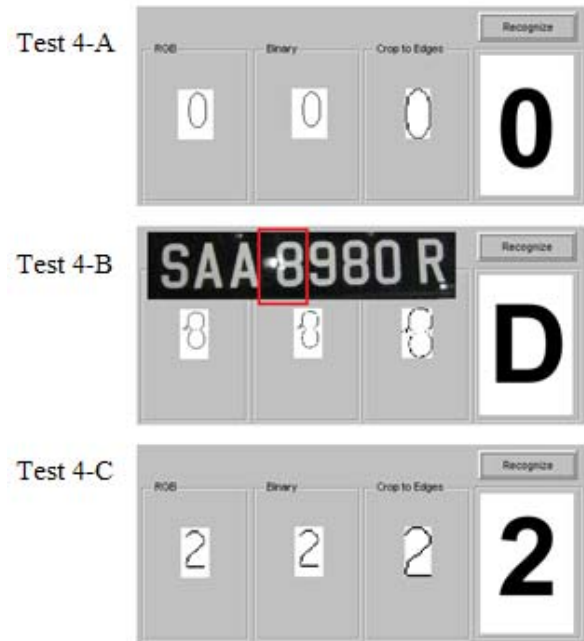


Figure 10. Test 4 - Evaluating phase three, license plate character recognition

However, the successful rate in both phases two and three of the system are heavily rely on the clarity and sufficiency of the license plate perceptual information. Mainly the failure rate is due to overly inclined of the license plate and shattered pixels in the character itself.

TABLE IV. ANALYSIS OF CONVENTIONAL CONNECTED COMPONENT ANALYSIS AND THE IMPROVED CONNECTED COMPONENT ANALYSIS

| Phase | Test of efficiency | No. of sample | No. of successful sample | Successful rate | Ave. execution time (ms) |
|--|--|---------------|--------------------------|-----------------|--------------------------|
| Phase 1: License plate localisation | Vehicle localisation via conventional Connected Component Analysis (CCA) | 50 | 30/50 | 60% | 34.4 |
| | SAICCA with adaptive searching | 50 | 46/50 | 92% | 823.65 |

TABLE V. PERFORMANCE ANALYSIS OF THE DEVELOPED SYSTEM

| Phase | Test of efficiency | No. of sample | No. of successful sample | Successful rate | Ave. execution time (ms) |
|----------------|---|---------------|--------------------------|-----------------|--------------------------|
| Phase 1: | License plate localisation - SAICCA with adaptive searching | 50 | 46/50 | 92% | 823.65 |
| Phase 2: | License plate character segmentation | 46 | 39/46 | 85% | 914.94 |
| Phase 3: | License plate character recognition | 39 | 35/39 | 90% | 645.8 |
| Overall system | | 50 | 35/50 | 70% | 3331.21 |

V. CONCLUSIONS

The intention of this paper is to investigate the possibility of designing a system for vehicle license plate character recognition system by using Signature Analysis properties and features extraction. The overall system comprises of three phases, namely vehicle license plate localisation, license plate segmentation and license plate character recognition system.

The methods used in phase three are discussed in this paper. The recognition sequence consists of three main parts. The existing Signature Analysis properties obtained from vehicle localisation process is gathered to be trained for the later character recognition. This approach may reduce the execution time of the overall system performance. Results of the overall system and its three phases are presented accordingly. There are some inevitable common failures that could occur in the proposed system. These failures are due to the fact that the plates were damaged or their physical appearances are not clear. Although in the first stage of the system, SAICCA achieved 92% of successful rate, however the performance of the overall system is very much affected by efficiency of the previous processing stage. To summarise, the developed system is viable to be implemented in a day to day natural scenes environment. The experimental results and characteristics of the system yields that it is feasible for localisation and recognition in both ideal and non-ideal environment. Processing time for a license plate localisation and recognition is still a crucial criterion that needs to be concerned. Therefore, this project has utilised several approaches to decrease the processing time to an optimal value. The proposed License Plate Character Recognition via Signature Analysis and Features Extraction has successfully recognised both ideal and non-ideal characters. The system also capable to tackle the common character misclassification problems due to similarity in characters such as '2' and 'Z', '5' and 'S', '8' and 'B'. This system needs to be further enhanced in the future to tackle the mentioned restrictions.

ACKNOWLEDGMENT

The authors would like to acknowledge the financial assistance from University Malaysia Sabah (UMS) under UMS Research Grant Scheme (SGPUMS) No. SBK0026-TK-1/2012, Postgraduate Research Grant Scheme (GPS) No. GPS0001-TK-1/2009 and the University Postgraduate Research Scholarship Scheme (PGD) by Ministry of Science, Technology and Innovation of Malaysia (MOSTI).

REFERENCES

- [1] L. Angeline, W.L. Khong, F. Wong, I. Saad, and K.T.K. Teo, "Multiple Vehicles' License Plate Tracking and Recognition via Isotropic Dilation," 3rd International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN), July 2011, pp. 54-59, doi: 10.1109/CICSyN.2011.24.
- [2] R. Porter and N. Canagarajah, "Robust Rotation-Invariant Texture Classification: Wavelet, Gabor filter and GMRF Based Schemes," IEEE Proceedings: Vision, Image & Signal Processing, vol. 144, issue 3, June 1997, pp. 180-188, doi: 10.1049/ip-vis:19971182.
- [3] C. He, J. Dong, Y.F. Zheng and S.C. Ahalt, "Object Tracking Using The Gabor Wavelet Transform And The Golden Section Algorithm," International Conference on Robotics and Automation, vol.2, 2001, pp. 1671-1676, doi: 10.1109/ROBOT.2001.932851.
- [4] D. Pramadihanto, H. Wu and M. Yachida, "Invariant Face Recognition By Gabor Wavelets And Neural Network Matching," IEEE International Conference on Systems, Man and Cybernetics. Information Intelligence and Systems, vol. 1, 1996, pp.59-63, doi: 10.1109/ICSMC.1996.569740.
- [5] F. Kahraman, B. Kurt and M. Gökmen, "License Plate Character Segmentation Based on the Gabor Transform and Vector Quantization," Lecture Notes on Computer Science 2869, A. Yazici and C. Sener, Ed., Springer-Verlag, 2003, pp. 381-388.
- [6] C.N. Anagnostopoulos, I. Anagnostopoulos, V. Loumos and E. Kayafas, "A License Plate Recognition Algorithm For Intelligent Transportation System Applications," vol. 7, no. 3, 2006, pp. 377-392, doi: 10.1109/TITS.2006.880641.
- [7] P.F. Hu, Y. Zhao, Z. Yang and J. Wang, "Recognition of Gray Character Using Gabor Filters," 5th International Conference on Information Fusion, vol. 1, 2002, doi: 10.1109/ICIF.2002.1021184.
- [8] A. Broumandnia and M. Fathy, "Application Of Pattern Recognition For Farsi License Plate Recognition," ICGST International Conference on Graphics, Vision and Image Processing, vol. 5, no.2, Jan 2005, pp. 25-31.
- [9] A. Amin and W. Mansoor, "Recognition of Printed Arabic Text using Neural Networks," 4th international Conference on Document Analysis and Recognition, vol. 2, 1997, pp. 612-615, doi: 10.1109/ICDAR.1997.620576.
- [10] C. Pornpanomchai and M. Daveloh, "Printed Thai Character Recognition By Genetic Algorithm," 6th International Conference on Machine Learning and Cybernetics, vol. 6, August 2007, pp. 3354-3359, doi: 10.1109/ICMLC.2007.4370727.
- [11] L. Angeline, K.T.K. Teo and F. Wong, "Smearing Algorithm for Vehicle Parking System," Proceeding of SEIT 2009, July 2009, pp. 331-337.
- [12] P. Comelli, P. Ferragina, M.N. Granieri and F. Stabile, "Optical Recognition of Motor Vehicle License Plates," IEEE Trans. On Vehicular Technology, vol. 44, no. 4, pp. 790-799, 1995, doi: 10.1109/25.467963.
- [13] Y.P. Huang, S.Y. Lai and W.P. Chuang, "A Template-Based Model for License Plate Recognition," International Conference on Networking, Sensing & Control, vol. 2, 2004, pp. 737-742, doi: 10.1109/ICNSC.2004.1297038.
- [14] W.L. Khong, W.Y. Kow, L. Angeline, I. Saad and K.T.K. Teo, "Overlapped Vehicle Tracking via Enhancement of Particle Filter with Adaptive Resampling Algorithm," International Journal of Simulation, Systems, Science and Technology (IJSST), vol. 12, no. 3, June 2011, pp. 44-51, ISSN: 1473-804x online.
- [15] L. Angeline, M.Y. Choong, F. Wong and K.T.K. Teo, "Tracking and Localisation of Moving Vehicle License Plate via Signature Analysis," Proceeding of ICOM 2011, 4th International Conference on Mechatronics, May 2011, pp. 1-7, doi: 10.1109/ICOM.2011.5937192.
- [16] H. Kwasnicka and B. Wawrzyniak, "License Plate Localization and Recognition in Camera Pictures," AI-METH 2002, Nov 2002, Gliwice Poland.
- [17] S.V.K. Gaddam and M. Lal, "Efficient Cancellable Biometric Key Generation Scheme for Cryptography," International Journal of Network Security, Sept. 2010, vol. 11, no. 2, pp. 61-69.
- [18] M. Blumenstein, B. K. Verma and H. Basli, "A Novel Feature Extraction Technique for the Recognition of Segmented Handwritten Characters," 7th International Conference on Document Analysis and Recognition, vol. 1, 2003, pp. 137-141, doi: 10.1109/ICDAR.2003.1227647.