

AUTOMATIC LICENSE PLATE LOCALISATION AND IDENTIFICATION VIA SIGNATURE ANALYSIS

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Abstract

A new algorithm for license plate localisation and identification is proposed on the basis of Signature analysis. Signature analysis has been used to locate license plate candidate and its properties can be further utilised in supporting and affirming the license plate character recognition. This paper presents Signature Analysis and the improved conventional Connected Component Analysis (CCA) to design an automatic license plate localisation and identification. A procedure called Euclidean Distance Transform is added to the conventional CCA in order to tackle the multiple bounding boxes that occurred. The developed algorithm, SAICCA achieved 92% successful rate, with 8% failed localisation rate due to the restrictions such as insufficient light level, clarity and license plate perceptual information. The processing time for a license plate localisation and recognition is a crucial criterion that needs to be concerned. Therefore, this paper has utilised several approaches to decrease the processing time to an optimal value. The results obtained show that the proposed system is capable to be implemented in both ideal and non-ideal environments.

Keywords:

Vehicle Localisation, Automatic License Plate Recognition, Signature Analysis, Adaptive Searching, Euclidean Distance Transform

1. 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 of these solutions is automatic license plate character recognition (ALPR). ALPR systems have been physically utilised in many facilities such as parking lots, security control of restricted areas and traffic surveillance. Every vehicle will carry a unique license plate and there are no external cards, tags or transmitter need to be recognized [1]. Therefore, image processing based algorithm is suitable 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 paper is organised as follows: The next section comprises reviews of related researches that have been addressed in the literature. Section 3 presents the methodology of the system. Experimental results, restrictions and discussions will be delivered in section 4 to manifest the feasibility of the system. Overall project and future extensions are presented in section 5.

2. REVIEW OF OTHER RELATED WORK

Automatic License Plate Recognition (ALPR) covered in existing research basically comprises 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 regarding the character recognition, despite specific application fields.

2.1 VEHICLE'S LICENSE PLATE LOCALISATION

Vehicle's license plate localisation is essential to the Automatic License Plate Recognition (ALPR) system. The main goal is to locate the region of interest (ROI) of the vehicle's license plate in the captured image.

An edge in an image is a significant local change in the image intensity. Discontinuities in the image intensity can be categorized into Step edges or Line edges. Step edges happened when the image intensity changes abruptly from one value on one side of the discontinuity to a different value on the opposite side. On the other hand, Line edges occur where image intensity abruptly changes value but then returns to the starting value within some short distances [2].

There are many ways to determine the edge points. The gradient method detects the edges by looking up for the maximum and minimum in the first derivative of the image. The Gradient method commonly used operators such as Roberts, Prewitt and Sobel.

Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. Generally both input and output of this operator is a grayscale image. The pixel values at each point at the output represent the approximated absolute magnitude of the input image spatial gradient at that particular point [3].

Prewitt edge detector is a way to estimate the magnitude and orientation of an edge. Theoretically, it is a discrete differentiation operator used to estimate the gradient of the image intensity function. At each point in the image, the outcome of the Prewitt operator is either the subsequent gradient vector or the norm of the vector.

Sobel operator is an approach in edge detection, which slightly alters the weight values of the Prewitt operator. Typically it is used to find the approximate absolute gradient magnitude at each point in a grayscale image. Theoretically, the operator consists of a pair of 3×3 convolution kernels, one estimating the gradient in the x-direction, and the other estimating in the y-direction [4].

One useful feature in edge detection is by searching the density of the edges. A license plate region is identified with patches of characters separated by vertical stripes of the background. These stripes appear as vertical strokes splitting license plate character and can be easily detected using a local

averaging operator. The operator yields a value proportional to the density of edges [5].

A novel texture descriptor carries out text detection in images and video sequences based on the line-segment features. Author in [6] suggested a descriptor based on Improved Connective Hough Transform (ICHT), which represents a perceptual characteristic of texture, in terms of directionality, regularity, similarity, alignment and connectivity. Next, an invariant descriptor developed by [7] is used for training and verifying the rightness of detected regions.

Researchers [8] proposed a new algorithm for character segmentation of a vehicle's license plate. The algorithm used Hough Transformation technique and the prior knowledge in horizontal and vertical segmentation respectively to avoid the abruptness and conglutination of characters, which are the main drawbacks from binary image. Hough Transformation can be used to detect lines in an image [9].

2.2 VEHICLE'S LICENSE PLATE IDENTIFICATION

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 is one of the major tools for texture analysis. This filter has been applied to various applications such as, texture analysis [10], tracking object in motion [11] and face recognition [12].

Gabor Transform is used to locate license plate as presented in [13]. This method is time consuming, although the results were encouraging [14].

Conventional Gabor filter has also been enhanced based on the features extraction to tackle recognition of low resolution grey character [15]. 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 [16] and [17]. Generally, error backpropagation is used to train this network. 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.

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.

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 produce the best match [18]. Pattern matching also known as template matching is also implemented successfully in [19] - [21].

3. METHODOLOGY

The license plate detection and recognition system comprises of four main stages. Table.1 outlined the four stages involved in developing the system.

Table.1. Overall System

S. No.	Automatic License Plate Localisation and Identification via Signature Analysis
1	Motion detection and pre-processing
2	Signature Analysis
3	Improved Connected Component Analysis
4	License plate character identification

3.1 MOTION DETECTION AND PRE-PROCESSING

Pre-processing is the requirement step to be applied for any image analyzing program. Without a proper pre-processing stage, the later segmentation and recognition procedures could be very inefficient and unyielding. The main reason for doing pre-processing is to perform image enhancement to obtain the desired region in the processed image. In this case, it will be the vehicle's license plate.

Firstly, the input is fed to the system and a program is coded to extract each of the colour image frames to be processed. The extracted frame consists of pixels with red, green and blue (RGB) colour variations. The system will convert the true colour image RGB to the greyscale intensity image using the standard NTSC method as in Eq.(1). This can be carried out by getting rid of the hue and saturation information while maintaining the luminance.

$$\text{greyscale} = 0.299 * \text{Red} + 0.587 * \text{Green} + 0.114 * \text{Blue} \quad (1)$$

Next, the background subtraction is performed on the greyscale level frame. Background subtraction is a process of filtering out the foreground objects from the background in a sequence of video frames. Frame difference is an approach where the previous frame is set as estimated background and thresholding the result to get the objects of interest Eq.(2). The program is set to jump four frames as in Eq.(3) to save the computational time.

$$|frame_i - background_i| > T_h \quad (2)$$

$$|frame_i - frame_{i-4}| > T_h \quad (3)$$

The small objects and noise occurring in the image will be filtered by using a median filter (2×2). A Median filter is a nonlinear operation which is often used in image processing as it can simultaneously decrease noise and preserve edges. Then, the image is ready to be passed to the next processing stage.

3.2 SIGNATURE ANALYSIS

There are numerous algorithms can be used to locate a vehicle's license plate. Signature analysis is proposed in this project as it is not limited to any specific color or significant edges to locate a license plate in a mixed image. The fundamental idea comes from the general assumptions such as, the plate is a rectangular region mostly filled with characters, the plate is situated near the vertical axis of the vehicle (rather low) and characters have high distinctive intensities from background. Therefore, license plate text forms a dense region of vertical strokes, irrespective of the standpoint change and inclination. This unique pattern of vertical strokes is identified as the signature of a license plate.

Based on the assumption that license plate is situated near the vertical axis of the vehicle, thus the lower part of the vehicle

will be segmented into five segments. Table.2 shows that the program will evaluate these five segments and search for the signature of a license plate. Three rows from each segment will be selected and scanned for the signatures. The program requires at least two rows to have a valid signature before the particular segment qualified for the next process.

Signature can be represented by a perceptual characteristic of texture in terms of repetition of components in vertical direction (peaks) and gap between two peaks. One characteristic of a text region is that it is mainly composed by vertical edges.

According to [22], text character can be regarded as a particular pattern. Hence Signature Analysis is suitable to be used to analyze the pattern of the consecutive peaks. The number of peaks (signature) generated is counted to determine whether it falls between the threshold. In this project, the threshold is set as 6 and 15. If the number of peaks generated is within the threshold, then it will be recognized as a signature.

Computational time can be a major concern in license plate tracking and localisation system. Hence, adaptive searching approach is used to increase the efficiency and improve the computational time. In this approach, instead of re-searching for the signature, segment by segment in each iteration, the first successfully calculated vehicle's height and 'signature-row' will be used as the 'reference' in the next iteration. Thus, in the next iteration, the program will move to the previous signature-row and scan for the signature pattern.

However, if a signature exists in that particular row, vehicle's height will be calculated and compared with the vehicle's previous height. If value of the reference height is smaller than the current height, it implies that the vehicle is moving forward, and vice versa. The Fig.1 illustrates the nested signature analysis in detecting and localizing the license plate. The Table.2 summarises the procedures involved in evaluating Signature Analysis, whereas Table.3 demonstrates the routines involved in adaptive searching approach.

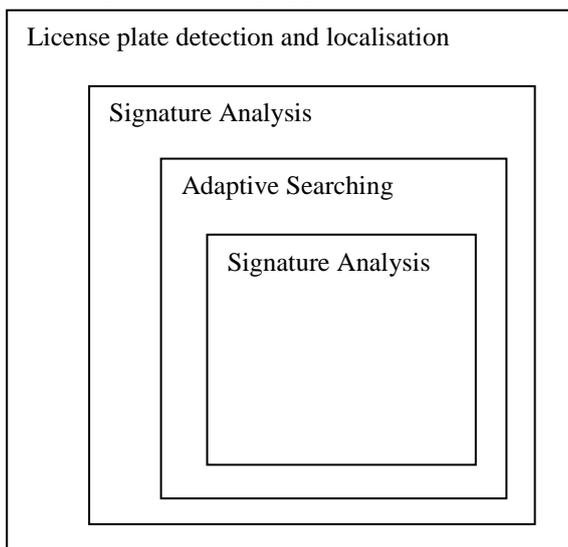


Fig.1. Nested Signature Analysis

Table.2. Signature Analysis

Pseudocode of Signature Analysis	
1	for i = 1:5 //divide image lower half into 5 segments
2	if i < 6? //run until the last segment for j = 1:3 //3-rows scan on each segment
3	if j < 4? {count num.of peak evaluate gap between peak} if 6 < num.of peak < 18 && gap < 20pixels {flag for signature candidate go to step 3} else go to step 3 else if signature found? {flag valid signature found i++ for next segment} else {flag invalid signature found i++ for next segment} Go to step2 else end

Table.3. Adaptive Searching

Pseudocode of Adaptive Searching for Signature	
1	Processing vehicle frame
2	$frame = l + 4$ //procedure skipped 4 frames
3	if signature been flagged? //checked if this is the first iteration, if it is //not, then adaptive searching start here find signature based on prev. frame if E.O.Frame? go to step 4 else go to step 2 else //This is the input's first iteration find signature in each row of each segment if E.O.Segment go to step 2 else go to step 3
4	end

The gap between two consecutive peaks is set not to exceed the threshold value of 20 pixels. This is based on the assumption that a text-like area will have a dense vertical edges region. Fig.2 shows the evaluation of signature analysis performed on a mixed image with the vehicle driving backward.

The Fig.2(a) shows an invalid signature for a vehicle's non-text area having gap greater than 20 pixels. While on the contrary, Fig.2(b) shows a valid signature with both number of peaks and gap between consecutive peaks fall in the range of the set threshold. Fig.2(c) shows the signature searching procedure below the license plate area with no signature found.

The Fig.3 shows the sample of signature generated from different angle of the vehicles. The sample data is evaluated using the procedure as presented in Table.2. After the image frame is processed using simple enhancement technique, the lower part of the image will be divided into five segments.

In order to ascertain the existence of signature in each segment, three rows in that particular segment will be scanned for signature. If there is a signature found in the first segment, then the procedure will flag for the signature found and passed the information to the next processing stage.

However, if there is no signature found, the routine will be passed to the next segment and scan for another three rows in that particular segment.

This procedure will be looped until it finds the signature candidate, or until the fifth segment and then only end the current frame processing. The current frame will be passed to 'exception frame' handling if there is no signature found in the particular frame. This is important in order to avoid system form halted in the middle of the frame processing. Hence, the system can carry on by processing the next frame iteration.

The Fig.4 illustrates the adaptive searching for the signature approach. The sample data is processed by using the procedures in both Table.2 and Table.3. At frame 40th, the lower part of the image is divided into five segments.

Before the procedure for signature searching starts, the procedure will check if the system has flagged for signature in the previous frame. In frame 40th, it was found that there is no flag for signature in the previous frame, thus the procedure is looking at each segment. As can be seen in the figure, the signature is found in the 5th segment at row 360.

In the next frame iteration (frame 44th), the procedure will check again if the system has flagged for signature. Since there is a signature found previously in frame 40th, instead of re-searching again the all five segments of frame 44th, the procedure will move to row 360 of frame 44th and search for signature at that particular region.

Same goes to the next iteration (frame 48th), the procedure will check if the system has flagged for signature before. As there is a signature found in the frame 44th, thus the procedure again will move to row 365 and search for signature at that particular region.

The adaptive searching procedure is proven to be efficiently saves computational time of the overall system.

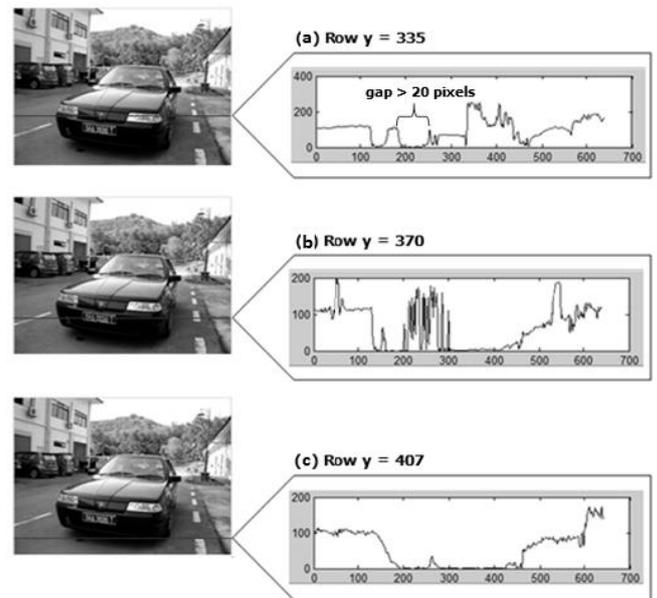


Fig.2. Evaluation of Signature Analysis

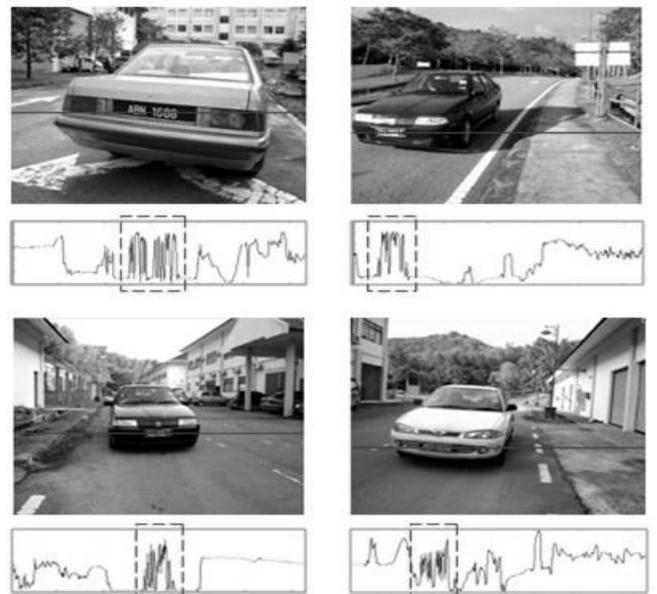


Fig.3. Sample of generated signature

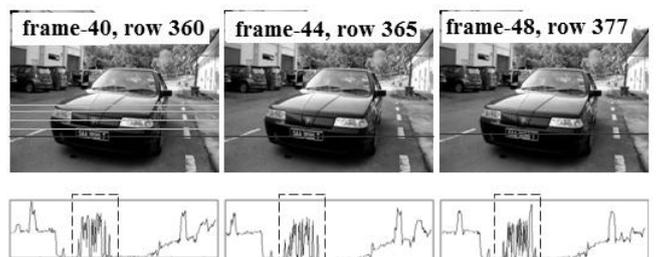


Fig.4. Illustration of adaptive searching

3.3 IMPROVED CONNECTED COMPONENT ANALYSIS

In this paper, a technique is used to improve the Signature Analysis that proposed in [23]. Generally, CCA works by

scanning an image, pixel-by-pixel from top to bottom and from left to right in order to identify connected pixel regions. The region of adjacent pixels is considered connected if they share the same set of intensity values. An algorithm is designed to traverse the matrix, labelling the vertices based on the connectivity and relative values of their neighbours. Two common connectivity of the region can be determined by checking their number of neighbours, 4-connected or 8-connected [24]. Fig.5 shows the notion of connectivity, while Fig. 6 shows its results on an ideal license plate character.

CCA is an important task in intermediate image processing with a large number of applications [25]. The problem is to assign a unique label to each connected component in the image while ensuring a different label for each distinct object. By assigning a unique label to each connected region, higher level image processing operations can identify, extract, and process each object separately.

However, in a blob analysis problem, any two region of interest (ROI) that is discontinuous are typically treated as separate blobs. To overcome this limitation, a procedure is added to the proposed Signature Analysis in [23], to find out which pixels are within a certain distance of the foreground in a binary image. The added procedure is simply referred to as Improved Connected Component Analysis (ICCA), which is used together with Signature Analysis (SA) to extract the whole license plate region from the mixed image.

The Fig.7 shows the conventional Connected Component Analysis performed on the license plate candidate region. Due to the connectivity set, three regions are detected on the sample although all the regions are actually connected to each other. In ICCA, Euclidean distance transform is computed for each pixel to its nearest foreground pixel. For each pixel in the image, the distance transform assigns a number that is the distance between that pixel (x_1, y_1) and the nearest nonzero pixel (x_2, y_2) of the image as in Eq.(4).

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{4}$$

The Fig.8 shows the Signature Analysis with the improved Connected Component Analysis (SAICCA) approach on the same license plate region.

For each pixel in the image, the distance transform assigns a number, which is the distance between that pixel (x_1, y_1) and the nearest nonzero pixel (x_2, y_2) of the image as in Eq.(4). The distance between two pixels is set at four pixels. This implies that for any two ROIs that discontinuous and having a distance of four pixels will be treated as non-unique.

However, the Euclidean Transform steps caused the ROI padded with too many pixels. Thus, all the elements in the resulted image are set to "0" corresponding to the background pixel in the input image. Finally, area of the labelled components are analysed to determine the valid ROI.

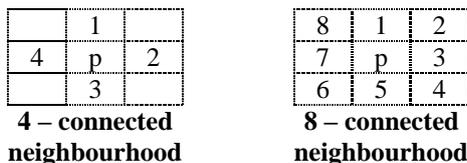


Fig.5. Notion of connectivity

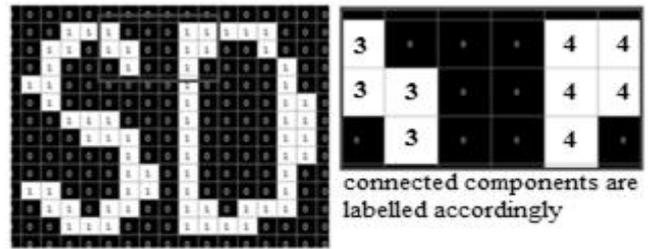


Fig.6. Connected Component Analysis (CCA) performed on an ideal license plate characters



Fig.7. Conventional Connected Component Analysis (CCA)

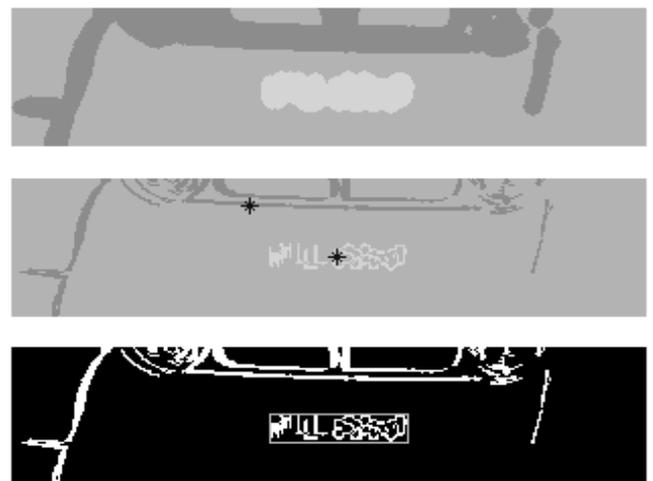


Fig.8. Signature Analysis with improved connected component analysis (SAICCA)

3.4 LICENSE PLATE CHARACTER IDENTIFICATION

In this paper, a simple multi-layer feed-forward backpropagation Neural Network with 56-input and 34 neurons in its output layer is used to identify the letters. The 56-input vector is formed by taking the width-to-height (WH) ratio from Signature Analysis, Euler number and features extraction of the character [26].

The system is designed to identify 34 alphanumeric characters (24 alphabets, excluded 'I' and 'O' and 10 numerals). Fig.9 shows the sample of the license plate character. Each features of the character will be extracted to be trained in the neural network. The hidden layer is set to 10 neurons. The

numbers of hidden layers as well as the respective neurons are defined after a trial and error procedure.

The network is trained to output a value of 1 in the correct position of the output vector and to fill the rest of the output vector with the value 0's. The logsigmoid transfer function at the output layer was picked because its output range (0 to 1) is perfect for learning to output the Boolean values.

The training performance for the proposed neural network (NN) is shown in Fig.10. 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.

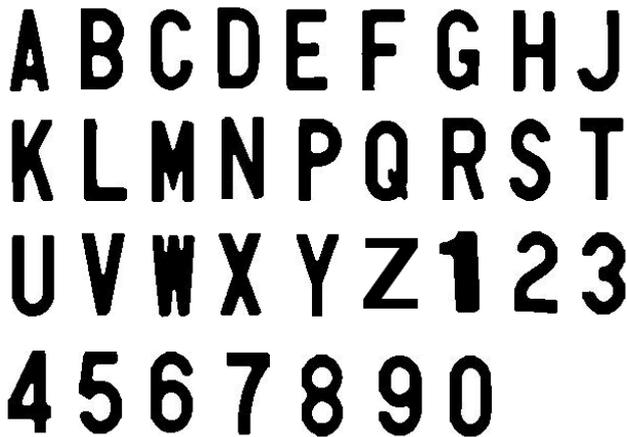


Fig.9. Sample of license plate characters

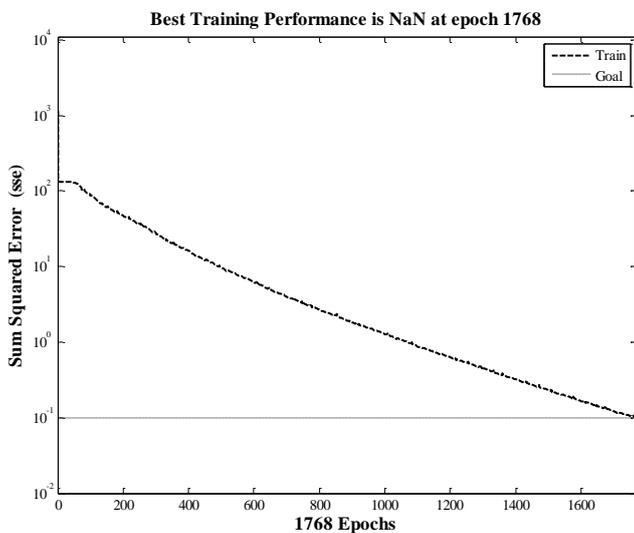


Fig.10. Training performance of the proposed neural network

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

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 × 480 pixels video with 30 fps. 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.

The major problems in the proposed algorithmic sequence revolve around the varying light levels encountered during a twenty-four period. In this section, two common restrictions mentioned will be further discussed in details.

Insufficient light level may become an issue when a vehicle that is not even clear to human eyes to be captured by the camera. This situation happens when a vehicle is entering the system's field of vision from a brighter place, such as the indoor parking system.

Low quality input during the acquisition stage may affect the later processing stages, which is the recognition of each character. The surrounding light intensity might also cause reflection on the license plate. Thus, this may lead to the distortion during license plate recognition.

The Fig.11 shows unsuccessful result due to the mentioned restrictions. In this figure, the license plate area of the vehicle is localised successfully in all iterations, although the quality of the license plate image is distorted. However, character 'W' of the vehicle license plate is wrongly recognised as 'X' due to the shattered pixels.

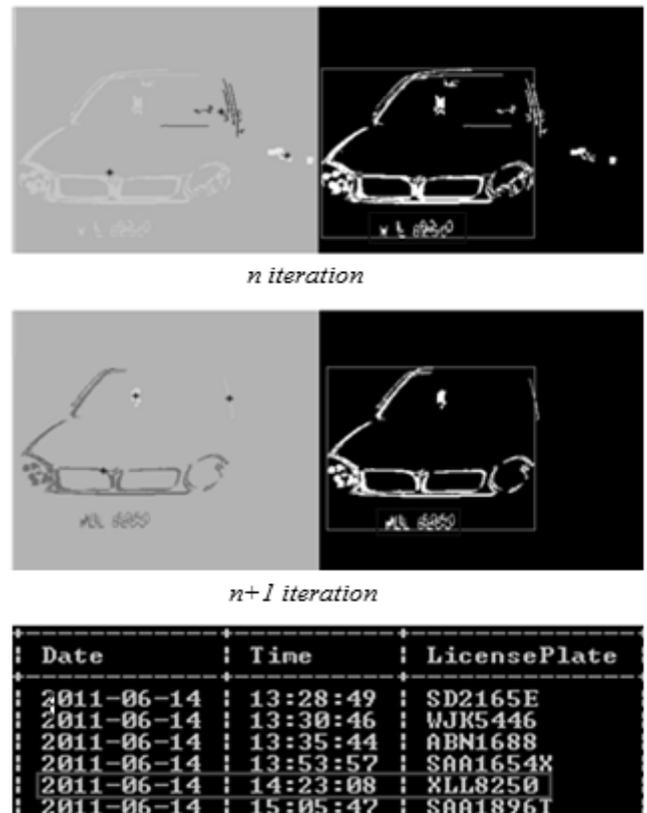


Fig.11. Unsuccessful results

The Fig.12 shows the tracking and localisation of two moving vehicles under the system's field of vision. The sample data consists of two vehicles moving forward to the camera. Vehicle 1 can be localised correctly, however vehicle 2 is not detected due to the lack of perceptual information. Two approaches are conducted, namely the conventional CCA and the improved CCA with Signature Analysis (SAICCA).

Under conventional CCA approach, the system detected multiple unique components although all the components are part of one vehicle (the components are non-unique).

The improved Connected Component Analysis (ICCA) developed by adding Euclidean distance transform onto the conventional CCA is used to identify the vehicles' license plate.

The proposed algorithm (SAICCA) is not only useful in differentiating multiple bounding boxes within the license plate region, but can also be further implemented in differentiating extra vehicle in the system's field of vision. As shown in the figure, the implemented SAICCA algorithm successfully locates the whole license plate region. In $n+1$ iteration and $n+2$ iteration, the components of the two vehicles are detected correctly. However, the system failed to locate the license plate of vehicle 2 due to the deficiency of perceptual information.

The Table.4 demonstrates the performance analysis of the overall license plate recognition system. The developed system is tested on 50 samples of data taken around the campus area. The analysis shows an improvement of 32% in license plate localisation by using Signature Analysis and the Improved Connected Component Analysis (SAICCA), as compared to the conventional Connected Component Analysis (CCA).

In this project, the time consumption for the routines added in improving the conventional CCA is acceptable. The SAICCA approach used in the system yields a good result without compromising too much of the overall execution time. In addition, 8% of the failed localisation rate is due to the mentioned inevitable restrictions such as the shadow effect, insufficient light level and clarity, besides insufficient license plate perceptual information. The failure rate is mainly due to the overly inclination of the license plate and shattered pixels in the character itself.

Table.4. Performance analysis of the developed system

	Test of efficiency	No. of sample	No. of successful sample	Successful rate	Ave. execution time (ms)
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%	823.7

5. CONCLUSION

The intention of this paper is to investigate the possibility of designing an automatic license plate localisation and identification via Signature Analysis. Signature analysis is used to search for the license plate candidate. Adaptive searching of the license plate candidate is used in the next iteration. This approach may reduce the execution time of the overall system performance. A procedure called Euclidean distance transform is added to the system to tackle the multiple bounding boxes that

occurred in the conventional CCA. Results of the overall system and performance of both conventional CCA and the improved CCA are presented accordingly.

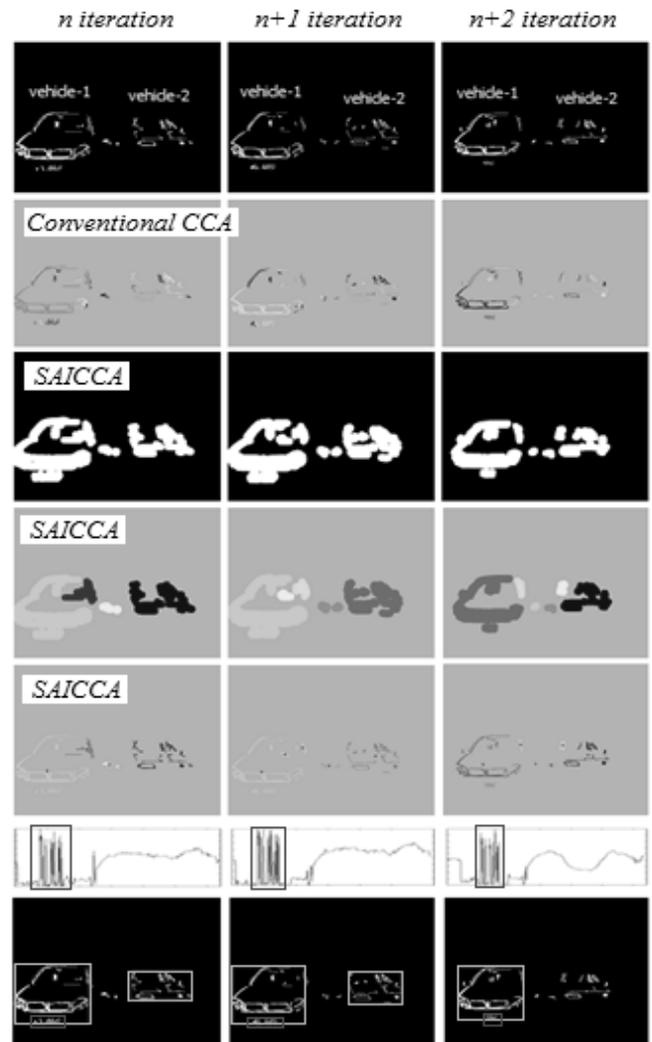


Fig.12. Successful results

There are some inevitable common failures that could occur in the proposed system such as the intensity and insufficiency of perceptual information. Although SAICCA achieved 92% successful rate, the performance of the overall system is very much affected by the environment difficulties. If any of the mentioned restrictions are occurring in the image processing phases, subsequently the system will be halted and failed to recognise the complete license plate

The experimental results and characteristics of the system yields that it is feasible for localisation and recognition in both ideal and non-ideal environment. However, this system needs to be further enhanced in the future to tackle the mentioned restrictions.

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REFERENCES

- [1] Serkan Ozbay and Ergun Ercelebi, "Automatic Vehicle Identification by Plate Recognition", *World Academy of Science, Engineering and Technology*, Vol. 9, pp. 222 - 225, 2005.
- [2] M. Abdulghafour, "Image Segmentation Using Fuzzy Logic and Genetic Algorithms", *Journal of WSCG*, Vol. 11, No. 1, 2003.
- [3] N. Senthilkumaran and R. Rajesh, "Edge Detection Techniques for Image Segmentation - A Survey of Soft Computing", *International Journal of Recent Trends in Engineering*, Vol. 1, No. 2, pp. 250 - 254, 2009.
- [4] K. Othman, K. Sheroz, R. Islam and A. Suleiman, "Malaysian Vehicle License Plate Recognition", *The International Arab Journal of Information Technology*, Vol. 4, No. 4, pp. 359 - 364, 2007.
- [5] A. Krol and T. Pamula, "Localization of Vehicle License Plates in Images Using Fuzzy Logic and Morphological Operations", *Silesian University of Technology*, pp. 95 - 101, 2009.
- [6] Chu Duc Nguyen, M. Ardabilian and L. Chen, "Robust Car License Plate Localization using a Novel Texture Descriptor", *Proceedings of the Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance*, pp. 523 - 528, 2009.
- [7] Nguyen, Chu Duc, M. Ardabilian and L. Chen, "Real Time License Plate Localization Based on a New Scale and Rotation Invariant Texture Descriptor", *Proceedings of the Eleventh International IEEE Conference on Intelligent Transportation Systems*, pp. 956 - 961, 2008.
- [8] Y. Zhang and C. Zhang, "A New Algorithm for Character Segmentation of License Plate", *Proceedings of the IEEE Intelligent Vehicles Symposium*, pp. 106 - 109, 2003.
- [9] J Yuan, Z Hu and Y Wang, "Finding Corners by Using Hough Transform", *Wuhan University Journal of Natural Science*, Vol. 44, No. 1, pp. 85 - 88, 1998.
- [10] R. Porter and N. Canagarajah, "Robust Rotation-Invariant Texture Classification: Wavelet, Gabor filter and GURF based schemes", *IEE Proceedings - Vision, Image and Signal Processing*, Vol. 144, No. 3, pp. 180 - 188, 1997.
- [11] C. He, J. Dong, Y.F. Zheng and S.C. Ahalt, "Object Tracking Using the Gabor Wavelet Transform and the Golden Section Algorithm", *Proceedings of the IEEE International Conference on Robotics and Automation*, Vol. 2, pp. 1671 - 1676, 2001.
- [12] 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*, Vol. 1, pp. 59 - 63, 1996.
- [13] 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, pp. 381 - 388, 2003.
- [14] C.N. Anagnostopoulos, I. Anagnostopoulos, V. Loumos, and E. Kayafas, "A License Plate Recognition Algorithm for Intelligent Transportation System Applications", T-ITS-05-08-0094.
- [15] P. Hu, Y. Zhao, Z. Yang and J. Wang, "Recognition of Gray Character Using Gabor Filters", *Proceedings of the Fifth International Conference on Information Fusion*, Vol. 1, pp. 419 - 424, 2002.
- [16] A. Broumandnia and M. Fathy, "Application of Pattern Recognition for Farsi License Plate Recognition", *Proceedings of the IEEE International Conference on Graphics, Vision and Image Processing*, Vol. 5, No. 2, pp. 25 - 31, 2005.
- [17] Adnan Amin and Watbiq Mansoor, "Recognition of Printed Arabic Text using Neural Networks", *Proceedings of the Fourth International Conference on Document Analysis and Recognition*, Vol. 2, pp. 612 - 615, 1997.
- [18] L. Angeline, K.T.K. Teo and Farrah Wong, "Smearing algorithm for vehicle parking system", *Proceedings of the Second Seminar on Engineering and Information Technology*, pp. 331 - 337, 2009.
- [19] P. Comelli, P. Ferragina, M.N. Granieri and F. Stabile, "Optical recognition of motor vehicle license plates", *IEEE Transactions on Vehicular Technology*, Vol. 44, No. 4, pp. 790 - 799, 1995.
- [20] Y.P. Huang, S.Y. Lai and W.P. Chuang, "A Template-Based Model for License Plate Recognition", *Proceedings of the IEEE International Conference on Networking, Sensing and Control*, Vol. 2, pp. 737 - 742, 2004.
- [21] 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*, Vol. 12, No. 3, pp. 44 - 51, 2011.
- [22] J. Matas and K. Zimmermann, "Unconstrained License Plate and Text Localization and Recognition", *Proceedings of the IEEE Intelligent Transportation Systems*, pp. 225 - 230, 2005.
- [23] L. Angeline, M.Y. Choong, Farrah Wong and K.T.K. Teo, "Tracking and localisation of moving vehicle license plate via Signature Analysis", *Proceedings of the Fourth International Conference on Mechatronics*, pp. 1 - 7, 2011.
- [24] R. Fisher, S. Perkins, A. Walker and E. Wolfart, "Connected Component Labelling", 2003.
- [25] J.L.C. Sanz and D. Petkovic, "Machine Vision Algorithms for Automated Inspection of Thin-Film Disk Heads", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, pp. 830 - 848, 1988.
- [26] L. Angeline, W.Y. Kow, W.L. Khong, M.Y. Choong and K.T.K. Teo, "License Plate Character Recognition Via Signature Analysis and Features Extraction", *Proceedings of the Fourth International Conference on Computational Intelligence, Modelling and Simulation*, pp. 1 - 6, 2012.