DETECTING LICENSE PLATE USING CLUSTER RUN LENGTH SMOOTHING ALGORITHM

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Abstract: Vehicle license plate recognition has been intensively studied in many countries. Due to the different types of license plates being used, the requirement of an automatic license plate recognition system is different for each country. In this paper, an automatic license plate recognition system is proposed for Malaysian vehicles with standard license plates based on image processing, clustering, feature extraction and neural networks. The image processing library is developed in-house which referred to as Vision System Development Platform (VSDP).After applying image enhancement, the image is segmented using blob analysis, horizontal scan line profiles, clustering and run length smoothing algorithm approach to identify the location of the license plate. Thoroughly each image is transformed into blob objects and its important information such as total of blobs, location, height and width, are being analyzed for the purpose of cluster exercising and choosing the best cluster with winner blobs. Here, new algorithm called Cluster Run Length Smoothing Algorithm (CLSA) approach was applied to locate the license plate at the right position. CLSA consisted of two separate new proposed algorithm which applied new edge detector algorithm using 3x3 kernel masks and 128 grayscale offset plus a new way (3D method) to calculate run length smoothing algorithm (RLSA), which can improve clustering techniques in segmentation phase. Two separate experiments were performed; Cluster and Threshold value 130 (CT130) and CRLSA with Threshold value 1 (CCT1). The prototyped system has an accuracy more than 96% and suggestions to further improve te system are discussed in this paper pertaining to analysis of the error.

1 INTRODUCTION

Automatic license plate recognition system (LPR) is an important area of research due to its many applications. For local authorities license plate recognition is required for the purposes of enforcement, border protection, vehicle thefts, automatic toll collection, and perhaps traffic control. Among the commercial license plate recognition systems available worldwide are Car Plate Reader (CPR) by Rafael et.al.(J.Barosso et al., 1997) and Automatic Number Plate Recognition(ANPR) by Chang et. al.(Chang et al., 2004). In Malaysia, vehicles license plates are in the form of single or double line with normal fonts which comprise of perhaps 95% of the all the vehicles. Most pictures have been taken in various states in Malaysia like Sabah, Wilayah Perseketuan, Johor, Selangor, Perak, Negeri Sembilan, Pahang and Terengganu. There are also special fonts as depicted in Figure1.

This dedicated LPR software covers at least five major processes consecutively; Capturing, Pre-Processing, Segmentation, Feature Extraction and Classification. However this paper will only concetrate on license plate detection, which covers image enhancement and segmentation.

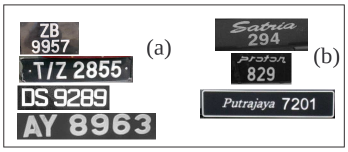

Figure 1: (a)Samples of common Malaysia license plates (b) Samples of special Malaysia license plates.

This section is divided into five sections. First section discusses on Image Segmentation while section two discusses on Clustering Technique. This clustering techniques is enhanced by applying RGB convolution with a new edge detector and 128 greyscale offset, and Run Length Smoothing Algorithm Approach. Both of these topics are explained in Section 3 and 4 consecutively. Discussion on three different experiments are briefly concluded in Section 5.

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2 IMAGE SEGMENTATION

Image segmentation is a process that separates words to single characters for easy identification(Al-Badr and S.A.Mahmoud, 1995). In this project, segmentation involves a process of separating a collection of character that has been filtered; to a sequence of characters that will be used in the feature extraction stage. This step is very significant due to overlapping characters that form the license plate. At the moment, LPSeeker applies clustering technique to identify important blobs. After processing image using simple image enhancement technique like Fixed Filter, Minimum Filter, Median Filter and Homomorphic Filter for the LPSeeker image enhancement which are provided in VSDP library (Vision System Development Platform). VSDP is a library that has been developed by CAIRO, UTMKL researchers.

3 CLUSTERING TECHNIQUE

After applying above image enhancement, the image is segmented using horizontal scan line profiles and clustering technique. Thoroughly each image is transformed into blob objects and its important information such as location, height and width, are being analyzed by the LPSeeker for the purpose of cluster exercising and choosing the best cluster with winner blobs. The blobs are clustered when difference between blob and cluster heights and difference between maximum Y value of the cluster and blob are less than a constant time to cluster's height as stated in clustering algorithm. Please refer to picture depicted in Figure 2. Then, the clusters are sorted ascendingly according to its member's size. Starting from the most maximum members, each of the clusters is being checked using RGB Convolution and a new edge detector with 128 grayscale offset, run length smoothing algorithm , (or)Thresholding with value 1 and Horizontal and vertical Projection. These processes will be described in following section. If the checking success, then the cluster is chosen as first winner cluster. This first winner cluster will search if there is any other cluster with the same height nearby. If yes, then the second winner cluster is set. Lastly, these winner blobs are extracted their feature individually before permitting to recognition or classification phase.

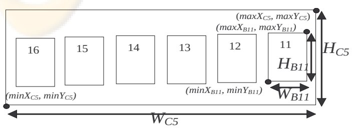

Figure 2: Important information for clustering approach.

4 RGB CONVOLUTION AND RUN LENGTH SMOOTHING APRROACHES

This setion consists of two sub sections; RGB Convolution and Thresholding, and Run Length Smoothing Approach (RLSA). The first section which is RGB Convolution, covers the process of applying new edge detector to an image and later the resulted imaged is thresholded into value 1. While the second section explains RLSA which involves the concept of interprating both resulted images (RGB convolved and thresholded images).

4.1 RGB Convolution and Thresholding Approach

RGB Convolution is an approach to transform a RGB pixel value into determining grayscale value. We introduced a new edge detector with 128 grayscale offset and thresholding. Here, 3x3 kernel mask and its matrix is shown in equation (1). Every pixel (in RGB format), RGB_{sum} in the image is summed and multiplied by equation (1). At the same time, K_{sum}, summation of 3x3 kervel mask value, kernel$V_{(x,y)}$ where x and y is from 0 until 2 is calculated. Later the RGB_{sum} is divided into K_{sum} and added to a grayscale offset value, b. Finally, the RGB_{sum} is converted again into grayscale value. This process is called RGB Convolution. The compositions of all new graycale values will transform an original image in Figure 3(a) into a new black-gray-white image display as illustrated in Figure 3(b). The new convolved image is set into a buffer and undergone a thresholding process with value one. The final black-white image, is shown as Figure 3(c).

$$128 + \frac{1}{11}\begin{bmatrix} 3 & 0 & -3 \\ 5 & 0 & -5 \\ 3 & 0 & -3 \end{bmatrix} \tag{1}$$

4.2 Run Length Smoothing Approach

Run Length Smoothing Algorithm (RLSA) has been used widely in optical character recognition (OCR) process especially in document analysis system (Wong et al., 1982)(Fisher et al., 1990). The previous method developed for the Document Analysis System (Nagy, 1968) consists of two steps. Firstly, a segmentation procedure subdivides the area of a document into regions (blocks), each of which should contain only one type of data (text, graphic, halftone image, etc.) and later some basic features of these blocks are calculated. A linear classifier which adapts itself to varying character heights discriminates between text and images. However, this technique usually applies only after horizontal or vertical projection to recognize the block segementation.

After manupulating the chosen cluster using RGB convolution with a new edge detector and 128 grayscale offset value, RLSA and(or) horizontal and vertical projection were applied to distinguish within non-character and character clusters. From the above resulted images Figure 3 (a), (b) and (c), character and non-character images were analyzed and a three dimensional horizontal projection rules are constructed to differentiate between non-character and character cluster.

The run length Figure 3 (b) of is stored if only black-gray-white pixels exist consecutively. For example, the image greyvalue pixel is transform into a series of pixel where b = black, g = gray, w = white as show below in Figure 4(a). Then, the runlengths for each black, gray and white (b-g-w) pixels is calculated Figure 4(b). Lastly, only total runlengths of b-g-w pixel consecutively are stored for each single line. Lastly, the average runlengths per line, *aveRL-whole*, number of runlengths per line, *aveCountRL-whole*, and ratio average runlength per line and number of runlength per line, *ratioRL* is computed (Figure 4(c)). These useful information were taken to construct a set of decision threshold rules at the very beginning purposely for recognizing character and non-character clusters .

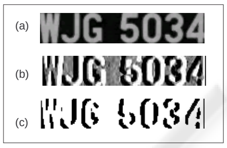

Figure 3: (a)An image of detected license plate (b) Image analysis using RLSA with a new edge detector and 128 offset value (b) Image after applying RLSA and Thresholding Value 1.

(a) wggwwwbbbggwwwbbbggwwwggggggggggggbbbbgwwwwggggbbbbbbggggwwwwwwggggggg
ggggggggggggggbbbgggggggggggggwwwwgggggbbbbbbgggwwwwwwgggggggbbbbbbbgggww
wwwwggggggggggggggbbbbbggwwb

(b) 1w2g3w3b2g3w3b2g3w12g4b1g4w4g6b4g6w21g3b13g4w5g6b3g6w7g7b3g6w14g5b2g2w1b

(c) R:8X:13Y:0 R:8X:21Y:0 R:9X:42Y:0 R:16X:62Y:0 R:20X:103Y:0 R:15X:123Y:0 R:16X:146Y:0
AveRLperline:13.14 NoOfRLperline:7 Ratio:1.88

Figure 4: Example of (a) a string of image (b) runlengths for each black, gray and white pixels and (c) runlength only for white pixels consecutively.

Figure 5: Example of correct license plate detection.

Figure 6: Types of detection errors; (a)Extra (b)Miss1 (c)Miss2 (d)Miss≻2(e) Fail.

Table 1: Type of errors.

Type	Description
Pass	Found license plate
Miss1	Miss 1 character
Miss2	Miss 2 characters
Miss≻2	Miss more than 2 characters
Extra	More than actual characters
Fail	Cannot locate license plate
Correct detection	Locate license plate correctly or summation number of Pass, Miss1, Miss2,Miss≻2 and Extra errors
Incorrect detection	Locate license plate incorrectly or number of fail errors

5 DISCUSSION AND CONCLUSION

Two different experiments were run. There were Clustering with Threshold 130 value (CT130), Clustering with RGB convolution and Threshold 1 value (CCT1). Error analysis were calculated based on several types; they are Pass, Miss1, Miss2, Miss≻2, Extra or Fail. Explainations on each type of analysis were outlined in Table 1. Correct detection rate or total correct is calculated based on summation of number of Pass, Miss1, Miss2, Miss≻2 and Extra divided by total image. Examples of error images are illustrated in Figure 6 (a), (b) ,(c) and d. On the other hand, Incorrect detection rate is formulated as number of fail divided by total image.

From Table 2, CCT1 value has obtained the highest pass rate (77.25%) comparing to others (76.68% for CT130 and 53.85% for CCT1). Numbers of Miss1, Miss2, Miss≻2 and Extra Errors in CT130 were distributed evenly compared to CCT1. CCT1 could dramatically reduce number of fail detection down to 44 or 3.56% detection rate whereas CT130 could only afford to achieve 72 number of fails or 5.83%. CT130 which applies threshold 130 value before undergoing clustering approach has decreased number of blobs to be clustered in the whole image. Pertaining to this matter, the CT130 may discard important blobs in between letters and cause high number of missing errors such as 32, 47, 55 and 82 for Miss1, Miss2 and Miss≻2 errors correspondingly. Another point to highlight for CT130 is missing blobs are normally occur in between characters when sometime 2 or more blobs are connected. Unlike CCT1, missing blobs only occurs at the begining or ending of the the whole license plates.

We can also highlight that total of pass, extra and Miss1 errors for CCT1 (954 + 193 + 16 = 1163) was higher than CT130 (1026). This has proved that RGB convolutions and Threshold method had its own significant in choosing the appropriate winner cluster. Additionally, CCT1 has successfully obtained the highest license plate detection rate 96.44% while CT130 achieved the second place with 94.17%.It can be concluded that combination of RGB Convolution with threshold one value techniques, can boost up the license plate detection up to 96.44%.

From the above results, a few advantages and disadvantages were notified with the proposed approaches, RGB convolutions and a new edge detector with 128 grayscale offset that were applied. The advantages are;

i. Eventhough the original image of the back or frontal car is having fusion problems, CCT1 can still successfully detected the locations of the license plate as shown in Figure 7.

ii.CCT1 can increase number of passing rate.

iii. CCT1 can increase number of extra blobs errors.

iv.CCT1 can reduce number of missing Miss1, Miss2, Miss$\succ$2 blobs consisted in the winner cluster(s). Besides that, those missing blobs are normally at the beginning or ending.

The disadvantages are:

i.The passing rate for CCT1 were only slightly increased compared to CT130. This is because CCT1 will consider all blobs in the image but not for CT130.

ii. RGB convolution with a new edge detector is very time consuming because the calculations of getting new grayscale output requires every pixel of the original image to be analyzed.

iii. Quite often memory becomes leaking when using RGB convolution because it requires high storage. As conclusion,CCT1 can boost up the detection rate of license plates by suggestions below,

i. Instead of using fixed thresholding in CT130, adaptive zoning thresholding can also help CCT1 to improve its detection rate.

ii. RGB convolutions can apply other edge detectors with 128 grayscale offset.

iii. Before applying RGB convoultions and Horizontal and Vertical Projections, perhaps checking the cluster's original image using binary projections can increase the whole performance.

iv. Incorparating uncertainty value while calculating maximum number of blobs and runlength of each clusters may increase the LPSeeker's performance.

This paper has generally discussed on concept of license plate recognition and segmentation techniques which covers clustering, RGB convolutions and Run Length Smoothing Algorithm. In conclusion, we can conclude combination of RGB convolutions, a new edge detector with 128 grayscale offset and Run Length Smoothing Algorithm has significantly raised detection rate of license plate's location in the segmentation phase.

Figure 7: Fusion Images that has been successfully detected by LPSeeker.

Table 2: Detection rate for three experiments: Cluster with Threshold Value 130, Cluster with RGB Convolution and Cluster with RGB Convolution and Threshold Value 1.

Error	**Cluster and Threshold 130 (CT130)**		**Cluster and RGB Convolve and Threshold 1(CCT1)**	
Type	Total	Percentage	Total	Percentage
Pass	947	76.68%	954	77.25%
Miss1	32	2.59%	193	15.63%
Miss2	47	3.81%	16	1.30%
Miss$\succ$2	55	4.45%	16	1.30%
Extra	82	6.64%	12	0.97%
Fail	72	5.83%	44	3.56%
total	1235	100%	1237	100%
Total correct	1163	94.17%	1191	96.44%
Total incorrect	72	5.83%	44	3.56%
total	1235	100%	1235	100%

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Wong, K., Casey, R., and Wahl, F. (1982). Document analysis system. *IBM Journal of Research and Development*, 26(6):647–657. rule based for text, horizontal solid nlack lines, graphic and halftone images, vertical solid black lines.