Multi-threshold approach for license plate recognition system

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Abstract—**The objective of this paper is to propose an adaptive multi threshold for image segmentation precisely in object detection. Due to the different types of license plates being used, the requirement of an automatic LPR is rather different for each country. The proposed technique is applied on Malaysian LPR application. It is based on Multi Layer Perceptron trained by back propagation. The proposed adaptive threshold is introduced to find the optimum threshold values. The technique relies on the peak value from the graph of the number object versus specific range of threshold values. The proposed approach has improved the overall performance compared to current optimal threshold techniques. Further improvement on this method is in progress to accommodate real time system specification.**

I. INTRODUCTION

Automatic license plate recognition (LPR) is an important research subject due to its many applications. For local authorities, LPR is required for the purposes of law enforcement, border protection, vehicle thefts, automatic toll collection and perhaps traffic control. There are five major steps in LPR system: image capturing, image processing, segmentation, feature extraction and pattern classification. An automatic LPR system is first required to identify the location of the license plate in a captured image and to recognize correctly the license plate characters and numbers. It is essential to clarify various variables that give impacts to the operations of an LPR system such as weather, vehicle type, plate color or other ambiguous factors in addition to the special characters/fonts.

There are two main issues to be discussed. Firstly is the color of the license plate and the second issue is the color of the car. Whenever there is a problem with histogram distribution or illumination, the fixed threshold is not usable. These major problems sometimes cause the license plate to be undetected and it may turn out to be a failure. Apart from that, character segmentation for localization is another point to be highlighted. Some characters may appear to be attached to one another and this may lead to the process of segmentation to be disqualified. Whenever the threshold selection process encounters a problem, the character-labellings process, which is a sub-process of the segmentation process, would also be affected.

The objective of this paper is to propose a multi-threshold method for thresholding both the number plate from the car image and the individual characters within the number plate region, and to compare its results with those obtained by Kittler and Illingworth's threshold, potential difference, as well as Otsu's thresholding method, which are related to a Malaysian license plate recognition system. In Malaysia, license plates are in the form of a single and a double line with normal fonts (Figure 1(a)) and special fonts (Figure 1(b)).

Fig. 1. (a) Samples of common license plates and (b) Samples of special license plates in Malaysia.

II. MOTIVATION

Thresholding is a method for analyzing a gray scale image into binary image. This approach provides apache for image segmentation. We can simplify that

$$f'(i,j) = \left\{ \begin{array}{ll} 1 & if \quad f(i,j) > t, \\ 0 & if \quad f(i,j) < t \end{array} \right. \tag{1}$$

There are various approaches to determine automatic thresholding. Quite often they use grey level co-occurence matrix as the population set to determine appropriate thresholding values such as; Local Entropy, Illingworth and Kittler's Minimum Entropy Threshold (MET) [1], and potential difference [2]. Grey level co-occurrence matrix approach is expected to improve the performance of thresholding technique as the correlation among gray levels is important in image thresholding and segmentation. In the co-occurrence matrix the image is constructed considering pairs of pixels that are either one below the other or one next to the other. For N gray level values, the co-occurrence matrix is $N \times N$ in size. Selecting a threshold value M divides the matrix into four quadrants (see Figure 2).
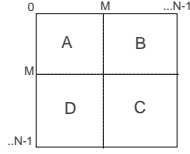
Fig. 2. The MET threshold minimises the entropy in quadrants A and C. For a bright object, quadrant C corresponds to pairs of object pixels.

1) Kittler and Illingworth's MET: From Kittler and Illingworth's MET [1], an image could be modeled by a mixture of two Gaussian distribution. This model can be used to describe foreground and background. This model is based on the concept of using relative entropy as a thresholding criterion. The criterion is used to calculate the information distance between two information sources. The two sources are getting closer in terms of their probability distributions as the value of the relative entropy is decreasing. This MET technique finds a grey level value that minimises the mismatch between the probability of an image histogram and the Gaussian distribution respectively. The minimum error thresholding for object ($MET_O(M)$) and the minimum error thresholding for background ($MET_B(M)$) can be defined as:

$$MET_O(M) = \sum_{i=0}^{M} \sum_{j=0}^{M} P_{ij} \log_2 P_{ij}^O \quad (2a)$$

$$MET_B(M) = \sum_{i=M+1}^{N-1} \sum_{j=M+1}^{N-1} P_{ij} \log_2 P_{ij}^B \quad (2b)$$

From equation 2a and 2b, the threshold that minimises the relative entropy is,

$$MET_(M) \equiv MET_O(M) + MET_B(M). \quad (3)$$

2) Potential Difference: The potential difference, $PDiff$ threshold value is defined as below:

$$PDiff = -\frac{\sum_{i=min}^{i=max} \sum_{j=min}^{j=i} p_j \times (i-j) \times (i-j)}{\sum_{i=min}^{i=max} \sum_{j=i}^{j=max} p_j \times (j-i) \times (j-i)} \quad (4)$$

where min and max are the minimum and maximum of grey scale values. It considers the maximum value of $PDiff$ as the optimal threshold value.

III. THE PROPOSED METHOD

Heuristic Threshold consists of three steps: (1) Calculate image category based on the histogram distribution, (2) Calculate the peak thresholds based on the object distributions and threshold values, and lastly, (3) Select threshold value(s) based on simple Heuristic decision rules. Each of the steps is explained as follows:

A. Calculate image category based on the histogram distribution

We calculate the histogram distribution, $\rho_{(0,1,...,255)}$ based on the original image. These image categories are given their names as 'dark', 'medium' and 'fair'. Then, we compute the image category, Θ, as Equation 5,

$$\Theta = \begin{cases} dark & \text{if} \quad \left(\sum_{g=0}^{g=85} \rho_g \geq \sum_{g=86}^{g=170} \rho_g\right) \cap \left(\sum_{g=0}^{g=85} \rho_g \geq \sum_{g=171}^{g=255} \rho_g\right) , \\ medium & \text{if} \quad \left(\sum_{g=86}^{g=170} \rho_g \geq \sum_{g=0}^{g=85} \rho_g\right) \cap \left(\sum_{g=86}^{g=170} \rho_g \geq \sum_{g=171}^{g=255} \rho_g\right) , \\ fair & \text{if} \quad \left(\sum_{g=171}^{g=255} \rho_g \geq \sum_{g=0}^{g=85} \rho_g\right) \cap \left(\sum_{g=171}^{g=255} \rho_g \geq \sum_{g=86}^{g=170} \rho_g\right) . \end{cases}$$
$$(5)$$

where,

ρ is the total of pixels within specific gray scale values either from 0 until 85, 86 until 170 or 171 until 255, and

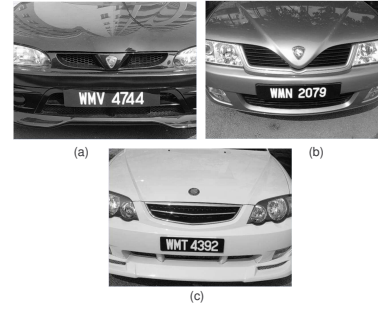ρ_g is the current gray scale value.

Fig. 3. Examples of (a) 'dark', (b) 'medium' and (c) 'fair' for the original license plate images.

B. Calculate the peak thresholds based on the object distributions and threshold values

We calculate the total number of blobs, $\Re_{(1,...,S)}$, using the analysis process based on $\Omega_{(0,1,...,k-1)}$ in the range of 10 from 0 until 255 gray scale, where k is 25. We categorize the threshold values with the peak number of objects according to Eq. 6.

$$\Omega_{Peak(0,1,...,p-1)} = \begin{cases} c \times 10 & \text{if} \quad (\Omega_c > \Omega_{c-1}) \cap (\Omega_c > \Omega_{c+1}), \\ 0 & \text{otherwise} \end{cases}$$
$$(6)$$

where, Ω_c is the number of objects at $c \times 10$ threshold value, c is the current counter for $\Omega_{(0,1,...,k-1)}$ array, $\Omega_{Peak(0,1,...,p-1)}$ is a series of the peak values derived from $\Omega_{(0,1,...,k-1)}$ array, and p is the total number of peak values.

The number of objects, versus $\Omega_{(0,1,...,k-1)}$ is plotted in the graph as in Figure 5 and there are only six, six and four peaks respectively which are kept sequentially as shown in Table I.

C. Select threshold value(s) based on simple Heuristic decision rules

We apply a simple Heuristic decision rule using Θ and $\Omega_{Peak(0,1,...,p-1)}$ variables to determine $\Omega_{Select(0,1,...,q-1)}$.
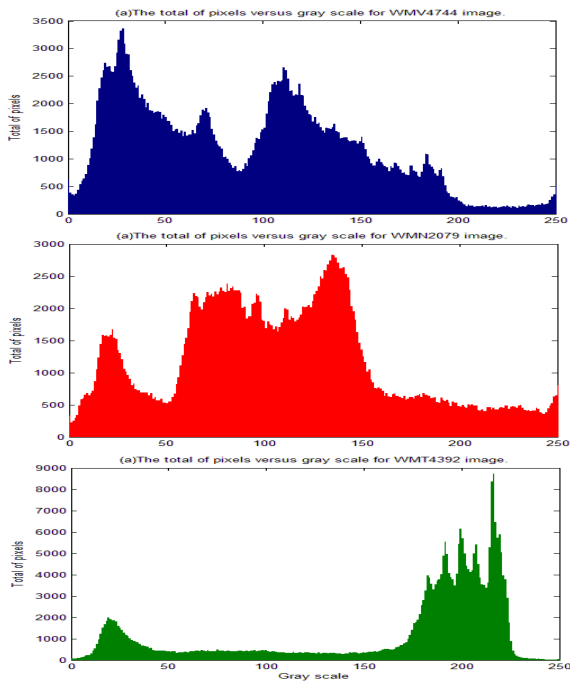
Fig. 4. The histogram distribution, $\rho_{(0,1,...,255)}$, for the (a) 'WMV4744', (b) 'WMN2079' and (b) 'WMT4392' car image.
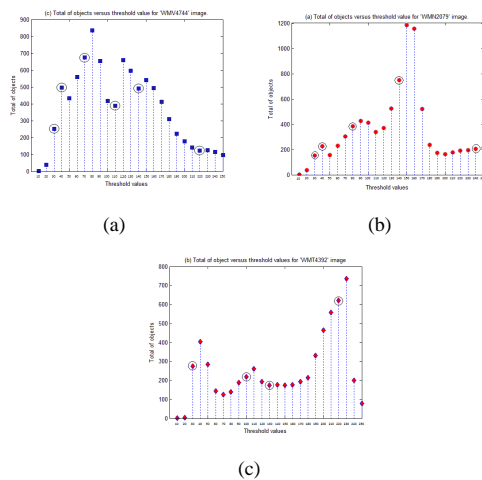

Fig. 5. Distributions of the number of objects created by each threshold for (a) 'WMV4744', (b) 'WMN2079', and (c) 'WMT4392' images.

TABLE I
THE THRESHOLDS THAT CREATE THE PEAKS IN THE DISTRIBUTIONS OF FIGURE 5.

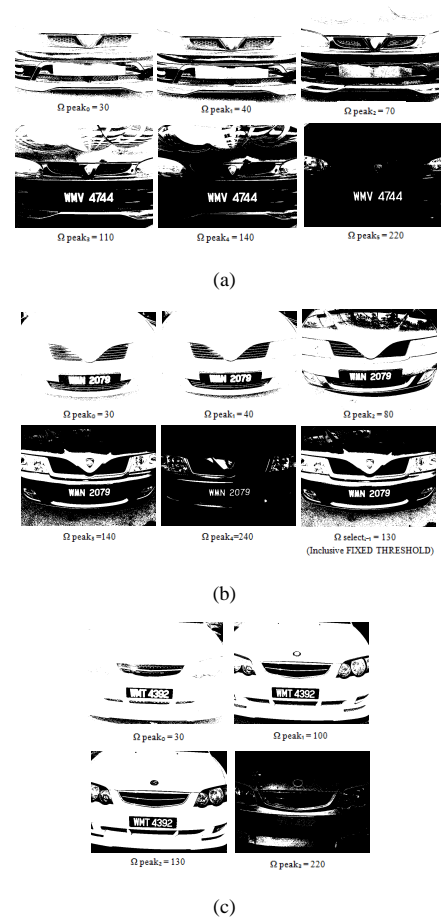| Peak index, p	Peak threshold values, $\Omega_{Peak_{(0,1,...,p-1)}}$		
	WMV4744	WMN2079	WMT4392
0	30	30	30
1	40	40	100
2	70	70	130
3	110	110	220
4	140	140	-
5	220	220	-

Fig. 6. Examples of the thresholding results using as thresholds the grey values that correspond to the peaks of the graphs in Figure 5 for (a) 'WMV4744', (b) 'WMN2079' (also includes the result for the 130 threshold value), and (c) 'WMT4392', respectively.

IV. BLOB AGGLOMERATION

All the white objects identified by the selected thresholds applied to an image are considered for further processing. Each blob is represented by its minimum enclosing rectangle. The width and height of each blob is considered and objects smaller than a certain size are removed as due to noise. In particular, if $Y_{current}$ is the vertical coordinate of the top left corner of the minimum enclosing box of the cluster, and $\breve{Y}$ is the vertical coordinate of the top left corner of a blob, and $H_{current}$ is the height of the minimum enclosing box of the cluster, the new blob is added to the cluster if,

$$\left| Y_{current} - \breve{Y} \right| \leq \alpha \times H_{current}$$

and

$$\left| H_{current} - \breve{H} \right| \leq \alpha \times H_{current}$$

where $\breve{H}$ is the height of the blob and α is some parameter.

V. NUMBER PLATE DETECTION

The cluster with the maximum number of objects is considered to be the detected number plate. Then we consider the objects in the cluster, one at a time. The characters of these objects are identified by the system as explained in [3].

VI. EXPERIMENTAL EVALUATIONS

This paper has presented the proposed thresholding method within the LPR system which uses geometric features [3], [4] and support vector machine (SVM). To compare the performance of the system, we explored and run more than one thresholding method. They were Kittler and Illingworth's MET [1], Potential difference [2], Otsu's method [5], and the proposed method and compare the results obtained with those of the original system.

Our test data consisted of 1216 images. If all clusters identified in an image consist of a single blob, then we say that no number plate was identified in this image. The percentage of images in which the number plate was not identified are summarized in the first row of Table II. In this table columns correspond to thresholding method and rows to the status of the license plate and the entries are the percentage of images for which one, two, or more characters were not segmented. The number plate was not identified is consider cases where a number plate region had been found but it was totally wrongly placed.

Fig. 7. Error Analysis for Kittler and Illingworth's MET [1], Otsu [5], potential difference [2], and the proposed framework in the (a)segmentation, and (b)classification phases.

TABLE II
SEGMENTATION RESULTS.

| | Thresholding method | | | |
	Kittler and Illingworth's MET [1]	potential difference [2]	Otsu [5]	Proposed
Not found	9.80%	4.49%	41.17%	0.33%
Miss 1	3.27%	3.67%	4.39%	1.40%
Miss 2	4.49%	4.57%	3.58%	1.07%
Miss >2	6.94%	7.26%	10.33%	0.99%
Extra	2.45%	2.77%	1.46%	1.23%

TABLE III
CLASSIFICATION RESULTS WITH MLP-BP.

| | Thresholding method | | | |
	Kittler and Illingworth's MET [1]	potential difference [2]	Otsu [5]	Proposed
Wrong 1	5.39%	5.46%	3.74%	1.48%
Wrong 2	1.23%	1.22%	0.49%	1.97%
Wrong > 2	0.49%	0.49%	1.87%	1.40%

The percentage of wrongly recognised characters for each of the tested methods are shown in Table III and also illustrated in Figure 7. The percentage of correctly segmented and recognised is given in the first and second rows of Table IV. Segmentation was correct when the number of objects
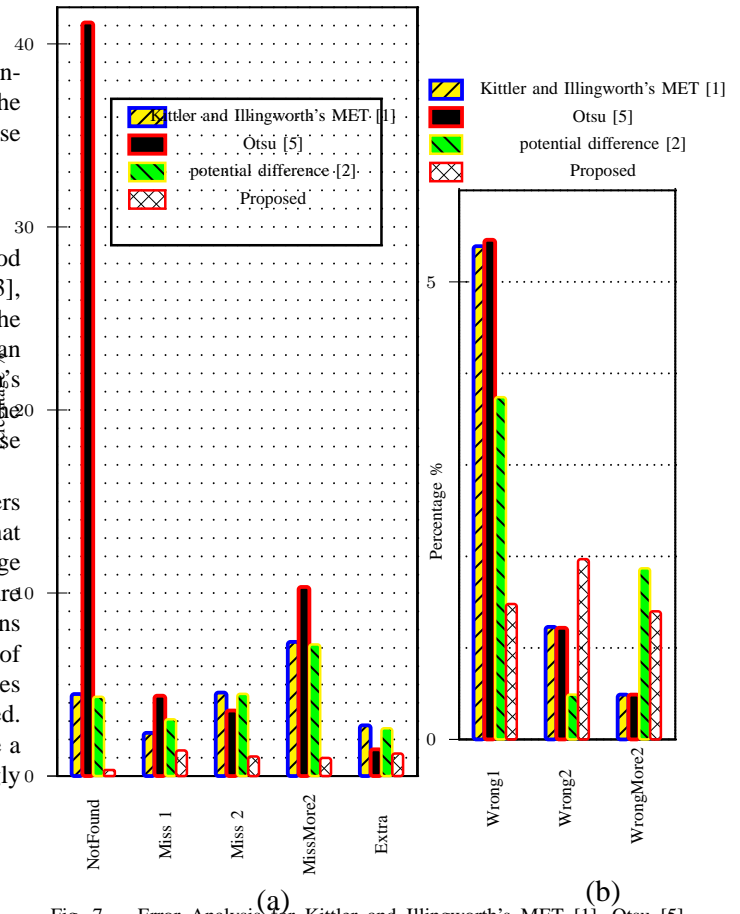
TABLE IV
BLOB ERROR ANALYSIS FOR KITTLER AND ILLINGWORTH'S MET [1], OTSU [5], POTENTIAL DIFFERENCE [2], AND THE PROPOSED FRAMEWORK BASED ON CORRECTLY SEGMENTED AND CORRECTLY RECOGNISED.

threshold types	Kittler and Illingworth's MET [1]	Potential difference [2]	Otsu [5]	Proposed
correctly segmented	65.77%	69.90%	39.06%	92.33%
correctly recognised	34.23%	30.10%	83.33%	97.61%

corresponds correctly to the true number of characters in the number plate. Only the one which passes both segmentation and recognition will be regarded as successful.

Table V and Figure 8 are constructed based on three types of accuracy rate: LPD, LPS and LPR. Finally, the overall evaluation result of the performance LPR system is reported in Table V, for the various thresholding methods, for license plate and constructed based on three types of accuracy rate : LPD, LPS and LPR. The rates are calculated as follows [6]:

$$LPD \quad rate \quad = \quad (1216 - Notfound - Smalloverlap) \div 1216, \quad (7a)$$

$$LPS \quad rate \quad = \quad (1216 - Miss1 - Miss2 - Miss > 2) \div 1216 - LPD \quad (7b)$$

$$LPR \quad rate \quad = \quad (1216 - Wrong1 - Wrong2 - Wrong > 2) \div 1216 - LPS \quad (7c)$$

Comparison among all the methods gives Otsu [5] the highest recognition time (3549.31ms) followed by potential difference [2] (3589.03ms), the proposed framework (4026.1382ms), and

TABLE V
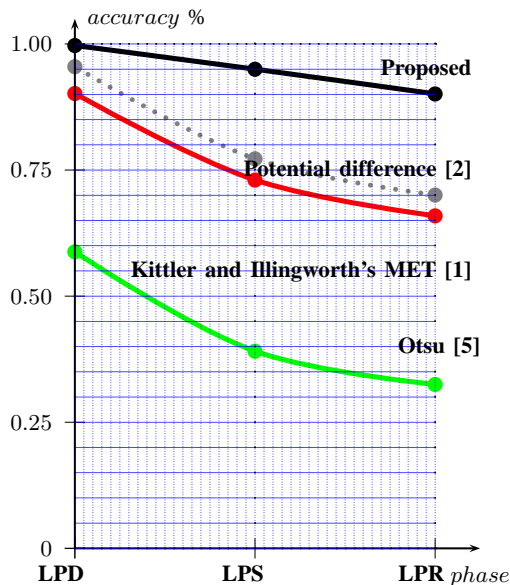LPD, LPS AND LPR RATE FOR KITTLER AND ILLINGWORTH'S MET [1],
OTSU [5], POTENTIAL DIFFERENCE [2], AND THE PROPOSED
FRAMEWORK.

Accuracy rate	Kittler and Illingworth's MET [1]	Potential difference [2]	Otsu [5]	Proposed
LPD	90.19%	95.51%	58.83%	99.67%
LPS	73.03%	77.24%	39.06%	94.98%
LPR	65.93%	70.06%	32.55%	90.13%

Fig. 8. LPD, LPS and LPR accuracy rates for Kittler and Illingworth's MET [1], Otsu [5], potential difference [2], and the proposed framework .

Kittler and Illingworth's MET [1] (4119.06ms). Examples of successful image results based on the proposed thresholding method is shown in Figure VI.

(a)   (b)

Fig. 9. Successful image results based on Heuristic Threshold, and MLP-BP classification techniques.

VII. CONCLUSION

A Malaysian LPR system developed recently uses a fixed threshold to segment the number plate and the characters. Experiment proved that via a Taylor-made thresholding method, the algorithm can be improved significantly. Clearly that the propose methods has been tested on off-line processing of images. Another advantage of this proposed approach, is that

the adaptive threshold values can relatively change according to environment when there is a high or low contrast situation such as during night, mid-day, underground and raining day.

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