

## Research Article

### Adaptive Image Thresholding Based on the Peak Signal-to-noise Ratio

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**Abstract:** The aim of this research is to enhance a Peak signal Noise Ratio based thresholding algorithm. Thresholding is a critical step in pattern recognition and has a significant effect on the subsequent steps in imaging applications. Thresholding is used to separate objects from the background and decreases the amount of data and increases the computational speed. Recently, there has been an increased interest in multilevel thresholding. However, as the number of levels increases, the computation time increases. In addition, single threshold methods are faster than multilevel methods. Moreover, for each new application, new methods must be developed. In this study, a new algorithm that applies the peak signal-to-noise ratio method as an indicator to segment the image is proposed. The algorithm was tested using the license plate recognition system, DIBCO, 2009 and standard images. The proposed algorithm is comparable to existing methods when applied to Malaysian vehicle images. The proposed method performs better than earlier methods, such as Kittler and Illingworth's Minimum Error Thresholding, potential difference and Otsu. In general, the proposed algorithm yields better results for standard images. In the license plate recognition application, the new method yielded an average performance.

**Keywords:** Image processing, image segmentation, optical character recognition, single thresholding

## INTRODUCTION

Thresholding is one of the important stages of pre-processing in any application of image processing. Thresholding is a method used to separate the foreground from the background of an image (PirahanSiah *et al.*, 2011). This study compares six thresholding methods: Otsu (1979) and Kittler and Illingworth (1986), potential difference (Acharya and Sreechakra, 1999), max entropy (Pun, 1980), multilevel threshold (Arora *et al.*, 2008) and the new method proposed in this study. All of these methods have been applied to four types of images: license plate, standard, printed and handwritten.

Thresholding is one of the critical steps in pattern recognition and has a significant effect on the subsequent steps in image applications. The important objectives of thresholding are separating objects from the background and decreasing the amount of data and increasing computational speed. There are two types of thresholding: single and multilevel. Single can produce a binary images (0, 1) and decrease the size of the data, leading to an increase in computational speed. Single thresholding is able to remove noise and perform object detection better than multilevel thresholding. Multilevel thresholding produces an image with a range between 0

and 255 of pixel value (Abdullah *et al.*, 2010a, b; PirahanSiah *et al.*, 2010, 2011). Single thresholding needs to be investigated and improved to search for the best way for to separate the object, decrease the size of data and increase speed. Recently, there has been significant research in multilevel thresholding. However these methods cannot increase computational speeds because they use several levels. Single thresholding is better able to separate the object than multilevel thresholding. Moreover, for each new application, new methods need to be developed. In addition, for mobile device applications, image-processing capabilities can be increased while using less storage, fewer processes and less battery. Thresholding still needs to be improved for new applications and devices. Furthermore, it will enable more efficient resource utilization (Abdullah *et al.*, 2010a, b; PirahanSiah *et al.*, 2010, 2011).

Tsai and Lee (2002, 2009) presented a novel method for object extraction and classification to analyze color documents. Badekas and Papamarkos (2003) has developed a system that is able binarized documents. Tsai and Lee (2002, 2009) have performed color document image linearization using features such as luminance and saturation. Srtouthopoulos and Papamarkos (2000) have worked on a multilevel

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thresholding method for mixed-type document applications. Virmajoki used multilevel thresholding using the fast pair-wise neighbor as the nearest threshold (Virmajoki and Franti, 2003; Franti *et al.*, 2006). Lazaro *et al.* developed thresholding algorithms for OCR software (Lázaro *et al.*, 2010).

According to previous research PirahanSiah *et al.* (2013a), no current thresholding algorithm can use in all applications. A multipurpose single algorithm is therefore required for use in a wide range of pattern recognition applications. Some methods applied in real-time applications produce better results with controlled environments, such as Otsu in face-recognition applications (Hung *et al.*, 2009). Some methods are less accurate in an un-controllable environment (e.g., max entropy). Others maintain less information with more noise after segmentation, such as with a max entropy standard dataset.

This motivates the development of a new method to investigate global image thresholding. The new methods should be able to adapt to different ambient illumination such as day, night, sun, shadow, variable background intensity, shadows, smear, smudge, low contrast, bleed-through or show-through (Abdullah *et al.*, 2010a, b; PirahanSiah *et al.*, 2010, 2011).

Pattern recognition is high research area in computer vision and there are number of research in this area such as Simultaneous Localization and Mapping (PirahanSiah *et al.*, 2013b), 3D vision (PirahanSiah *et al.*, 2012) is hot topic today. License Plate Recognition system (LPR) applications experience challenges in detecting and segmenting the appropriate locations of license plates due to the threshold value. The image, which has an inappropriate threshold value, can fail in the recognition phase. It can bypass the segmentation phase if the chosen threshold value is significant and appropriate (Abdullah *et al.*, 2007a; Abdullah *et al.*, 2010a, b; PirahanSiah *et al.*, 2010, 2011). This issue affects whole parts of the LPR system, impacting the speed in the real-time system and the accuracy. There are several reasons to develop new algorithms for single thresholding. In addition to LPR, handwriting recognition is an important issue, which is used in applications in mobile devices. The peak signal-to-noise ratio is one of the methods used to measure the quality of images. Our proposed method applies the Peak Signal-to-Noise Ratio (PSNR) as an indicator to segment an image. Results obtained using our proposed method compare well with several existing methods. The algorithm can be optimized to increase the performance.

Single thresholding technique is older than multilevel thresholding. After performing single thresholding we have a black-and-white image (0 and 1 pixel values). Consequently, the storage requirements are less than those required for multilevel thresholding

(Abdullah *et al.*, 2010b) and multilevel thresholding uses a wide range of pixel values. Second, a limited amount of data is required to improve the speed of image processing. Finally, single thresholding separates the foreground and background of images better than multilevel thresholding and the object detection is faster than in multilevel thresholding (Arora *et al.*, 2008). Recently, many topics have been developed in multilevel thresholding technique (Liou *et al.*, 2009; Hammouche *et al.*, 2010; Hao *et al.*, 2010; Horng, 2010; Malyszko and Stepaniuk, 2010; Abidin *et al.*, 2011). However, due to its advantages over multilevel thresholding, single thresholding warrants further development. In fact, mobile devices, such as cell phones, have developed new image-processing applications. In these devices, limitations such as low storage capacity, battery life and limited processes cause a need for a better algorithm for image processing (PirahanSiah *et al.*, 2010, 2011). The objective of this research is to developed threshold method which overcome issues such as low capacity of storage and less information for process.

## MATERIALS AND METHODS

Thresholding is the step preceding the segmentation phase of image processing. Usually embedded in the blob-labeling process, thresholding is a critical step because it segregates the important objects from the background and directly affects the success rate in object-recognition applications. We categorize thresholding methods into three techniques: single, multilevel and multi thresholding. Kittler and Illingworth's Minimum Entropy Threshold (MET) (Kittler and Illingworth, 1986) and potential difference (Acharya and Sreechakra, 1999) are examples of single thresholding methods. Multilevel threshold methods, such as that of (Arora *et al.*, 2008), separate object based on gray values. Multi-threshold (Abdullah *et al.*, 2010b) techniques choose a selection of threshold values based on certain behaviors such as number objects inside the image after threshold. We discuss some state-of-the-art methods in the following subsections.

**Single thresholding:** Single thresholding means one threshold value,  $t$ , is used to change the image to black and white (Naeimizaghiani *et al.*, 2011, 2013). The thresholding process is a critical step during the segmentation phase. It is also an important part of image processing and pattern recognition. Thresholding is implemented for different reasons, such as to increase computational speed or to use less storage space. The segmentation accuracy can be maximized by an appropriately chosen threshold value. The single threshold condition is given as:

$$f'(i,j) \begin{cases} 1 & \text{if } f(i,j) > t \\ 0 & \text{if } f(i,j) \leq t \end{cases} \quad (1)$$

Various approaches are used to automatically determine the threshold value. Methods such as local entropy, Kittler and Illingworth's MET (Kittler and Illingworth, 1986) and potential difference (Acharya and Sreechakra, 1999) often use a gray level co-occurrence matrix as the population set to determine the appropriate threshold value.

**Multilevel Threshold (Arora et al., 2008):** In multilevel thresholding, more than one threshold value is used to change the image to a gray-scale image. Multilevel thresholding methods were developed because a single threshold is not always suitable for global segmentation (Sahoo et al., 1988; Sezgin and Sankur, 2004; Chang et al., 2006; Fabijanska, 2010; Hammouche et al., 2010). Arora et al. (2008) proposed a multilevel threshold method that identifies threshold values globally based on a gray scale distribution. A recursive algorithm is applied to determine a sequence of threshold values based on the mean and standard deviation at each step. The multilevel algorithm is described in Algorithm 1.

**Algorithm 1:** The Multilevel Thresholding Algorithm by (Arora et al., 2008).

- 1 : While increasing PSNR>0.1 is true do
- 2 : r = [a, b]. (in the first step a = 0 and b = 255)
- 3 : Find the mean and standard deviation for all of the pixels in the image range r
- 4 : t1 = mean-k1\* standard deviation; (k1 is a random number)
- 5 : t2 = mean+k2\* standard deviation; (k2 is a random number)
- 6 : The mean value of range (a, t1] is set as the threshold value of the partial range.
- 7 : The mean value of range [t2, b) is set as the threshold value of the partial range.
- 8 : a = t1+1
- 9 : b = t2-1
- 10 : end while
- 11 : t1 = mean
- 12 : t2 = mean+1
- 13 : repeat step 6
- 14 : Obtain new image with multilevel thresholding

**Multi-Threshold (Abdullah et al., 2010b):** Multi threshold is another approach that applies multiple threshold values (Abdullah et al., 2010b). This method uses a series of threshold values and computes the total number of blobs or objects in an image for each threshold. The peak threshold values are those with the highest total number of blobs as compared to their

threshold neighbors. The Heuristic threshold algorithm is described in Algorithm 2.

**Algorithm 2:** The Multi Threshold Algorithm by Abdullah et al. (2010b).

**Input:** License plate images.

**Output:** Threshold values.

- 1: Start.
- 2: Obtain the histogram distribution.
- 3: Calculate the total number of gray-scale pixels according to three levels.
- 4: For (0<t<256) step 10 is true do
- 5: Obtain the total number of objects, num<sub>t</sub>, in the source image when the threshold value t is used.
- 6: end for
- 7: Search for and select the peak values from num (1 ... 255).
- 8: Choose the selected threshold values if the number of objects is maximum.
- 9: Execute the character segmentation module.

**Otsu's method for thresholding (Otsu, 1979):** Otsu, in 1979, presented an unsupervised and nonparametric method of automatic threshold selection for image segmentation (Otsu, 1979). Bounding boxes of fragments are used as local areas for local threshold searching. The mean ( $\mu$ ) and variance ( $\sigma^2$ ), of the pixel distribution,  $P_i = (P_1, P_2, \dots, P_{Max})$ , are used to select the optimal thresholds by maximizing the between-class variance.

**Proposed method for thresholding:** In the same spirit as Arora et al. (2008), Abdullah et al. (2010b) and PirahanSiah et al. (2010, 2011), our proposed algorithm uses a gray-scale histogram, thresholding range and the Peak Signal-to-Noise Ratio (PSNR). Based on our experience, the mean value of the gray scale histogram is strongly connected to pixel intensity. To avoid the effect of luminosity in images, we use the mean value of the gray scale histogram to predetermine the image type: dark, medium or bright. The mean value corresponds to the dominant pixel value in the image. Based on rigorous experiments, s1, s2 and s3 are determined parameters to map the mean value to the image type. We use the PSNR quality measure proposed by (Arora et al., 2008) because it can measure the similarities between the original image and the binarized image. A higher PSNR indicates more similarity between the two images. The PSNR value is defined as follows:

$$PSNR = 10 * \log_{10} \left[ \frac{Max^2}{\frac{\sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2}{M * N}} \right] \quad (2)$$

In Eq. (2), Max is a maximum value in the image (for example, in a gray-scale image, Max is 255) while

$M$  and  $N$  are the height and weight of the image, respectively.  $I(i, j)$  is the original value of the image and  $K(i, j)$  is the value after a change. Based on (Abdullah *et al.*, 2010a), we calculate PSNRs for every threshold value, in increments of 10, in the range between [1, 256]. We calculate the difference between PSNR ( $t$ ) and PSNR ( $t+10$ ). If PSNR ( $t$ ) is greater than PSNR ( $t+10$ ), the threshold value is retained. We determine the prior threshold by comparing PSNR ( $t$ ) and the difference PSNR ( $t$ ) -PSNR ( $t+10$ ) with parameters, alpha and beta. These parameters are used to separate any small changes in PSNR. We adjust the prior threshold value based on its image type. This adjustment is required to accommodate the different illuminations in the image. After testing the method on 10 images for each of the three image types (dark, medium, or bright),  $k_1$ ,  $k_2$  and  $k_3$  are set to 75, 50 and 45, respectively. Algorithm 3 summarizes the proposed threshold algorithm.

**Algorithm 3:** The Proposed Threshold Algorithm

**Input:** Gray level images, img.

**Output:** The selected threshold values, t.

- 1: Find the mean value of img to determine the image type of img: dark, medium or bright.
- 2: For ( $0 < t < 256$ ) where ( $t = t+10$ ) then find PSNR<sub>t</sub> of imgt end for
- 3: For ( $0 < t < 256$ ) where ( $t = t+10$ ) then
- 4: If ((PSNR<sub>t</sub> > PSNR<sub>t+10</sub>) and (PSNR<sub>t</sub> > α) and (PSNR<sub>t</sub> - PSNR<sub>t+10</sub> > β))
- 5: Then threshold = t

- 6: end for
- 7: If (type of img is bright) then threshold = threshold -k1
- 8: Else if (type of img is medium) then threshold = threshold -k2.
- 9: Else threshold = threshold+k3.

**RESULTS AND DISCUSSION**

**We have tested our proposed method using four image datasets:** DIBCO (2009) (handwritten and printed images), standard images and license plate recognition systems. DIBCO (2009) data sets contain handwritten and printed images. We compare our proposed method to several state-of-the-art methods, namely Otsu (1979) and Kittler and Illingworth (1986), potential difference (Acharya and Sreechakra, 1999) and max entropy (Pun, 1980), using the PSNR and F-measure. The F-measure denotes the percentage of the binary image classification as shown below:

$$F - measure = \frac{2 * recall * precision}{recall + precision} \tag{3}$$

where,  $recall = \frac{TP}{TP+FN}$  and  $precision = \frac{TP}{TN+FP}$ . TP is the true-positive value, FN is the false-negative value and FP is the false-positive value. The PSNR measurement denotes the similarity between two images. A high PSNR value denotes high similarity between two images as defined by Eq. (2).

Table 1 show the F-measure and PSNR results for all approaches. In the printed category, the proposed

Table 1: The F-measure and PSNR results obtained using Otsu (A) (Otsu, 1979), Kittler and Illingworth (B) (Kittler and Illingworth, 1986), potential difference (D) (Acharya and Sreechakra, 1999) and max entropy (C) (Pun, 1980) and the proposed method

Method	Printed images		Handwritten images		Standard images	Average	
	PSNR	F-mean	PSNR	F-mean	PSNR	PSNR	F-mean
Otsu (Otsu, 1979)	8.548	86.648	6.425	65.889	13.028	9.333	76.268
Kittler and Illingworth (Kittler and Illingworth, 1986)	8.800	73.795	7.022	53.057	22.141	12.654	63.426
Max entropy (Pun, 1980)	8.580	81.509	6.094	75.187	12.516	9.064	78.348
Potential difference (Acharya and Sreechakra, 1999)	8.880	70.887	6.802	50.497	13.359	9.680	60.692
Proposed	9.050	73.448	6.162	56.805	17.611	10.941	65.127

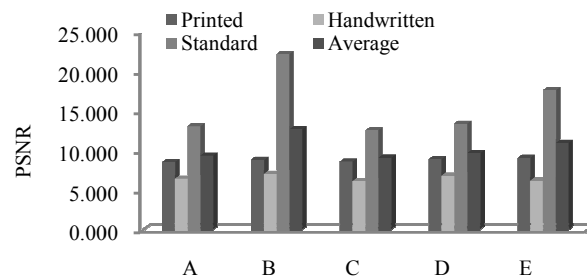


Fig. 1: A comparison of PSNR values obtained for printed, handwritten and standard images using the (A) Otsu (1979), (B) Kittler and Illingworth (1986), (C) max entropy (Pun, 1980), (D) potential difference (Acharya and Sreechakra, 1999) and (E) proposed thresholding methods. The average of the PSNR is also shown for each method

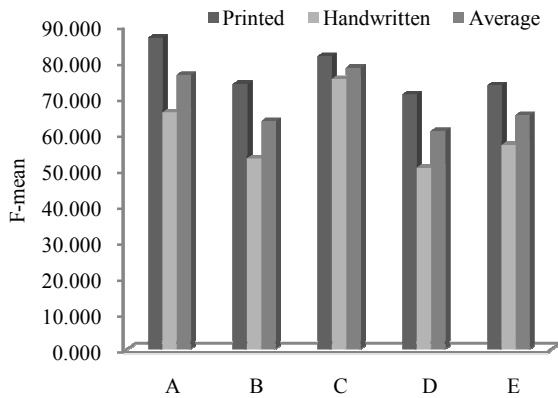


Fig. 2: A comparison of the F-mean values obtained for printed and handwritten images using the (A) Otsu (1979), (B) Kittler and Illingworth (1986), (C) max entropy (Pun, 1980), (D) potential difference (Acharya and Sreechakra, 1999) and (E) proposed thresholding methods. The average of the PSNR is also shown for each method

method has the highest PSNR and an acceptable F-measure. For both the handwritten and standard images, results obtained using the Kittler and Illingworth method have the highest PSNR scores, approximately 7.022 and 22.141, respectively. However, according to the F-measure, Otsu's method performs best for the printed images. The max entropy and Kittler Illingworth method exhibit extraordinary results in the handwritten and standard image categories, respectively.

The largest average PSNR value, 12.654, is obtained using the Kittler and Illingworth method. This method can produce better-quality images after separating the foreground and background. The largest average F-measure, 78.348, is obtained using the max entropy method. The results obtained using the proposed method are promising, as it produces the second-and third-best results in terms of the average PSNR and F-measure, respectively (Fig. 1 and 2).

Figure 3 shows the result of the five methods which are Otsu (Hung *et al.*, 2009), Kittler and



Fig. 3: (i) The DIBCO (2009) handwritten images: b, c and d are spotted and low-quality images; a, c and e are thin pen stroke, low-contrast and small-sized images. Also shown are the image results obtained using the (ii) Otsu (1979), (iii) Kittler and Illingworth (1986), (iv) Max entropy (Pun, 1980), (v) Potential difference (Acharya and Sreechakra, 1999) and (vi) proposed thresholding methods



Fig. 4: (i) The DIBCO (2009) handwritten images: a and b are multi-color and multi-font-size images; b, c and d are spotted and low-quality images; and e is a very low contrast and small-sized image. Also shown are the image results obtained using the (ii) Otsu (Hung *et al.*, 2009), (iii) Kittler and Illingworth (Liou *et al.*, 2009), (iv) Max entropy (Abidin *et al.*, 2011), (v) Potential Difference (Malyszko and Stepaniuk, 2010) and (vi) our proposed thresholding methods

Illingworth (Liou *et al.*, 2009), max entropy (Abidin *et al.*, 2011) potential differences (Malyszko and Stepaniuk, 2010) and proposed thresholding methods based on the results for a all the methods used except the proposed and Otsu could not detect the true line of characters. Using the proposed method, the (b) can be recognized clearly it can show the first line words clearly, unfortunately, all the other methods showed unclear words of line 2 and 3 first words. For (c), the proposed methods can recognize more than 90% of all words clearer than other methods. In fourth images (d) the proposed method does not get accepted result but for detect the number is good. In the last images (e) the proposed method has clear words compare to fill words in other methods. Finally, we can conclude the proposed thresholding algorithm showed good to be applied for handwritten images. The proposed method can be solved different size fonts; a spotted, low quality image; thin pen stroke; low contrast and small size; a poor quality and very low contrast image; a non-uniform illumination; a non-uniform illumination with thin pen stroke; low quality images but it has problem in local binryiation where the stroke and small size pen in part of images.

Figure 4 discuss the result of all the five methods which are Otsu (Hung *et al.*, 2009), Kittler and Illingworth (Liou *et al.*, 2009), max entropy (Abidin *et al.*, 2011), potential differences (Malyszko and Stepaniuk, 2010) and proposed thresholding methods based on the results for:

- a) All the methods used except the proposed could not detect clearly words without noise. However, the proposed method could detect the all words and it can be read clearly. Using the proposed method, the,
- b) Can be recognized clearly it can show the words clearly.
- c) The proposed methods can recognize more words than other methods and hat clearer than other methods.
- d) The proposed method has noise.
- e) The proposed method has very clear manuscript compare to other methods.

Finally, we can conclude the proposed thresholding algorithm showed good to be applied for printed images. The proposed method can be solved different size fonts; a spotted, love quality image; thin pen stroke; low contrast and small size; a poor quality and very low contrast image; a non-uniform illumination; a non-uniform illumination with thin pen stroke; low quality images but it has problem in local binryisation where the stroke and small size pen in part of images. Figure 3 and 4 show examples of results obtained for handwritten and printed images using the (ii) Otsu (1979), (iii) Kittler and Illingworth (1986), (iv) Max entropy (Pun, 1980), (v) Potential Difference (Acharya and Sreechakra, 1999) and (vi) proposed thresholding methods.



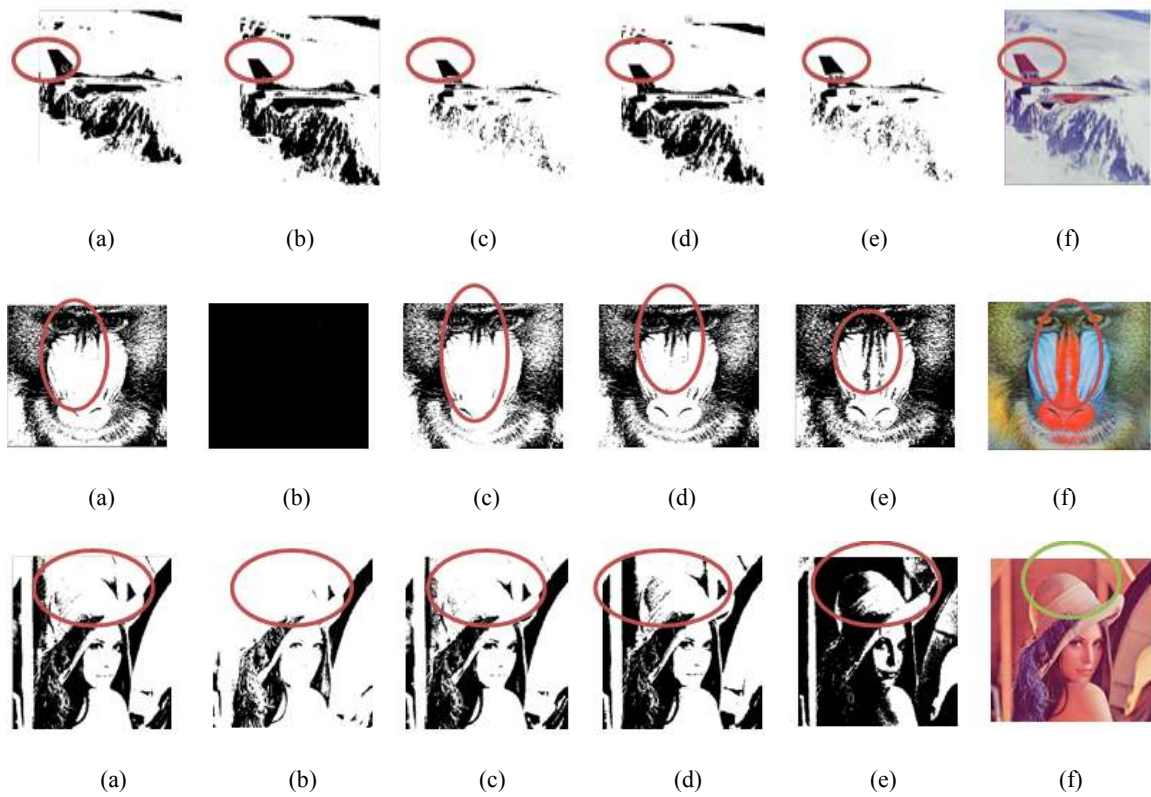


Fig. 5: The results of thresholding methods on standard images; (i) airplane, (ii) baboon and (iii) Lena. The images obtained using the (a) Otsu (Hung *et al.*, 2009), (b) (Kittler and Illingworth, 1986), (Liou *et al.*, 2009), (c) max entropy (Abidin *et al.*, 2011), (d) potential differences (Malyszko and Stepaniuk, 2010), (e) and proposed thresholding methods are compared to the original images (f)

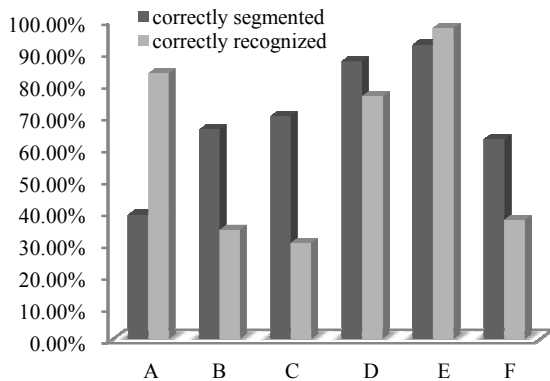


Fig. 6: A comparison of correctly segmented and recognized result of LPR system values using the (A) Otsu (1979), (B) Kittler and Illingworth (1986), (C) max entropy (Pun, 1980), (D) potential difference (Acharya and Sreechakra, 1999) and (E) proposed thresholding methods

Figure 5 compares the image of a baboon obtained using the following methods: (a) Otsu (1979), (b) Kittler and Illingworth (Abdullah *et al.*, 2007a) (c) max entropy (Abdullah *et al.*, 2007b), (d) potential difference (Abdullah *et al.*, 2010a) and (3) the proposed method. The proposed method is better able to

recognize the noise and the thresholding value as compared with the other methods. In addition, the image of Lena obtained using the same five thresholding algorithms. The result obtained using the proposed method is a better image for recognizing the shape of the hat and the thresholding value is more acceptable as compared with the other methods.

We discuss three types of images:

- Air plane
- Baboon
- Lena

Figure 5 discuss the result of my all the five methods which are Otsu (Hung *et al.*, 2009), Kittler and Illingworth (Liou *et al.*, 2009), max entropy (Abidin *et al.*, 2011), potential differences (Malyszko and Stepaniuk, 2010) and proposed thresholding methods based on the results for Air plane all the methods used except the proposed could not detect the air plane number (F16). However, the proposed method could detect the number and it can be read clearly. Using the proposed method, the Baboon face can be recognized clearly it can show the nose and lips clearly, unfortunately, all the other methods showed unclear face of Baboon. For Lena, the proposed methods can

recognize face and hat clearer than other methods. Finally, we can conclude the proposed thresholding algorithm showed good to be applied for standard images.

In conclusion, based on standard images, the proposed method provides a clear distinction between the object and background in outdoor images.

**Result of testing with the LPR system:** This section presents the proposed thresholding method within the LPR system that uses the Kirsch Edge Feature extraction and Multi-layer Perceptron-Back-propagation training method (Abdullah *et al.*, 2007b). To compare the performance of the system, we obtained results using Kittler and Illingworth's MET (Kittler and Illingworth, 1986), Potential difference method (Acharya and Sreechakra, 1999), Otsu's method (Otsu, 1979) and proposed thresholding methods and compared the results with those of the original system. Our test data consisted of 1216 images. The results are summarized in Table 2 the rows correspond to the thresholding method and the columns correspond to the license-plate recognition accuracy. The segmentation error is classified into three types: one, two, or more characters were not segmented correctly. The number plate was not recognized; this includes cases where a number in the plate region had been found but was placed incorrectly.

In Table 2, "Correctly Segmented" means that the segmentation in the license-plate recognition system was accurate. This table illustrates that the percentage of correctly segmented images obtained using the

proposed method is slightly less than that obtained using the Kittler and Illingworth and Potential Difference methods.

The characteristics of the indicators used in Table 3 are as follows. "Wrong 1", "Wrong 2", "Wrong >2" mean that the system has detected one, two, or more than 2 characters incorrectly. For example, the actual character is "A" and the character detected by the system is "C."

The lowest percentage of wrong 1, 1.48%, is obtained using the multi threshold algorithm (Abdullah *et al.*, 2010b) and the highest, 6.10%, is obtained using the multilevel thresholding algorithm (Arora *et al.*, 2008). The results obtained using the proposed method, 5.81%, are in the middle of the range. For wrong 2, the lowest percentage is obtained using Otsu's method (Otsu, 1979), 0.49% and the highest percentage is obtained using the multi threshold algorithm (Abdullah *et al.*, 2010b), 1.97%. The results obtained using the proposed methods are again in the middle of the range, 1.88%. For "wrong >2" (wrong more than two), the lowest percentage is obtained using the Kittler and Illingworth (1986) and potential difference (Acharya and Sreechakra, 1999) method, 0.49%. The highest percentage, 1.87%, is obtained using Otsu's method (Otsu, 1979). The results obtained using the proposed methods were wrong in more than 2 characters for 0.82% of the images. In short, the proposed method is the second-worst method in the LPR system.

In Table 4 and Fig. 6 shows the performance of the proposed method performs in LPD (14.7%) and in LPS (4.33%) is better than that in the LPR. By comparing

Table 2: Correctly segmented and recognized result of LPR system

Thresholding method	Correctly segmented (%)	Correctly recognized (%)
Otsu (Otsu, 1979)	39.06	83.33
Kittler and Illingworth's MET (Kittler and Illingworth, 1986)	65.77	34.23
Potential difference (Acharya and Sreechakra, 1999)	69.90	30.10
Multilevel thresholding (Arora <i>et al.</i> , 2008)	87.08	76.2
Multi threshold algorithm (Abdullah <i>et al.</i> , 2010b)	92.33	97.61
Multi-threshold based on entropy (Abidin <i>et al.</i> , 2011)	72.94	59.70
Proposed	62.65	37.35

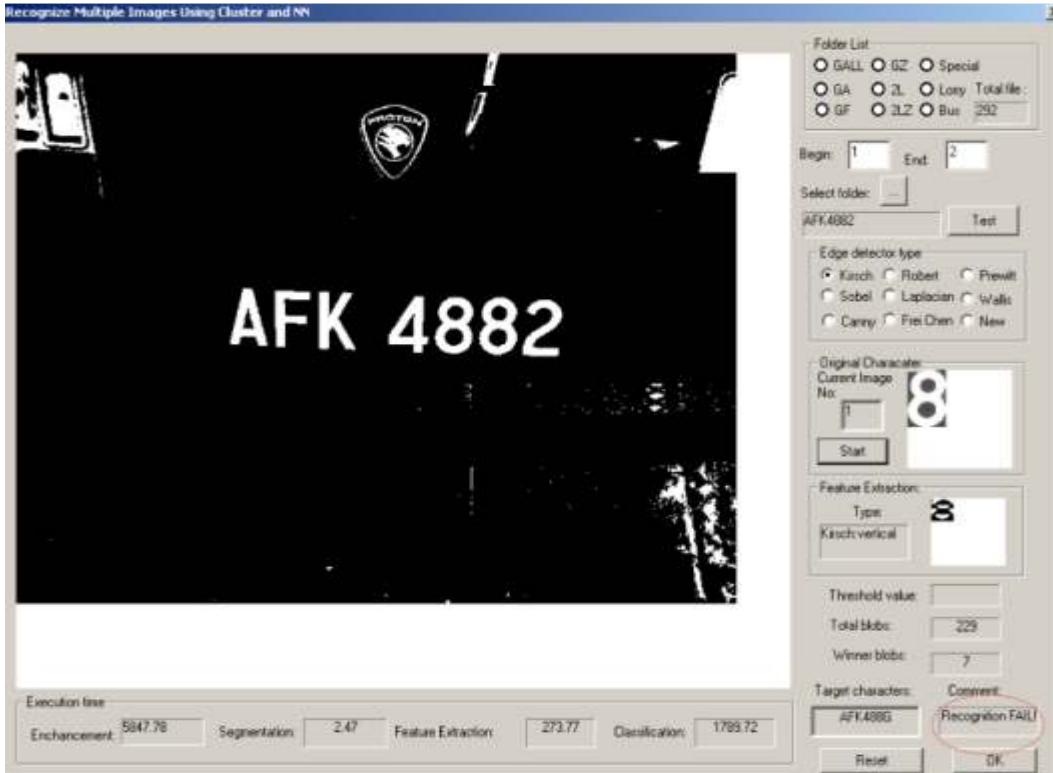
Table 3: Error analysis based on segmentation and classification results with MLP-BP

Thresholding method	Wrong 1 (%)	Wrong 2 (%)	Wrong >2 (%)
Otsu (Abdullah <i>et al.</i> , 2007a)	3.74	0.49	1.87
Kittler and Illingworth's MET (Abdullah <i>et al.</i> , 2010a)	5.39	1.23	0.49
Potential difference (Abdullah <i>et al.</i> , 2010b)	5.46	1.22	0.49
Multilevel thresholding (Arora <i>et al.</i> , 2008)	6.10	1.77	0.93
Multi threshold algorithm (Chang <i>et al.</i> , 2006)	1.48	1.97	1.40
Multi-threshold based on entropy (Hung <i>et al.</i> , 2009)	4.57	4.32	7.34
Proposed	5.81	1.88	0.82

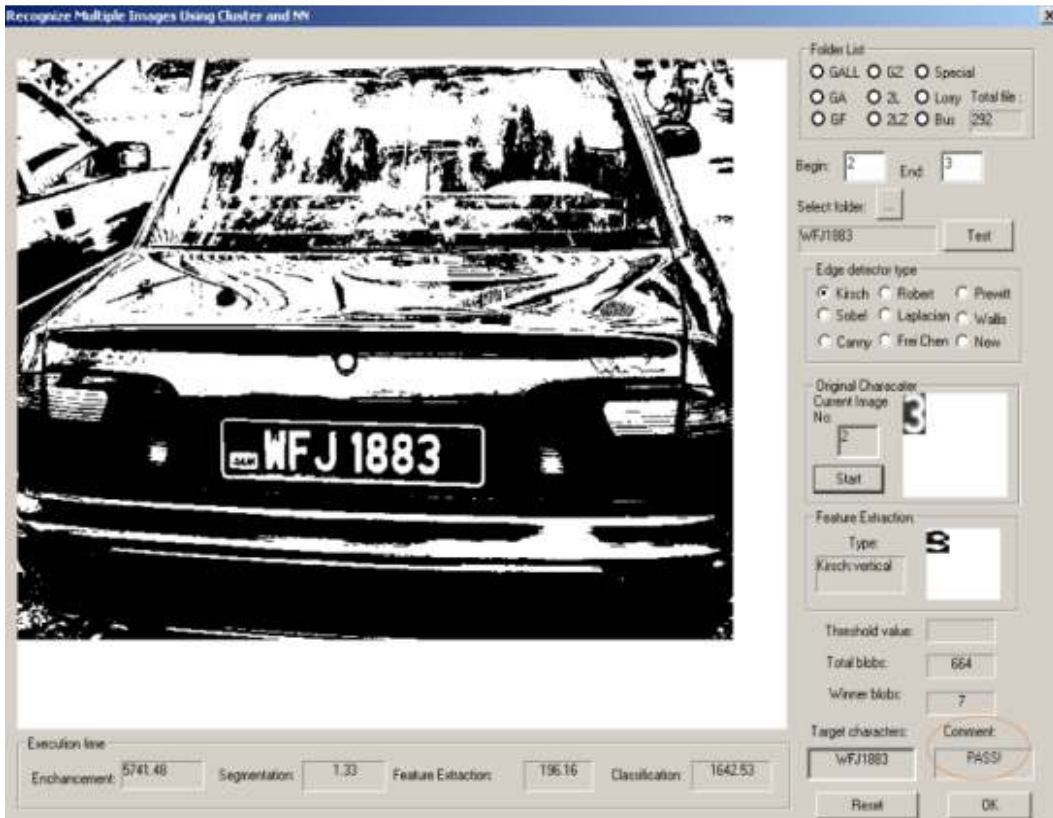
Table 4: LPR, LPS and LPD

Thresholding method	LPD (%)	LPS (%)	LPR (%)
Otsu (Otsu, 1979)	58.83	39.06	32.55
Kittler and Illingworth's MET (Kittler and Illingworth, 1986)	90.19	73.03	65.93
Potential difference (Acharya and Sreechakra, 1999)	95.51	77.24	70.06
Multilevel thresholding (Arora <i>et al.</i> , 2008)	94.85	67.21	59.11
Multi threshold algorithm (Abdullah <i>et al.</i> , 2010b)	99.67	94.98	90.13
Multi-threshold based on entropy (Abidin <i>et al.</i> , 2011)	93.06	72.40	59.00
Proposed	90.75	71.17	62.65

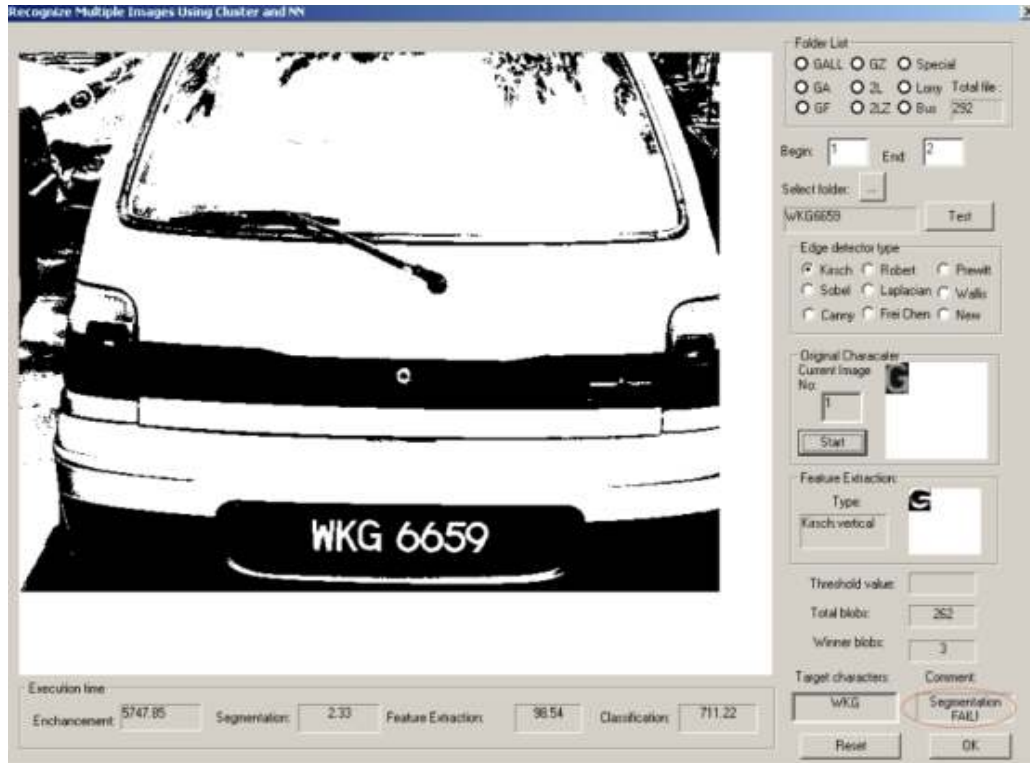




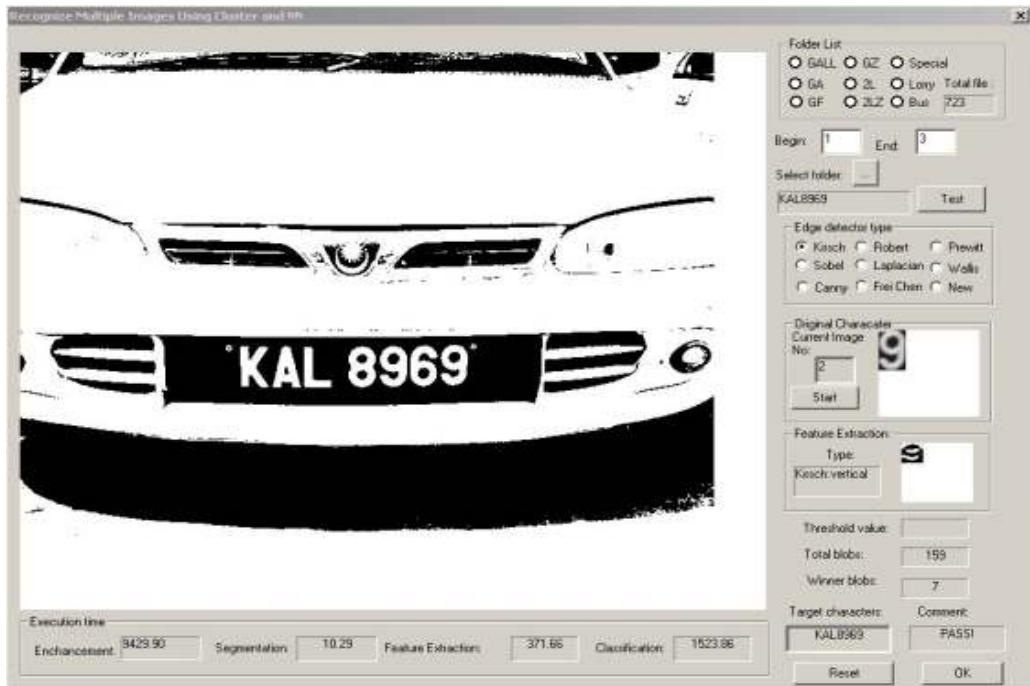
(a)



(b)



(c)



(d)

Fig. 7: A. Example of results obtained using the proposed method of thresholding for the license-plate recognition system. Recognition fails for 230 of the thresholding value images. Figure B. Examples of results obtained using the proposed method of thresholding for the license-plate recognition system. A pass in recognition is obtained for 150 of the thresholding value images. Figures C and D. Examples of results obtained using the proposed method of thresholding for the license plate recognition system. Segmentation fails for 40 of the thresholding value images

the range of the values in the above table, the proposed method is ranked 4th among the six methods used for comparison. The Multi-Threshold algorithm, at 99.67%, performed the best, followed by the Potential Difference method, 95.51%, Multilevel Thresholding, 94.85% and the proposed method, 90.75%. The following is the order of accuracy of the algorithms: Multi Threshold, Potential Difference, Multilevel, Proposed method, Kittler and Illingworth and Otsu. It is suggested that the Otsu thresholding algorithm not be used for LPR because the average accuracy with the LPR system is less than 35%.

The accuracy of the proposed algorithm is within 4.30% of the well-known thresholding algorithms for LPD, LPS and LPR applications. This performance is significantly better than older methods, such as Otsu. Moreover, it is very competitive with top algorithms, such as Multi Threshold and Multilevel Thresholding (Fig. 7).

## CONCLUSION

The proposed adaptive threshold method, based on the Peak Signal-to-Noise Ratio (PSNR), has the potential to be applied in all domains, such as LPR and OCR. Based on the experiments, the proposed algorithm achieves competitive results in four databases, including Malaysian vehicle, standard, printed and handwritten images. The proposed algorithms achieve better results compared with older methods. However it produced slightly worse results compared to newer methods, such as multi-level thresholding. In addition, the multi threshold technique does not work in real-time systems, but works in the LPR system. With other databases, the results of the proposed method are satisfactory for global images.

Recently, PSNR has been widely used as a stopping criterion in multilevel threshold methods for segmenting images. Alternatively, we have applied the PSNR as a criterion to determine the most suitable threshold value. We evaluated the proposed method with the license-plate recognition system. At the same time, we compared the proposed method with state-of-the-art multilevel and multi-threshold methods. The proposed method produced acceptable results in all conditions, such as different contrast or brightness.

The older methods, such as Otsu, Kittler and Illingworth, Max entropy and potential difference, are still valid. However, the newer methods, like multi-threshold and multilevel (recursive) thresholding, perform better in special usage/domains. Unlike these other methods, the proposed method yielded average result in all domains.

The objective of this research was to develop a new single adaptive thresholding algorithm that works for a wide range of pattern recognition applications. The proposed method has been implemented in four different types of applications and compared with other

methods. The results show that the proposed algorithm achieves the objective because it has obtained reasonable results in all four areas/domains.

A recently developed Malaysian LPR system uses a fixed threshold to segment the number plate and the characters. Experiments proved that via a Taylor-made thresholding method, the algorithm can be improved significantly. Clearly, the proposed method has been tested off-line. Another advantage of the proposed approach is that the adaptive threshold values can be changed according to the environment, such as for high or low contrast encountered during photographing at night, mid-day, underground or on a rainy day.

The proposed algorithm is suitable for use in the LPR system and is competitive with the newer methods for LPR. Because of its low accuracy in the LPR system, it is suggested that we do not include the Otsu method in future studies. The PSNR of the proposed method was better than that of the Kittler and Illingworth PSNR on standard database images. The Otsu method, which performed poorly in the LPR system, is adequate for producing a PSNR evaluation of standard images.

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