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DENSE-CLUSTER BASED VOTING APPROACH FOR LICENSE PLATE IDENTIFICATION

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Abstract

License plate recognition is a challenging due to different colors of foreground and background especially in Malaysia, where private vehicle (e.g., cars) displays dark background and public vehicle (e.g., taxis/cabs) displays white background. This paper presents a new method called Dense Cluster based Voting (DCV) for identifying an input license plate image as normal or taxi such that suitable recognition algorithms can be used to achieve better recognition rate. The proposed method uses Canny edge image to separate edges as foreground and non-edges as background. Then the proposed method exploits the intensity values corresponding to foreground and background pixels from the input gray image. Next, k-means clustering is proposed to classify intensity values into a Max cluster, which contains high values and a Min cluster, which contains low values for both intensity of foreground and background pixels. This process gives four clusters for the input image. The number of pixels in clusters (dense cluster) and the standard deviation are computed for deriving new hypotheses. Finally, we propose voting for the responses of hypotheses for identification. Classification results with existing methods show that the proposed method outperforms existing methods since the it works based on the distribution of foreground and background pixels rather than character shapes. Furthermore, the recognition results from classification show that recognition rate improves significantly compared to prior classification.

Keywords: Dense cluster voting, Foreground and background, K-means clustering, License plate detection, License plate recognition.

1. Introduction

In a country like Malaysia, there are instructions from the government that taxi should have license plates with white background and private vehicle must have license plates with a dark background. This is a part of security to identify vehicles easily by police. For example, the sample image is shown in Fig. 1(a) is a normal license plate, which contains numbers of dark color background, while the images shown in Fig. 1(b) are taxi license plate images, which contain numbers on the white mixed color background. Note that foreground and background colors of taxi license plates change due to poor maintenance, high usage, etc., as shown in Fig. 1(b). This is one of the major causes for not achieving accurate and high recognition rates for the recognition systems in Malaysia. It is evident from the illustration shown in Figs. 1(c)-1(d), where it is noted that both the binarization algorithm in [1], which works well for images of different contrasts, and the OCR in [2] gives poor results a prior to classification for both normal and taxi plate images as shown in Fig. 1(c). While the same methods give better results after classification as shown in Fig. 1(d). This motivated us to propose a method for license plate identification. In other words, the main objective of the proposed work is to develop a simple and effective method for classifying normal and taxi license plate images such that one can choose or develop an appropriate recognition method to achieve better recognition rates. In addition, it can be used for the live real-time environment.

(a) Normal license plate image with black color background.

(b) Taxi license plate images with different background color.

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(c) Binarization recognition results before classification for the normal and taxi plate images.

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(d) Binarization recognition results after classification for the normal and taxi plate images.

Fig. 1. Illustrating the complexity of the problem (recognition results are shown within a quote).

Many methods are developed for license plate recognition in the literature [3], which are robust to low contrast, high contrast, dirty plates, illumination affected images, blur images, etc. However, to the best of our knowledge, the methods usually assume fixed colors for background and foreground to tackle the above challenges. Therefore, these methods may not be suitable for images where foreground and background color change. Hence, there is a need for the classification of normal and taxi license plate images, especially in Malaysia.

For example, Saha et al. [4] proposed an Indian license plate recognition system, which extracts features at the pixel level. Therefore, it is sensitive to background changes. Safaei et al. [5] proposed real-time search free multiple license plate recognition via likelihood estimation of saliency, which works based on adaptive thresholding. Since it uses thresholds for detecting characters, it is not robust to the background or foreground changes. Panahi and Gholampour [6] proposed accurate detection and recognition of dirty vehicle pate numbers for high-speed applications, which uses intensity values in different domains for extracting features. The performance of the method depends on images captured by specific devices.

Bulan et al. [7] proposed segmentation and annotations free license plate recognition with deep localization and failure identification, which explores Hidden Markov Model for recognition. Since HMM requires predefined lexicons, it may not work well for different datasets especially for the images with background variations. Gou et al. [8] proposed vehicle license plate recognition based on extremal regions and restricted Boltzmann machines, which explores a probability model and an SVM classifier for recognition. Kim et al. [9] proposed effective character segmentation for license plate recognition under illumination changing environments, which uses adaptive thresholding for recognition. Recently, Polishetty et al. [10] proposed a next-generation secure cloud-based deep learning for license plate recognition for smart cities, which explores deep learning for recognition. It is noted that optimizing parameters for different data in case of deep learning is not so easy [11]. It is observed from the above review that despite the methods are robust to several causes, they ignore the cause created by different background colors.

Similar to the identification of license plates, there are methods for the classification of the different type of text in the video in literature with the same objective of the proposed work. For example, Xu et al. [12] proposed graphics and scene text classification in the video, which uses gradient and clustering. Shivakumara et al. [13] proposed a separation of graphics and scene texts in video frames, which explores contrast and characteristics of text components. Roy et al. [14] proposed new tampered features for the scene and caption text classification in video frames, which proposes DCT features for classifying two types of texts in the video. These methods work well when the shapes of the characters are preserved. This constraint is not necessarily true for license plate images. Raghunandan et al. [15] proposed new sharpness features for image type classification based on textual information, which explores sharpness based on the quality of the image. The quality does not matter for license plate images in this work because both normal and taxi plate images may have the same quality. Qin et al. [16] proposed video scene text frames categorization for text detection and recognition. The method is sensitive to background changes.

In the same way, there are methods for recognizing texts of different backgrounds, degradations and contrast variations through binarization. Su et al. [17] proposed a

robust document image binarization technique for degraded document images. Howe [18] proposed Laplacian energy for document binarization. Roy et al. [1] proposed a Bayesian classifier for multi-oriented video text recognition. Miyaev et al. [19] proposed image binarization for an end to end understanding of natural scene images. It is noted from the review of recognition methods that the main focus of these methods is to have images with the homogeneous background but not images affected by multiple causes. Overall, from the above discussion, it can be concluded that none of the methods is adequate to address the challenges posed by license plates especially the background and foreground color changes.

2. Proposed Methodology

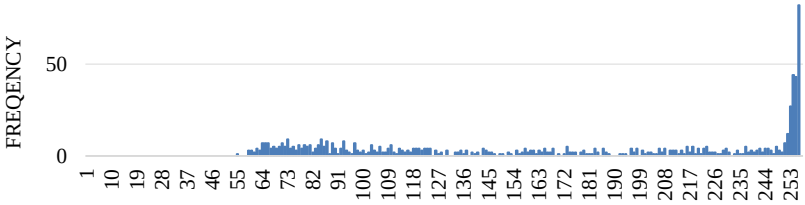
In this work, we consider detected license plates as the input for identification. This is because license plate detection is pre-processing step for recognition, there are several methods which work well regardless of background and foreground color changes [3]. It is observed from Fig. 1(a) and Fig. 1(b) that the background and foreground of normal plates are represented by black and white colors, respectively. Similarly, background and foreground of the taxi plate are represented by white and black colors, respectively. This shows that the intensity values of the background of a normal plate are lower than those of background of a taxi plate. This is valid because usually dark color is represented by the values near to 0, while white color is represented by the values near to 255. In addition, it is also true that the number of pixels which represent background usually is higher than that of pixels which represent foreground. These observations lead to propose dense cluster-based voting for the classification of normal and taxi plates in this work.

It is true that Canny edge detector gives fine edges regardless of background and foreground color changes as shown in Fig. 2(a), where we can see edges are represented by white pixels for both the images. To extract the above observation, we separate edge pixels as foreground and non-edge pixels as background for the input image. Then the proposed method extracts intensity values corresponding to foreground and background pixels from the gray image of the input image. To visualize the difference in intensity distribution, we perform histogram operation on intensity values of foreground and background of the normal and taxi plate images as shown in Figs. 2(b)-2(e). It is observed from Figs. 2(b) and 2(c) that the dense distribution can be seen for the pixels which have intensity values near to 255 in case of the foreground-normal plate, while the dense distribution can be seen for the pixels which have intensity values near to 0 in case of background-normal plate image. It is vice versa for the foreground-taxi and background-taxi as shown in Figs. 2(d) and 2(e). This is the main basis for the proposing Dense-Cluster based Voting (DCV).

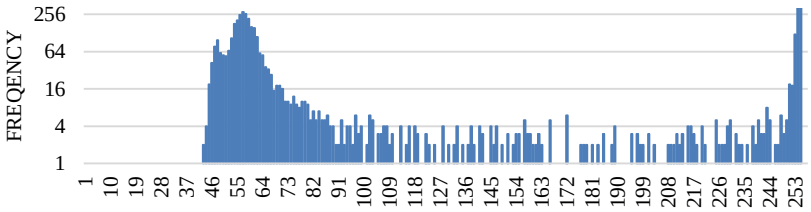
To extract such observations, we divide the intensity values of foreground and background into two clusters as Max which gets high values and Min which gets low values using K-means clustering with K=2. This results in four clusters for the input image, namely, foreground-Max cluster, Foreground-Min cluster, Background-Max cluster and Background-Min cluster. For each cluster, the proposed method computes mean, standard deviation and the number of pixels (density) to derive hypotheses to identify license plate images. For example, the product of standard deviation and the number of pixels of the background-min cluster is greater than the product of standard deviation and the number of pixels of the background-max cluster for normal plates. This results in response “1”. In this way, the proposed method derives three hypotheses and finds the responses. If the

hypothesis gives two responses as “1” out of three, it is identified as a normal plate else taxi plate. The whole logic of the proposed method is shown in Fig. 3.

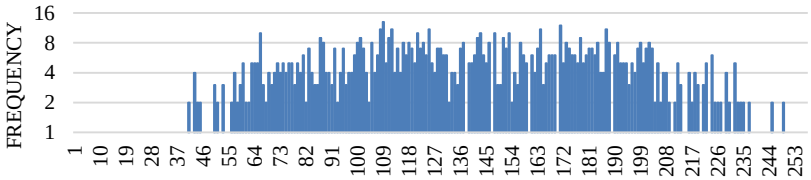
(a) Canny images of normal and taxi plate images.



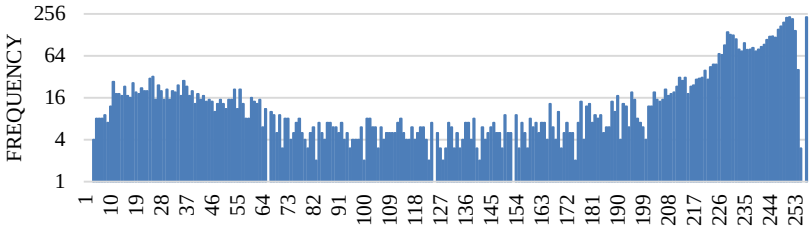
(b) Histogram for gray of foreground of normal plate.



(c) Histogram for gray of background of normal plate.



(d) Histogram for gray of foreground of taxi plate.



(e) Histogram for gray of background of taxi plate.

Fig. 2. Intensity distribution of foreground and background of normal and taxi plate images.

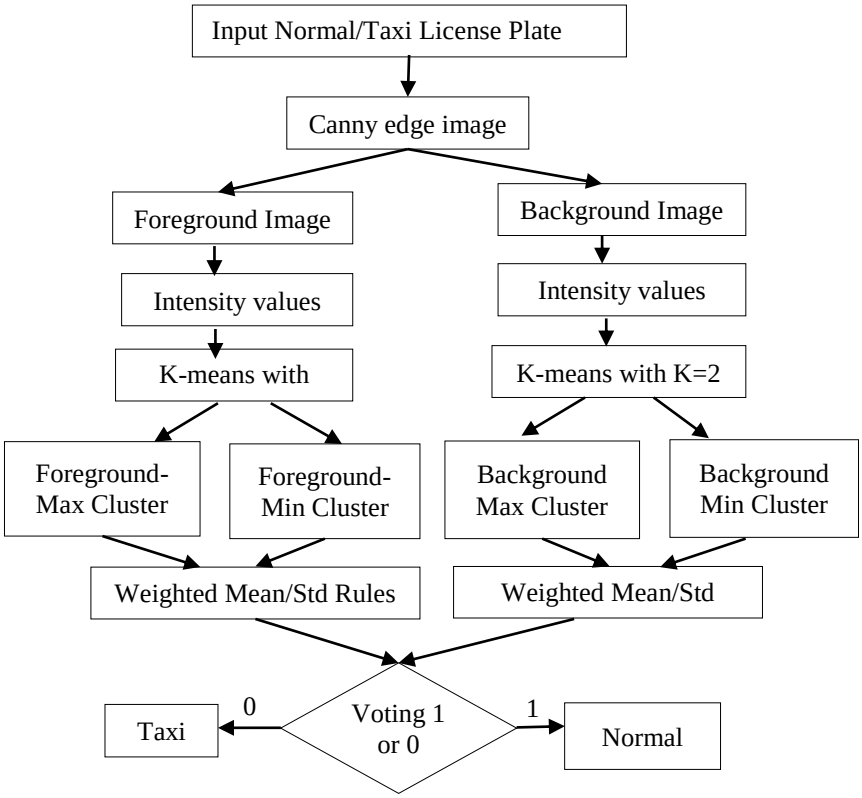


Fig. 3. Flow of the proposed method.

2.1. Foreground and background separation

As discussed in the previous section, to separate foreground and background, the proposed method considers edge pixels given by Canny as foreground information and non-edge pixels as background information as shown in Figs. 4(a) and 4(b), respectively, where Canny provides edges without losing shapes for both normal and taxi plate images. Then the proposed method extracts intensity values in the gray image *G* corresponding to foreground and background pixels, say *GF* and *GB* as defined in Eq. (1) and Eq. (2) for the normal and taxi plate images as respectively shown in Figs. 4(c) and 4(d), where we notice there is a color change in foreground and background of normal and taxi plate images. Therefore, for the input image, the proposed method separates foreground and background using edge information.

$$GF_{x,y} = \begin{cases} \mathrm{G}_{x,y} & \text{if } \mathrm{Canny}(\mathrm{x},\mathrm{y}) = 1 \\ 0 & \text{else} \end{cases} \tag{1}$$

$$GB_{x,y} = \begin{cases} \mathrm{G}_{x,y} & \text{if } \mathrm{Canny}(\mathrm{x},\mathrm{y}) = 0 \\ 0 & \text{else} \end{cases} \tag{2}$$

(a) Foreground of the normal and taxi plate images.

(b) Background of the normal and taxi plate images.

(c) Gray values for the foreground pixels of the normal and taxi plate images.

(d) Gray values for the background pixels of the normal and taxi plate images.

Fig. 4. Foreground and background separation using edge pixels.

2.2. Dense-cluster voting for license plate identification

As for the foreground and background images given by the method presented in the previous section, the proposed method applies K-means clustering with K=2 on intensity values of foreground and background of normal and taxi plate images to classify the pixels, which have high intensity values into Max cluster and the pixels which have low intensity values into Min cluster as shown in Figs. 5(a) - 5(d), respectively. It is noted from Figs. 5(a) and 5(b) that the number of pixels classified into the Min cluster is higher than that of the Max cluster.

Though the Max cluster gets high values, the number of pixels in the cluster is lower than the number of pixels in the Min cluster. Therefore, the number of pixels in the cluster as considered as weight and it is multiplied by the standard deviation. On the other hand, it is noted from Figs. 5(c) and 5(d) that the number of pixels, which are classified into the Min cluster, is lower than that of the Max cluster. This cue helps us to derive hypothesis using the number of pixels in clusters and the standard deviations to identify normal and taxi plate images.

The hypotheses are illustrated in Fig. 6, where one can see the number of pixels in background-min cluster (BN_{min}) is greater than that in background-max cluster (BN_{max}), the product of the number of pixels in background-min cluster (BN_{min}) and the standard deviation of background of min-cluster ($BStd_{min}$) is greater than the product of the number of pixels in background-max cluster (BN_{max}) for the normal image as shown in Fig. 6(b). However, the number of pixels (dense) in the foreground-min cluster (FN_{min}) is less than that of pixels (dense) in the background-max cluster (FN_{max}) for the normal image as shown in Fig. 6(a).

(a) Min and Max clusters for the foreground of normal plate image.

(b) Min and Max clusters for the background of normal image.

(c) Min and Max clusters for the foreground of taxi image.

(d) Min and Max clusters for background of taxi image.

Fig. 5. Min and Max clusters for foreground and background images of normal and taxi license plate images.

This results in three hypotheses (H-1, H-2, H-3) as defined in Eqs. (4) to (6), respectively. The proposed method considers each response of hypothesis as "1" if it satisfies the condition, else it is considered as a response "0". Out of the three responses, if two responses are "1", the input image is identified as a normal one, else it is a taxi image. Figures 6(c) and 6(d) show that H-1 and H-2 do not satisfy the conditions, while H-3 satisfies the condition. Therefore, if two responses are "0", the image is identified as a taxi. In this way, the proposed method tests all eight combinations of three responses for the input image. This process is called as Voting as defined in Eq. (7), where ∂ is the majority variable, which is set to be greater than or equal to 2 for normal and less than 2 for taxi.

$$\mathrm{Std_j} = \sqrt{\frac{\left(\sum_{\gamma=1}^{m} \mathrm{M_j} - \mathrm{X_\gamma}\right)^2}{\mathrm{m}}} \tag{3}$$

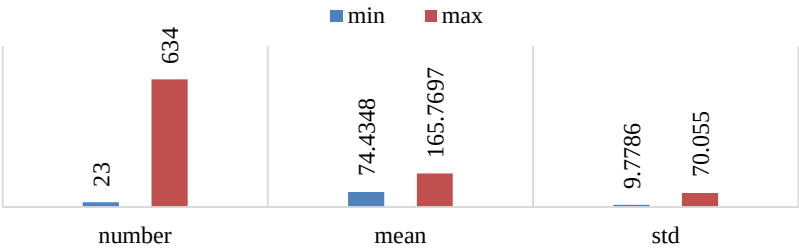
where M_j is the mean of the j cluster, X denotes intensity values, and m is the total number of the pixels in cluster j.

$$\text{H-1} = \begin{cases} 1 & \text{if } \mathrm{FN_{min}} > \mathrm{FN_{max}} \\ 0 & \text{else} \end{cases} \tag{4}$$

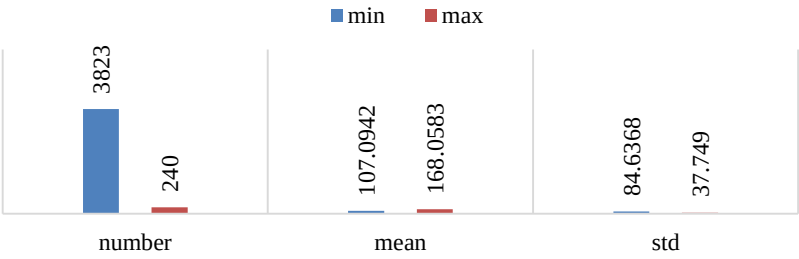
$$\text{H-2} = \begin{cases} 1 & \text{if } \mathrm{BN_{min}} > \mathrm{BN_{max}} \\ 0 & \text{else} \end{cases} \tag{5}$$

$$\text{H-3} = \begin{cases} 1 & \text{if } \mathrm{BN_{min}} * \mathrm{BStd_{min}} > \mathrm{BN_{max}} * \mathrm{BStd_{max}} \\ 0 & \text{else} \end{cases} \tag{6}$$

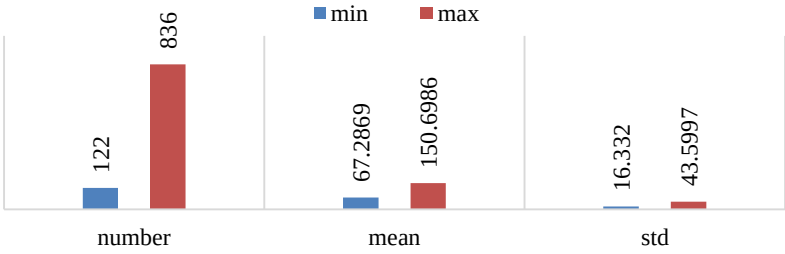
$$\text{Voting} = \begin{cases} 1 & \text{if } (\text{H-1}) + (\text{H-2}) + (\text{H-3}) > \partial \\ 0 & \text{else} \end{cases} \tag{7}$$



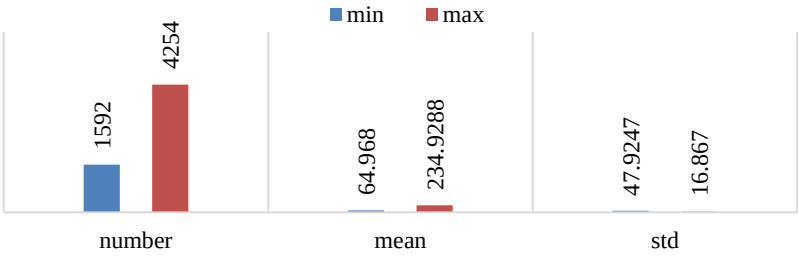
(a) Number of pixels, mean and standard deviation for Min and Max clusters of foreground of normal image.



(b) Number of pixels, mean and standard deviation for Min and Max clusters of background of normal image.



(c) Number of pixels, mean and standard deviation for Min and Max clusters of foreground of taxi image.



(d) Number of pixels, mean and standard deviation for Min and Max clusters of background of taxi image.

Fig. 6. Hypothesis using min, max clusters of foreground and background of normal and taxi plate images.

3. Experimental Results

To evaluate the proposed method, we consider 980 normal and 1000 taxi plate images, which gives 1980 images for experimentation. This dataset consists of images affected multiple adverse factors such as low resolution, blur and severe illumination effect, images with different background colors, images affected by head light, the speed of vehicles, etc. It is provided by a research institute and funded by the government where it is a live project.

To measure the performance of the proposed and the existing methods, we consider classification rate with confusion matrix for experiments on classification and recognition rate at character level for recognition experiments. Since there is no ground truth for the dataset, we count manually to calculate measures. For recognition experiments, we consider prior to classification and after classification to show the usefulness and effectiveness of the classification method. A prior to classification includes data from two classes for experimentation using different binarization methods. After classification includes data of individual class for experiments using the same binarization methods. Besides, the same experimentation set up is repeated for each existing classification method to show that the proposed classification is better than the existing classification methods.

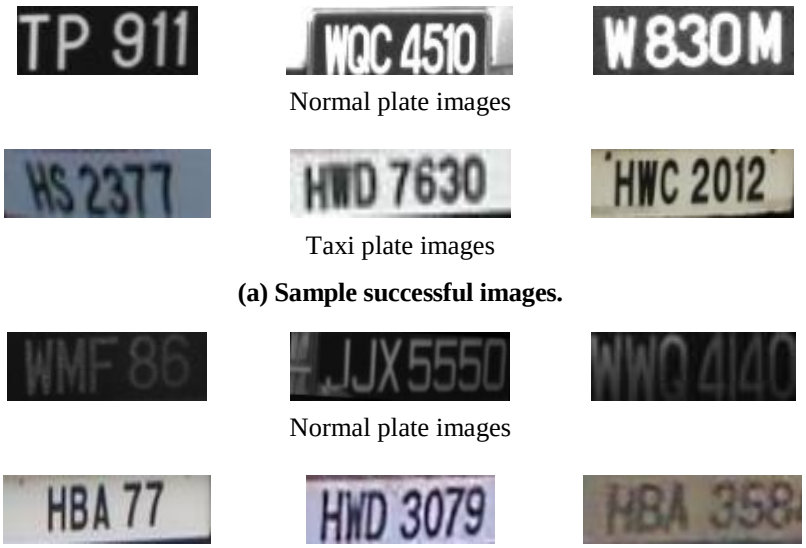
To show the proposed method is superior to the existing methods, we implement two latest classification methods. The first one is Xu et al.'s method [12], which explored the uniform color of text components for classification of caption and scene text in the video. The second one is Roy et al.'s method [14], which proposed tampered features for separating caption and scene texts in the video. The main reason to choose these two existing methods for the comparative study is that both the methods have the same objective as the proposed method. The methods consider scene texts are unpredictable, which suffer from distortions affected by multiple causes as taxi plates in this work. Similarly, the methods consider caption texts have good clarity and contrast, which is the same as normal license plates compared to taxi license plates. Therefore, caption and scene texts are the same as normal and taxi license plate images.

Similarly, we implement the state of the art binarization methods for recognition experiments a prior to classification and after classification, namely, Howe's method [18], which focuses on printed and handwritten document images with color bleeding effect, Su et al.'s method [17], which focuses on degraded document images, Milyaev et al.'s method [19], which focuses on natural scene images, and Roy et al.'s method [1], which focuses on both natural scene and video images. The reason to consider these different methods for experiments a prior to classification and after classification is that each method addresses its own challenge. Most importantly, our intention here is to show that recognition rate improves significantly if we perform classification of different types of images.

3.1. Evaluating classification method

Sample successful and unsuccessful classification images of the proposed method are shown in Figs. 7(a) and 7(b), respectively. Figure 7 shows that the proposed method works well for images with blur, low contrast, and illumination effects. However, the proposed method fails to classify images, which have too many distortions and blur. Therefore, there is a scope for improvement and extension of the proposed method.

To show the proposed method is effective, we compare the proposed method with two existing methods as discussed in the previous section. The results of the proposed and existing methods are reported in Table 1, where it is noticed that the proposed method gives better results than the existing methods. The reason for poor results of the existing methods is that the existing methods depend on character shapes while the proposed method depends on the distribution of foreground and background pixels. For instance, tampered features proposed by Roy [14] exists only for caption text but not license plate images.



(a) Sample successful images.

(b) Sample unsuccessful images.

Fig. 7. Sample successful and unsuccessful images of the proposed method.

Table 1. Confusion matrix of the proposed method and existing methods (%).

Plate Numbers	Proposed Method		Xu et al [12]		Roy et al. [14]	
	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)
Normal	77.54	22.46	57.6	42.4	53.5	46.5
Taxi	19.78	80.22	33.69	66.31	31.98	68.02

3.2. Evaluating usefulness of the classification method

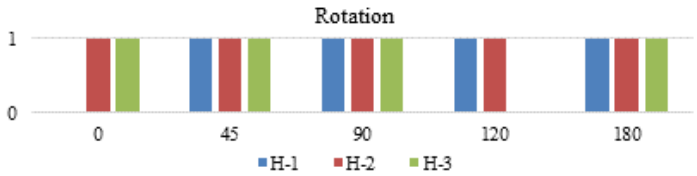
To validate the usefulness of the proposed classification, we conduct recognition experiments using several binarization methods before and after classification as reported in Table 2. Table 2 shows that the binarization methods report better recognition rates after classification compared to prior to classification. This is valid because we tune parameters of binarization methods according to the complexity of input classes after classification. For example, we set different window sizes for Milyaev et al.'s and Roy et al.'s methods to achieve better results after classification. This is the advantage of the classification method. When we compare recognition rates of binarization methods with classification methods, all

the binarization methods score better recognition rates for the proposed classification compared to the other existing classification methods.

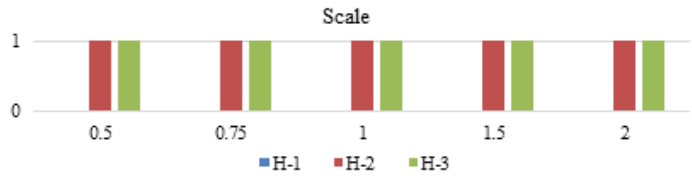
We conduct experiments on different rotations, scale and the images affected by different distortions to show that the proposed method is invariant to rotation, scaling and to some extent to distortion as shown in Fig. 8, where one can see the hypotheses of normal images satisfy the voting condition for different rotations, scale and distortion respectively in Figs. 8(a) - 8(c). Overall, the objective of the work as mentioned in the introduction, namely, developing a simple and effective license plate identification method to improve recognition rate, is satisfactorily achieved. Since the proposed solution is simple, it can be fit in the real-time environment without many changes.

Table 2. Recognition rate of the binarization methods for before and after classification on each classification methods (%).

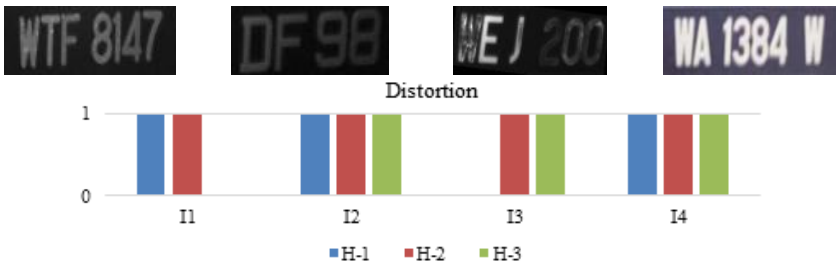
Binarization methods	Before classification	After classification					
	Normal + Taxi (%)	Proposed		Xu et al. [12]		Roy et al. [14]	
		Normal (%)	Taxi (%)	Normal (%)	Taxi (%)	Normal (%)	Taxi (%)
Roy et al. [1]	14.8	22.3	20.7	19.9	17.3	20.8	19.5
Howe [18]	22.07	31.6	24.2	25.1	21.4	29.6	23.4
Su et al. [17]	19.34	26.4	23.7	24.8	22.2	25.2	21.2
Milyaev et al. [19]	16.9	24.6	21.4	23.5	18.1	23.3	18.9



(a) Hypotheses for different rotations of normal image.



(b) Hypothesis for different scaled normal image.



(c) Hypothesis for different distortion such as low contrast, poor quality and blur of normal images.

Fig. 8. Robustness of the proposed method.

4. Conclusion and Future Work

In this work, we have proposed dense cluster-based voting for identifying Malaysian normal and taxi license plate images. The proposed method separates foreground and background for an input image, based edge information. The extracted intensity values corresponding to foreground and background information are classified into Max and Min clusters with the help of K-means clustering. This process results in four clusters, namely, Max-Min for foreground and Max-Min for the background of the same image. The number of pixels in clusters (dense) and standard deviation of clusters are used to derive three hypotheses, which give three responses for the input image. The proposed method considers the majority of responses for classifying normal and taxi plate images. It is noted that classification rate is not very high. Therefore, it is challenging to achieve high classification rate for different situations. This would be our future course of research.

Nomenclatures

BN_{max}	The number of pixels in background-max cluster
BN_{min}	The number of pixels in background-min cluster
FN_{max}	The number of pixels in foreground-max cluster
FN_{min}	The number of pixels in foreground-min cluster
GB	Gary value of Background
GF	Gary value of foreground
H	Hypothesis
m	Total number of the pixels in cluster *j*
M_j	The mean of the *j* cluster
std	standard of deviation
X	Intensity values

Abbreviations

DCV	Dense cluster-based voting
OCR	Optical character recognition

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