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License Plate Localization using a Naïve Bayes Classifier

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Abstract— **This paper presents a probabilistic technique to localize license plates regions for cars adhering to the standard set by the Malaysian Road Transport Department. Images of the front/rear-view of cars displaying their license plates are firstly preprocessed, followed by features extraction generated from connected components analysis. These features are then used to train a Naïve Bayes classifier for the final task of license plates localization. Experimental results conducted on 144 images have shown that considering two candidates with the highest posterior probabilities better guarantees license plates regions are properly localized, with a recall of 0.98.**

I. Introduction

Recognizing characters and/or numbers on license plates (LP) is useful for applications such as traffic control, vehicle management in parking lots and stolen vehicle detection [1]. However, to achieve the ultimate goal of recognition, LP regions have to firstly be localized to allow any further processing and analysis. As mentioned in [13], complete LP recognition systems consist of three basic components, namely (i) LP localization, (ii) characters/numbers segmentation, and (iii) characters/numbers recognition. This paper focuses only on the first component. A probabilistic Naïve Bayes (NB) approach is proposed that takes into consideration features obtained from binary image connected components analysis (CCA). The posterior probabilities of each connected component are then calculated, where intuitively, the one with the highest probability score is deemed to be the actual number plate region.

A probabilistic approach is proposed to relax the need for explicit rules specifications, specifically pertaining to the size properties of LPs. At this point in time however, the scope of this work is limited to cars and medium sized vehicles such as vans, MPVs, jeeps and pickups (motorcycles and large trucks are not included in the evaluations).

II. License Plate Localization

LP localization is commonly performed by retaining image regions that belong to LPs. One way of doing this is to use rule-sets relating to size properties. For example, if a segmented region's width, height, and/or aspect ratio conform to predefined threshold values, then these regions are retained [2]-[4]. In [1] on the other hand, besides only applying size thresholds, rules regarding intensity and image-border restrictions were also imposed. Although such rule-based these techniques work quite well, strict rule-sets need to be defined through arduous manual observations.

Besides using rules, localization was also done using machine learning algorithms. AdaBoost was used along with Haar-like features in [5, 8-10]. An optimization technique was used in [11]-[12] where a GA (Genetic Algorithm) identified the maximum and minimum thresholds for LP color. Shape features were further utilized to identify the final LP region.

In this paper, we relax the need for rules specifications, especially pertaining to size properties. We attempt a supervised learning approach using simple features. The learning algorithm employed is the Naïve Bayes classifier, which is quite easy to implement due to the conditional independence assumption being imposed. Note that at this stage of the research, we are only dealing with cars' and medium sized vehicles' LPs that conform to the Malaysia license plate format set by the Road Transport Department, Malaysia [7].

The rest of the paper is organized as follows. *Section-III* describes the proposed approach, followed by experimental results and discussions in *Section-IV*. Section-V concludes with remarks regarding future works.

III. The Proposed Approach

The basic flow of the proposed approach is shown in Fig. 1. Explanations of the subcomponents are provided in the following subsections.

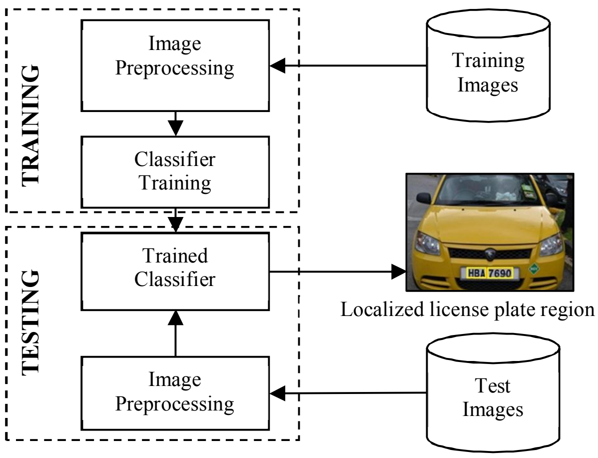

Fig. 1. The flow of the proposed LP technique

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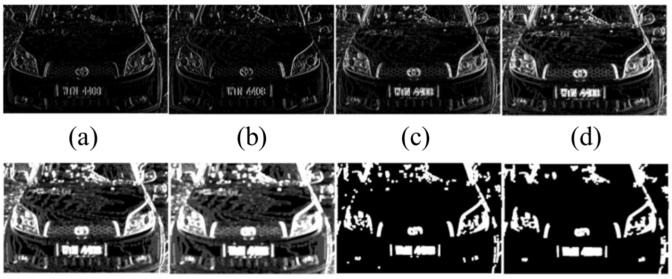
A. *Image Processing and Analysis*

Prior to training the NB classifier, preprocessing and analysis are performed on the grayscale image of a car displaying its LP. Firstly, two 3 X 3 Sobel filters are applied to emphasize the vertical edges, using a smoothing effect though approximation of vertical gradients. The first filter uses two-dimensional correlation, whereas the second using two-dimensional convolution. This produces two filtered images, which are then added together. The intuition behind this is to highlight the LP region.

Dilation using a square 2 X 2 structuring element (STREL) is then performed followed by a 4 X 4 maximum filter. Another dilation process is applied using a 3 X 4 rectangular STREL. This is followed by thresholding where pixels with intensities greater than 240 are retained. The resulting image is then put through binary closing using a 1 X 6 rectangular STREL followed by removing any remaining regions with less than 225-pixels. Illustrations of these processes are shown in Fig. 2(a) – 2(h).



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 2. (a) Sobel filter - correlation, (b) Sobel filter - convolution, (c) Result of adding *a* and *b*, (d) 2X2 dilated image, (e) 4X4 maximum filtered image, (f) 3X4 dilated image, (g) thresholded image, and (h) Removal of white regions smaller than 255-pixels and the resulting 1X6 closed image.

B. *Training the Naïve Bayes Classifier*

The Naïve Bayes classifier was chosen due to its straight forward nature to train and implement the algorithm as no parameters have to be considered; as compared to other algorithms such as the Support Vector Machine, Artificial Neural Network or Hidden Markov Model. According to the Bayes theorem, the posterior probability of a given class C_i can be calculated by:

$$P\,(C_i|\boldsymbol{x}) = P(\boldsymbol{x}|C_i)\,P(C_i)/P(\boldsymbol{x}) \tag{1}$$

where the posterior probability $P(C_i|\boldsymbol{x})$ can be estimated from the training data $\boldsymbol{x}$. However, obtaining $P(\boldsymbol{x}|C_i)$ is relatively difficult if all n-features within the $\boldsymbol{x}$ are conditionally dependent. The Naïve Bayes (NB) approach makes the assumption that all n-features are conditionally independent, given the class label. This relaxes the calculation of the prior probabilities, which can then be obtained using Eq. 2. Although seemingly untrue in most cases (since most data are conditionally dependent to some extent on one another), the resulting model is easy to fit and works well for many classification tasks [6].

$$P(\boldsymbol{x}|C_i) \approx \prod_{k=1}^{n} P(\boldsymbol{x}_k|C_i) \tag{2}$$

In this paper, the classifier is trained to recognize LP (C_1) and non-LP (C_2) regions. Training is performed using a 7-dimensional feature vector $\boldsymbol{x} = \{x_1, x_2, x_3, \dots, x_7\}$, which are selected properties of the extracted regions obtained from binary image CCA. The features in $\boldsymbol{x}$ are:

1) Bounding box properties (x_1, x_2, x_3 and x_4): A 4-element vector where the first two elements hold the upper-left coordinates of the smallest rectangular bounding box encapsulating a connected region. The remaining elements represent the width and height of the bounding box, respectively;

2) Area (x_5): A scalar identifying the area of the region's bounding box; and

3) Centroid (x_6 and x_7): A 2-dimensional vector of the centroid coordinates, which is the connected region's center of mass.

Training was conducted using 150-images of vehicles obtained from parking lots around a university and a hotel. Each image underwent the preprocessing steps mentioned in Section *III-A*. These images are then manually separated, where images with regions not belonging to LPs are treated as negative (–ve) examples and images containing regions belonging to the LPs are treated as positive (+ve) examples. An illustration is given in Fig. 3.

(a) (b) (c)

Fig. 3. (a) After going through preprocessing in Section *III-A*, (b) a negative training image, and (c) a positive training image.

The features mentioned in Section *III-B* are extracted from each connected component within each training image. This produces a skewed training set where -ve examples greatly outnumber +ve examples. The classifier training stage makes use of all the +ve and –ve examples.

C. *License Plate Region Localization*

To test the trained NB classifier, a test image T is subjected to the same preprocessing and feature extraction steps mentioned in Sections *III-A* and *III-B*, respectively. Assuming m-number of connected regions per image, m-sets of feature vectors for image T are produced, as represented as Eq. 3:

$$T = \{\boldsymbol{x}^1, \boldsymbol{x}^2, \dots, \boldsymbol{x}^m\} \tag{3}$$

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The main objective then is to discover the region i^* with the maximum posterior probability $P(C_1 | \boldsymbol{x}^i)$ for $i = 1, \ldots, m$, as the intuition is for the actual LP region to exhibit the highest posterior probability score.

In this work however, since sometimes LP regions can be accidentally divided into two separate regions (i.e. the characters and the numbers) after the steps in Section *III-A*, we have decided to consider two scenarios:

1) Single-candidate consideration: In this case, only one candidate is selected as the final license plate region, which is the one with the highest posterior probability; and

2) Two-candidate consideration: Two candidates are selected as the final LP regions, which are the two regions with the highest posterior probabilities.

IV. Experimental Results

Implementation was done using MATLAB R2009b. 144 test images showing cars with LPs were taken using two DSLR cameras (a Nikon D3100 and a Canon 5D Mark3). All images were rescaled to a resolution of 640 X 427 pixels using Fotosizer (http://www.fotosizer.com). For reference, some sample images are shown in Fig. 4. To measure the accuracy of the proposed approach, the single and two-candidate considerations were evaluated using *precision* and *recall*, similar to that used in [5]. The formulas are given in Eqs. 4 and 5, respectively. Sample classification results based on the single-candidate consideration are shown in Fig. 5, whereas results for the two-candidates consideration are shown in Fig. 6. For reference, Figs. 8 and 9 show results for other selected test images.

$$precision = \frac{correct}{correct+false} \tag{4}$$

$$recall = \frac{correct}{correct+misses} \tag{5}$$

Fig. 4. Sample of images taken by the DSLR cameras.

TABLE I
PRECISION AND RECALL FOR LICENSE PLATE LOCALIZATION

Implementation	Correct	False	Miss.	Prec.	Rec.
1-candidate	99	3	45	0.98	0.61
2-candidates	141	98	3	0.59	0.98

A. *Discussions*

In Fig. 5, it can be seen that there are many misses when considering only one candidate. Table 1 quantifies the results where a total of 45 misses (~31%) were recorded. This is undesirable, where in a hypothetical automated barrier gate parking system, a car might be denied access to the parking lot. Although precision is high, this does not guarantee that the complete set of characters and numbers on the LP are detected.

For the two-candidate consideration scenario, almost all of the LP regions were identified. Misses however still occurred. In Fig. 6 (c) for instance, the miss happened due to an undersized STREL during closing, whereas in Fig. 6 (d) was due to a missing number on the LP itself. Precision however suffers as many non-LP regions (such as the car's logo and front grill) were detected as well. This happens when the entire LP region has already been detected since two candidates will be considered no matter what. Nonetheless, due to the high recall, it is almost guaranteed that the entire LP is detected. This can allow further processing to properly take place for the purpose of individual character segmentation and recognition (in the case of a full-fledged LP recognition system).

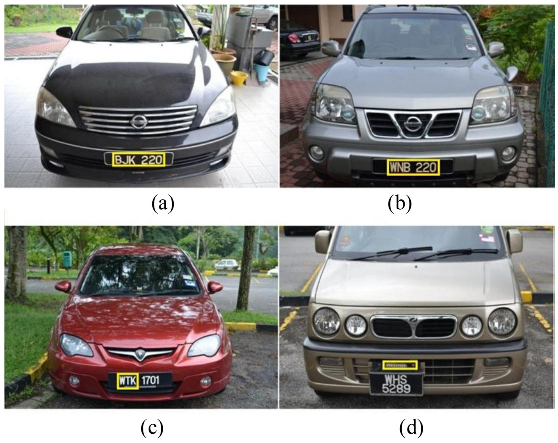

Fig. 5. (a-b) Correct, (c) missed, and (d) false.

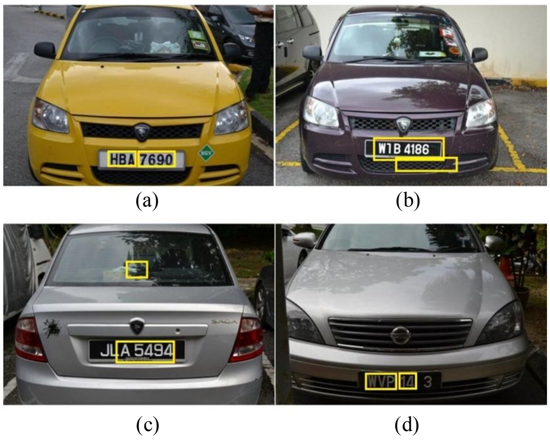

Fig. 6. (a) Correct, (b) correct + false, (c) correct + missed + false, and (d) correct + missed due to missing number on license plate.

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V. Conclusion

Localization is the most important step in a LP recognition system, since segmentation and recognition rely heavily on correctly detected LP regions. In this paper, a car LP localization technique has been presented based on the Naïve Bayes probabilistic approach. Two scenarios were considered, namely taking only one, and then two-candidates with the highest posterior probability scores. The high recall rates for the two-candidate consideration suggests that it has good potential and can be further refined in the future. From the experiments conducted, we hope to improve the current work from the following angles:

1. *Preprocessing errors*: In Fig. 7, the morphological operations produce oversized connected regions. This was caused by LPs having high reflectance properties. Resultantly, bright regions adjacent to the letters form white regions when thresholded, and gets connected with the actual LP region after dilation and opening;

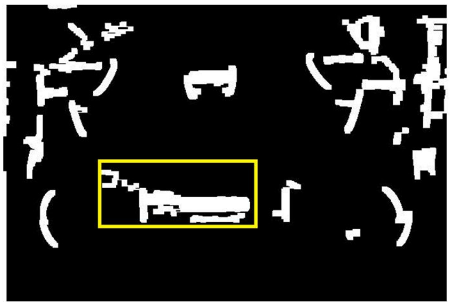

Fig. 7. An erroneous and oversized connected region.

2. *Relaxing some rules during preprocessing*: Although we claim to relax rules specifications, this is true only in the actual localization part. Preprocessing is still hampered by hard thresholds pertaining to intensity and size, as well as specific values for STRELs;
3. *Further refinement*: From the two-candidate case, almost all actual LP regions are successfully localized. However, many false alarms were also present;
4. *Training data and feature considerations*: Training data is limited quite limited. We hope to expand the training set and possibly include other feature considerations, such as texture and shape;
5. *Larger Images*: All the images were rescaled to 640 X 427. This has caused issues especially during morphological processing, as pixels tend to get connected although belonging to different letters/numbers.

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Fig. 8. Sample output of other selected test images for the single-candidate case.

Fig. 9. Sample output of other selected test images for the two-candidate case.

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