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Extraction of Number Plate Images Based on Image Category Classification Using Deep Learning

Yoshihiro Shima
School of Science and Engineering
Meisei University
Hino, Tokyo, Japan
shima@ee.meisei-u.ac.jp

***Abstract*— Automated Number Plate Recognition is a technique involving image processing which is used to identify a vehicle by reading its number plate. A proposed method is capable of extracting the number plate region in the image captured from its rear end at various car distances. The system analyzes the input image and identifies the location of the number plate. The plate candidate region is extracted by using dilation morphology and scoring based on the height-width ratio and the number of connected components in the region. The candidate region images are classified in two classes, namely number plate and outlier images. As image feature extractor, pre-trained CNN (convolutional neural network) is used and as classifier, SVM (support vector machine) is used. The algorithm was implemented by programming language C++ in morphological image processing and MATLAB in pre-trained CNN and SVM parts. The paper shows experimental verification of the algorithm and test results for 126 car images.**

***Keywords*— robot car; number plate; location detection; morphological operation; deep learning; image classification; CNN; SVM;**

I. Introduction

Number plate is to be the essential vehicle identifier. Therefore, future robot cars, sensing the environment, rely on robust Automated Number Plate Recognition systems(ANPR) [1][2]. ANPR is to automatically read number plate characters by using optical character recognition (OCR). Two types of ANPR are used: stationary, which uses cameras at fixed points, and mobile, which uses vehicle-mounted cameras. Recognition system is able to extract the sub-image regions that make up a number plate and translate the characters on the plate to a digital format. The plate data is then sent to a database where it is compared in real-time to a list of plate numbers that belong to vehicles of interest. If the system detects a match, it sends information to the user. ANPR has many big data application including: recovering stolen cars, traffic law enforcement, monitoring road traffic, controlling parking lot access, and automatic toll collection.

It is necessary to cope with the variations of the plates and environments for recognizing number plate images. Plates exist in different locations of an image. Plates may have different sizes due to the camera distance and the lens factor. The image background may contain patterns similar to plates, such as numbers stamped on a vehicle and bumper with vertical patterns. The variations of the plate types or environments cause challenges in the detection of number plates.

Conventional approach to extract number plate is based on morphological image processing[3]-[11]. A convolutional neural Network (CNN) is a powerful machine learning technique in the field of deep learning[12][18]. A neural network is a machine learning technique in the field of character recognition. A huge amount of labeled data are needed for training. An easy way to leverage the power of CNNs without investing time and effort into training, is to use a pre-trained CNN as a feature extractor. The focus of this paper is on a region extraction technique combined with morphological image processing and deep learning. Region image classification is based on CNN and SVM. A pre-trained CNN is used for image feature extractor and SVM classifier is used for 2-class classification of candidate areas[20].

The paper is organized as follows. In Section II, a review of related researches is presented that have been reported in the literature. A number plate extraction method is presented in Section III. The morphological image processing technique and image category classification technique using deep learning is proposed. In Section IV and Section V, sample images and experimental results are presented. Finally, conclusions and future extensions are presented in Section VI.

II. Review of Other Number Plate Extraction Techniques

A. Morphological Image Processing

Edge features and rectangular shape with a known aspect ratio have been used to extract number plates[2]. Edge detection methods are commonly used to find these rectangles. Connected component analysis (CCA) is a morphological technique in binary image processing[3][4]. Texture and color features are also used. For detecting the number plate location, machine learning technique is not used in these morphological image processing.

1) Edge Features: The number plate has a rectangular shape with a known aspect ratio. By finding all possible rectangles in the image, the number plate can be extracted. Edge detection methods are commonly used to find these rectangles. The boundary of the number plate is represented by edges in the image. Hough transform detects straight lines in the image to locate the number plate [5].

2) Global Image Features and Rectangular Shapes: Connected component analysis (CCA) is a morphological technique in binary image processing. It scans a binary image and labels its pixels into components based on pixel connectivity. Spatial measurements, such as area and aspect ratio, are used for number plate extraction [6][7].

3) Texture and Color Features: Since the number plate has characters, significant change is occurred in the grey-scale level between characters color and number plate background color. It also results in a high edge density area due to color transition [8]. Projection profile analysis is often used. In Japan and some countries, their number plates have specific colors. The basic idea is that the color combination of a plate and characters is unique, and this combination occurs almost only in a plate region [9]-[11].

4) Character Features: The character images have features with strokes. Number plate extraction methods based on character features, have also been proposed. These methods examine the image for the presence of characters. If the characters are found, their region is extracted as the number plate region [2][14].

B. Neural Network

Neural networks have been used to recognize clipped character patterns[13]-[15]. The segmentation module extracts the license plate in the detected car image using neural networks as filters for analyzing the color and texture properties of the license plate[16].

1) Character Recognition: A trainable recognition engine based on a neural network is used for seperated character patterns[14]. A huge amount of labeled data and training time are needed for training of character patterns. It is the big problem to invest time and effort into training, when using neural networks.

2) Plate Image Detection: Neural networks are used to detect texture features and color feature for finding candidate regions[2]. By using 7-layers CNN, license plate and the negative objects are recognized directly from pixel images[17]. In those CNN, plate images are manually clipped before training process. Training of plate images is also time-consuming.

III. Number Plate Extraction Method

Fig. 1 shows an example of number plate extraction for sample car image in database of Caltech categories Cars 1999, 2001. A flow of proposed method is shown in Fig.2. Plate extraction method consist of combination of morphological image processing and deep learning.

Candidate region is extracted by morphological image processing. The image of candidate region is classified by pre-trained 23-layers CNN and two-class SVM classifier.

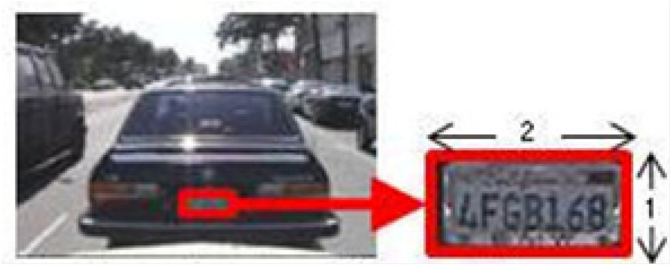


Fig. 1. Example of number plate extraction (Caltech categories Cars 1999,2001).

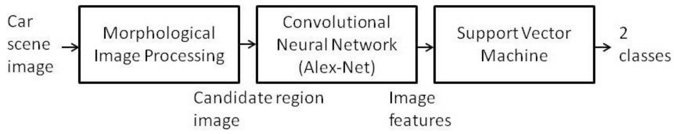


Fig. 2. A flow of number plate image extraction using deep learning.

A. Morphological Image Processing to Extract Images of Candidate Areas

Fig. 3 shows a flow diagram of morphological image processing. It is necessary to cope with the variations of the plates and environments. Plates exist in different locations of an image. Plates may have different sizes due to the camera distance and the lens factor. The image background may contain patterns similar to plates, such as numbers stamped on a vehicle and bumper with vertical patterns. The technique for candidate area extraction consists of six steps, including the edge detection, binarization of edge images, noise elimination, morphology-based dilation, scoring-based candidate area selection. These steps will be described in detail in this section according to the processing order. Fig. 4 shows an example of processed images in the middle steps of number plate extraction for the sample car image.

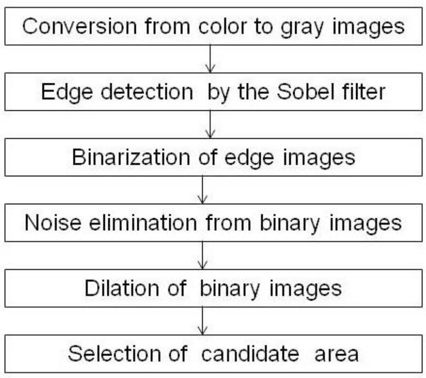


Fig. 3. A flow of morphological image processing.

1) Edge Detection: Plate regions tend to have a high density of edges. So I can measure the edge density by summing all edge pixels. The Sobel filter of size 3x3 is used to detect vertical edges. Due to the color transition between the number plate and the car body, the boundary of the number plate is represented by edges in the image. Due to the color transition between the characters and backgrounds in the number plate, the vertical strokes are also represented by edges. Thus the density map of edges is obtained as the gray image.

2) Edge Density Binarization and Noise Elimination: The gray image of edge density is binarized. The Otsu method is used to threshold the density map that we get at previous step. To eliminate the noise, the connected component analysis algorithm is applied to the processed images. The small connected components of which area size is under 10 pixels are removed as the noise.

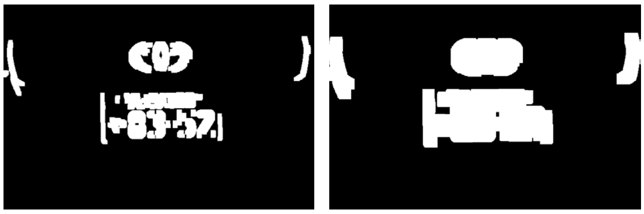
(a) Inputted color image (b) Gray image

(c) Detected edge image (d) Binary edge image

(e) Dilated image (d) Extracted number plate region

Fig. 4. Example of processed images in the middle steps of number plate extraction (Caltech categories Cars 1999,2001).

3) Morphology: Variable Frequent Dilation: Dilation process consists of convoluting an image with some kernel. The kernel has a defined anchor point, usually being the center of the kernel. As the kernel is scanned over the image, I compute the maximal pixel value overlapped by the kernel and replace the image pixel in the anchor point position with that maximal value. This maximizing operation causes bright regions within an image to “grow” (therefore the name dilation). I dilate the image use a square kernel. The size of the kernel is 9×9. This step can join the small closed blocks to a larger one, which will be helpful to the next step. The connected component analysis is also applied to the processed images. So we get the bounding rectangle of the object and the number of the object pixels in these rectangles. The number of connected components in the bounding rectangle before dilation process is also obtained. Dilation process is repeated at two stages according to the maximum size of connected components. The kernel size of dilation is switched by the maximum size of connected components. One of three types of kernels is selected. The size of kernel is 34x34, 17x17 or 9x9 pixels. Fig. 5 shows an example of dilated images.



(a) The first stage of dilation (b) The second stage of dilation

Fig. 5. Example of dilated images by Variable Frequent Dilation technique.

4) Candidates Selection: Rectangle Feature Scoring : In candidate region selection, some prior knowledge, such as aspect ratio (the height to width ratio of the number plate), the area (the number of pixels in the region), and the density of the region (the ratio between the black regions and the area of the bounding rectangle), are combined using their weighed sum. With the important information from the CCA, some features of region are applied. Let A denote the area size of the region of rectangle. Let R denote the aspect ratio of the region of rectangle with width W and height H, then the aspect ratio $R = W/H$ and the area size $A = W \times H$. Let D denote the density. Let N denote of the number of the object pixels in the rectangles, then the density $D = N / (W \times H)$. Let C denote of the number of the connected components in the region of the rectangle. The technique of scoring based on combining these features such as A, R, D, and C, is applied to plural candidate regions. If the candidate regions have the low scoring points, those regions are deleted.

B. Image Category Classification by using CNN and SVM

As a pre-trained Convolutional Neural Network (CNN), “Alex-Net” is downloaded and used for image feature extractor[18][20]. Alex-Net has been trained on the ImageNet dataset, which has 1000 object categories and 1.2 million training images. Layer architecture of Alex-Net is shown in Fig.6. The first layer defines the input image dimensions, 227-by-227-by-3. The intermediate layers are a series of 5 convolution layers and 3 fully connected layers, interspersed with rectified linear units (ReLU) and max-pooling layers. The final layer is the classification layer and has 1000 classes.

A pre-trained CNN is used as a feature extractor. Fig. 7 shows first convolutional layer weights[18][20]. The first layer of the network has learned filters for capturing blob and edge features. A pre-trained CNN extracts the image features. By using the CNN image features from training image data set, a multiclass SVM classifier is trained. In test process, the test features extracted by the CNN, are then passed to the SVM classifier. These test procedure is repeated for test set.

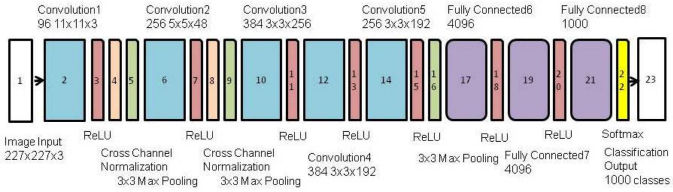


Fig. 6. Layer architecture of pre-trained convolutional neural networks (Alex- Net)[18].

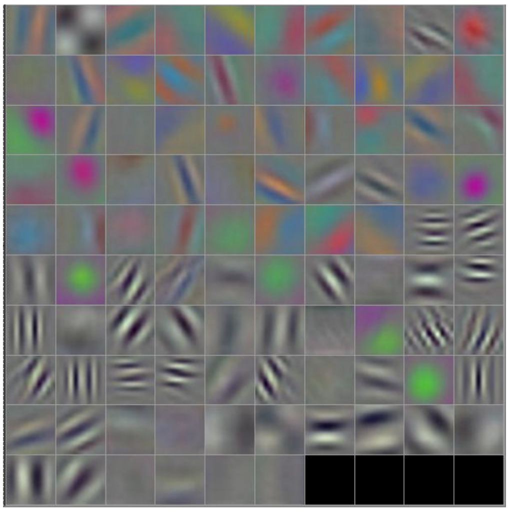


Fig. 7. First convolution layer weights (96 11x11x3 convolutions)[18].

C. Traing for 2-class SVM Classifier for Candidate Areas

As training sample images, the Caltech Cars (1999) dataset[19] and other Cars dataset[3] are used. Car images of dataset were taken from the rear in the university parking lots.

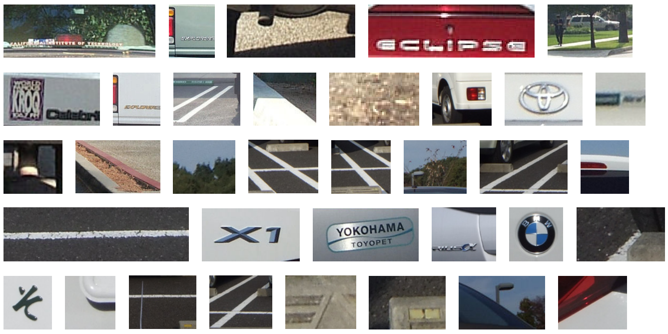
Fig.8 shows an example of positive and negative training sample images for two-class classification. One category is positive, "number plate", and another category is negative, "outlier," namely other traffic sub-image.

Positive training set of number plate images is built by both automatically detecting and manually cropping. Most of positive number plate images are collected by the morphological image processing.

The various sizes of number plate images are collected as positive images. Negative training set of outlier images is collected from the candidate regions obtained by the morphological image processing. No intensity normalization is applied on the number plate and outlier images, such as histogram equalization.

Training performance by using pre-trained CNN and SVM is shown in TABLE I. The number of samples is 269 for positive number plate images and 370 for negative training outlier images, respectively. Training error rate is 0.8% for negative images. There is no training error for positive images.

(a) category: number plate (30 positive images)



(b)category: outlier (35 negative images)

Fig. 8. Example of some training images for two-class classification using deep learning.

TABLE I. TRAINING ERROR RATE FOR TRAINING IMAGES

Ground truth	Number of samples	Classify as	
		Number plate (positive)	Outlier (negative)
Number plate (positive)	269 (100%)	269 (100%)	0 (0%)
Outlier (negative)	370 (100%)	3 (0.8%)	367 (99.2%)
Total	639	272	367

IV. PRELIMINARY EXPERIMENT OF MORPHOLOGICAL IMAGE PROCESSING

A preliminary experiment is done to check the performance of morphological image processing. A 3D digital camera, FINEPIX REAL3D W1 (Fuji Film), is used to take still pictures. One image is selected from stereo right and left images. The size of captured images is 640x480 picture elements. The digital camera is located at 0.885m high above the ground.

A. *Sample Images*

Sample images contain 56 rear images captured by the digital camera. I have 14 camera-to-car distance variations for each car[3]. The model type of cars is four, namely, Toyota, BMW, Mazda, and Mercedes. Fig. 9 shows an example of sample images captured at the distance from 0.5m to 5.0m.

B. *Extracted number plate images*

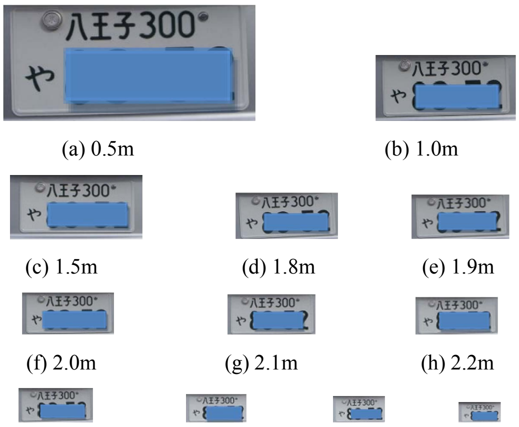
Fig. 10 shows an example of extracted number plate images. The number of Toyota sample images is 14, which is capture from 0.5m to 5.0m. The number plates of 12 samples are extracted successfully among 14 samples.

(a) 0.5m (b) 1.0m

(c) 2.0m (d) 3.0m

(e) 4.0m (f) 5.0m

Fig. 9. Example of sample images captured at the distance from 0.5m to 5.0m. (Toyota(silver)).



(a) 0.5m (b) 1.0m

(c) 1.5m (d) 1.8m (e) 1.9m

(f) 2.0m (g) 2.1m (h) 2.2m

(i) 2.5m (j) 3.0m (k) 3.5m (l) 4.5m

Fig. 10. Example of extracted number plate images. (Toyota (silver)).

C. *Success Rate of Morphological Image Processing*

TABLE II shows the result of success rate of number plate extraction. The success rate of number plate extraction is 75% for 56 sample images. Fig. 11 shows the relation between success rate and distance of capturing image. The area size of the number plate at the distance 1.0m and at the distance 4.0m are 247 x 140 pixels for Toyota, and 70 x 38 pixels for Mazda, respectively. The reason why BMW samples have low success rate is that the rear emblem of BMW is close to the number plate area and they are connected and merged by dilation..

TABLE II. SUCCESS RATE OF MORPHOLIGICAL IMAGE PROCESSING

Car type(body color)	Number of samples	Number of success	Success rate (%)
Toyota (silver)	14	12	86
BMW(white)	14	5	36
Mazda(blue)	14	12	86
Mercedes(beige)	14	13	93
Total	56	42	75

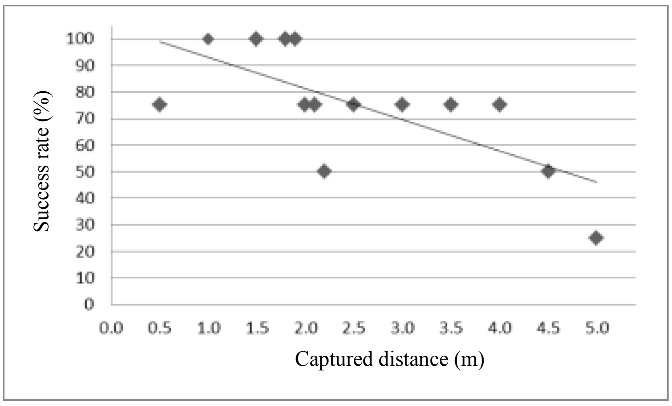


Fig. 11. Success rate and captured distance. (average at each distance).

V. EXPERIMENTAL RESULTS OF NUMBER PLATE EXTRACTION TEST

The performance of the proposed method is presented in this section. From all 126 car images, number plate images are extracted. The candidate area images are classified as positive and negative. The area images classified as negative outlier, are rejected in the final output procedure.

The algorithm was implemented by programming language C++ in morphological image processing and MATLAB in pre-trained CNN and SVM parts.

A. *Test Sample Images for Number Plate Extraction*

The Caltech Cars (1999) dataset[19] includes 126 images with cars in complex city backgrounds, which are shown in Fig.12. The size of color image is 896 x 592 pixel.

B. *Candidate Selected by Morphological Image Processing*

Intermediate result of the morphological image processing is shown in Fig.13. Candidate areas are shown as blue boxes in Fig.14 (a)(c)(e)(g)(i). The selected areas with the highest score in the candidate selection procedure are shown in Fig.14 (b)(d)(f)(h)(j). The performance of morphological image processing is shown in TABLE III. In morphological image processing procedure, 113 area images are correctly extracted out of 126 car images, and extraction rate is 89.7%.

(a) image_0088.jpg

(b) image_0098

(c) image_0091

(d) image_0101

Fig. 12. Example of test images in the Caltech Cars (1999) dataset.

TABLE III. CANDIDATE SELECTION RATE BY MORPHOLOGICAL IMAGE PROCESSING

Correct (Number plate)	Fail (Outlier)	Total
113 (89.7%)	13 (10.3%)	126 (100%)

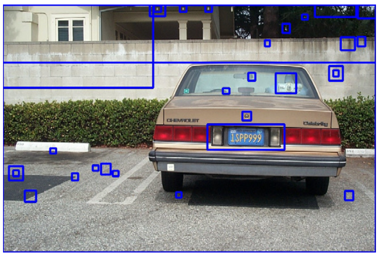
(a) inputted

(b) edge detected

(c) dilated

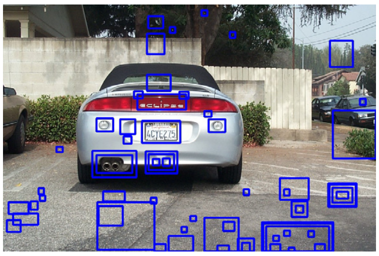
(d) candidate area

Fig. 13. Example of intermediate result of morphological image processing.



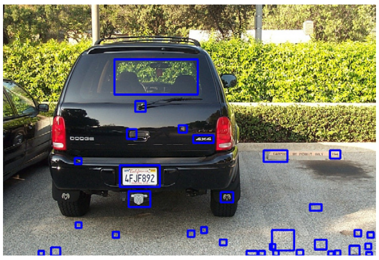
(a) candidate areas :image_0005

(b) candidate area (185x61)



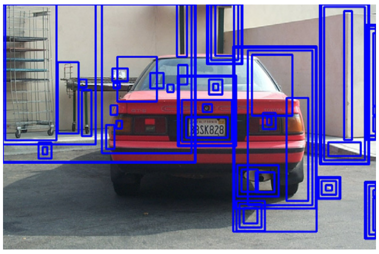
(c) candidate areas :image_0006

(d) candidate area (88x47)



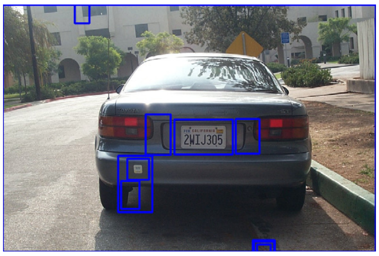
(e) candidate areas :image_0075

(f) candidate area (138x87)



(g) candidate areas :image_0114

(h) candidate area (100x50)



(i) candidate areas :image_0126

(j) candidate area (120x64)

Fig. 14. Example of selection of candidate images.

C. *2-class Classification Results for Candidate Areas*

There was some overlap between the training and testing set for SVM classifier. The 13 outlier images out of 126 test sample images are shown in Fig.15. From the 13 outlier images, 12 images are correctly classified as outlier category and these are rejected in the final output procedure. One outlier image is miss-classified as number plate category, shown in Fig. 15 (h). This miss-classified outlier is counted as error sample. 113 area images are correctly classified as number plate category. TABLE IV shows classification error rate for 128 test images.

(a)image_0006 (b)image_0016 (c)image_0019 (d)image_0040

(e)image_0041 (f)image_0048 (g)image_0056 (h)image_0064[error]

(i)image_0077(j)image_0079 (k)image_0080 (l)image_0083 (m)image_0109

Fig. 15. Reject and error images in the Caltech Cars (1999) dataset (all 13 images).

TABLE IV. CLASSIFICATION ERROR RATE FOR TEST IMAGES

Candidate regions after morphological image processing	Classify as	
	Number plate	Outlier
Success (number plate) 113 (89.7%)	113 (100%)	0 (0%)
Fail (outlier) 13 (10.3%)	1 (7.7%)	12 (92.3%)
Total 126 (100%)	114	12

D. *Success Rate of Number Plate Extraction*

The success rate of number plate extraction is shown in TABLE V. Out of 126 car images, 113 area images are correctly extracted as number plate. 12 area images are correctly classified as outlier and are rejected. One outlier image is miss-classified as number plate. The success rate is 89.7% and the reject rate is 9.5%. The error rate is 0.8%.

TABLE V. SUCCESS RATE OF NUMBER PLATE EXTRACTION

Correct	Error	Reject	Total
113 (89.7%)	1 (0.8%)	12 (9.5%)	126 (100%)

The error image shown in Fig. 15 (h) is easily recognized by humans. The reason of error may be the training data is not large enough. This shows that further improvements are to be expected with more training data.

VI. CONCLUSION

A method of extracting number plates from car images is presented. Proposed method is based on the combination of morphological image processing and deep learning with pre-trained CNN. Morphological image processing is based on connected components, edge detection. The candidate regions are classified in two classes by deep learning. Alex-Net, that is pre-trained CNN, is used for feature extractor. And SVM is used as classifier. Based on the experimental result, the performance of the proposed technique is promising for the rear images. The success rate of number plate extraction is 89.7% for 126 sample images. It is relatively robust to cars in complex city backgrounds. Future work will be done for segmentation-free recognition of number plate and the robustness in dark scene or rainy scene.

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