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Automatic License Plate Recognition Using Deep Learning

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Abstract: *This project presents a core module for intelligent transportation based on the method Haar-like cascade classifier for high accuracy license plate detection. Many real-time car license plate detection is reasonable and effective only under certain conditions and assumptions. Therefore a real-time method Haar-like cascade and Tesseract search for Optical Character Recognition (OCR) has been proposed. Using accurate prediction and fast analysis strategy our proposed system can constructively out pass the problems in real-time scenarios. After binge analyzing the system with various inputs to establish that the proposed system is superior to the existing systems in terms of accuracy and time consumption. The video from the traffic block is divided into different frames and a single frame is taken. An image is taken from the video frame in which the license plate will be detected in real time. After Detection of the License plate, the characters in the license plate are recogonized.*

Keywords: Haar

I. INTRODUCTION

In this modern technologically growing world, the number of automobiles are increasing widely each and every year. This has resulted in violations of many traffic rules, careless accidents and extreme problems. Traditional or physical management of this wide range of automobiles is too difficult which has stimulated the rise of automatic systems to manage automobiles. Specifically, license plate detection can be used to monitor the cars in real-time. This approach has attracted many types of research to develop systems. In future, this automatic car license plate detection can be implemented in various dayto-day scenarios, e.g., unattended toll plaza, parking lot ticket collection in malls, traffic rules violations. Many problems have to be addressed to develop a state of the art license plate detector system, which includes: Plate variations: The plate size, colour, character style may differ from vehicle to vehicle. Environment variations: Weather conditions, quality of the input image can be a factor for false detection. Image variations: Clarity, resolution, properties may affect the detection process.

To avoid such problems people have widely started adopting methods based on CNN, which automatically learn features from the acquired data. But the disadvantage of using a Convolutional Neural Network (CNN) is that the time consumption is higher. To avoid the problem of time consumption and to increase the accuracy in detecting the license plate the method we propose is deep learning based "Haar-like cascade classifier". Haar-like cascade is superior to the existing CNN based model in factors like time and scenario based on the detecting.

II. LICENSE PLATE RECOGNITION

Automatic license plate recognition (LPR) plays an important role in numerous applica- tions such as unattended parking lots, security control of restricted areas, traffic law enforcement, congestion pricing, and automatic toll collection. Due to different working environments, LPR techniques vary from application to application. Most previous works have in some way restricted their working conditions, such as limiting them to indoor scenes, stationary backgrounds, fixed illumination , prescribed driveways, limited vehicle speeds, or designated ranges of the distance between camera and vehicle. The aim of this study is to lessen many of these restrictions. Of the various working conditions, outdoor scenes and nonstationary backgrounds may be the two factors that most influence the quality of scene images acquired and in turn the complexity of the techniques needed. In an outdoor environment, illumination not only changes slowly as daytime progresses, but may change rapidly due to changing weather conditions and passing objects (e.g., cars, airplanes, clouds, and overpasses). In addition, pointable cameras create dynamic scenes when they move, pan or zoom. A dynamic scene image may contain multiple license plates or no license plate at all. Moreover, when they do appear in an image, license plates may have arbitrary sizes, orientations and positions. And, if complex backgrounds are involved, detecting license plates can become quite a challenge.

Typically, an LPR process consists of two main stages:

1) locating license plates

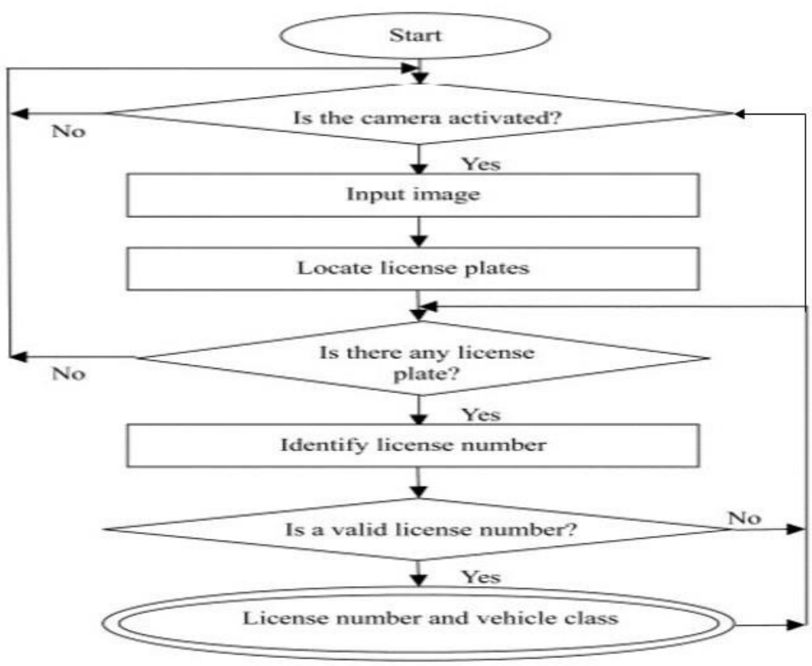
2) Identifying license numbers.

In the first stage, license plate candidates are determined based on the features of license plates. Features commonly employed have been derived from the license plate format and the alphanumeric characters constituting license numbers. The features regarding license plate format include shape, symmetry, height-towidth ratio, color, texture of grayness, spatial frequency, and variance of intensity values. Character features include line, blob, the sign transition of gradient magnitudes, the aspect ratio of characters, the distribution of intervals between characters, and the alignment of characters. In reality, a small set of robust, reliable, and easy-to-detect object features would be adequate.

III. RECOGNITION PROCESS

In this section, the styles of license plate that are considered in this study are discussed, followed by a brief description of the proposed LPR process. Table I shows assorted styles of license plates found on vehicles in Taiwan. Each style is associated with a particular class of vehicle. The classes include private automobile, taxi, tour bus, truck, and government vehicles. Other categories of vehicles, such as diplomatic cars and military vehicles, are not addressed since they are rarely seen. Styles of license plates can easily be distinguished based on two attributes: 1) the combination of colors used and 2) the compositional semantics of license numbers.

Each style has a different foreground and/or background color. However, in all only four distinct colors (white, black, red, and green) are utilized in these license plates. We shall pay attention to these four colors when searching for license plates in an input image. The compositional semantics of license numbers provides additional information for differentiating styles of license plates. As can be seen in Table I, every license number is composed of two parts.



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We assume that the process is incorporated in an event detection system, e.g., a vehicle detector or a traffic law enforcement system. Once the system detects an event, the camera along with the system is activated. The image acquired by the camera is then sent to the LPR process, in which potential license plates are extracted from the image. If no license plate is found, the process returns to await another input image. However, oftentimes multiple license plate candidates are detected. They are closely examined at the license number identification stage. There are two essential tasks involved in this stage, character segmentation and recognition. These two tasks are alternatively invoked in order to achieve optimal results for both segmentation and recognition. The characters recovered from a license plate candidate at this stage are next verified at the confirmation stage. The group of characters will be deemed to form a valid license number if it agrees with the compositional semantics of license numbers mentioned earlier. Both the valid license number and the associated vehicle class will be returned by the LPR process. The identification and confirmation stages repeat for all of the license plate candidates. Afterwards, the process returns to await another input image.

IV. PROPOSED SYSTEM

Here, a license plate detection algorithm is proposed using both global statistical features and local Haar-like features. Classifiers using global statistical features are constructed firstly through simple learning procedures. Using these classifiers, more than 70 percent of background area can be excluded from further training or detecting. Then the AdaBoost learning algorithm is used to build up the other classifiers based on selected local Haar-like features. Combining

the classifiers using the global features and the local features, we obtain a cascade classifier. The classifiers based on global features decrease the complexity of the system. They are followed by the classifiers based on local Haar-like features, which makes the final classifier invariant to the brightness, color, size and position of license plates. The encouraging detection rate is achieved in the experiments.

4.1 Video Conversion to Frames

With ever increasing number of vehicles, vehicular management is one of the major challenges faced by urban areas. Automation in terms of detecting vehicle license plate using real time automatic license plate recognition (RT-ALPR) approach can have many use cases in automated defaulter detection, car parking and toll management. It is a computationally complex task that has been addressed in this work using a deep learning approach. The first step of the algorithm is to load the input video as a list of images. If the input is an image, skip this step. The frame rate of splitting can be controlled. In the video, if the speed of vehicle is high, split the video into 50-80 frames to achieve good results. If the speed of the vehicle is quite slow (for example, on a speed breaker) then even 10 frames will be sufficient.

4.2 License Plate Detection

The image is prepared for robust plate localization. First of all, noise is removed from the vehicle's image to get more accurate results. The image is converted to greyscale and different morphological operations were applied to get an image with enhanced edges and contrast. Second step is to blur the image to bring uniformity to it and finally, adaptive thresholding is applied to eliminate less important information (objects other than number plates). Techniques like converting to greyscale, histogram equalization, sharpening, OTSU masking. Top Hat and Black Hat morphological methods, adaptive thresholding and blurring were applied. All this is done to remove objects other than license plate from the image as much as possible. After removing noise from image, the next step is to detect the x and y coordinates of the license plate in the image. Contours are detected from the pre-processed image. OpenCV documentation defines a contour

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as a curve joining all the continuous points having same color or intensity. The contours are a useful tool for shape analysis and object detection and recognition. The coordinates of these contours were used to extract parts of image, store it as python class object of each individual contour (character in the plate) that store the boundaries, area, aspect ratio, width, height and angle. The list of these possible plates is then used as input in next phase.

Various operations like detecting contours, putting geometric constraints, grouping etc are applied on the result of pre-processing. These operations extract all contours, eliminate the contours that do not appear to be characters by their geometry, group together the contours that belong to a single plate and extract the number plate from the original image. The algorithm was executed for all the possible plates and returned them in the form of a list. This list contains the object images which have the highest probability of being the real license plate.

4.3 Character Segmentation

Cropped license plates are now put for optical character recognition. First requirement to apply OCR is to crop individual character images from license plates. Most of the time the license plate cut out is not suitable for direct character segmentation. Thus, unwanted symbols were to be removed from the license plate. Image processing steps were repeated to remove noise in the plate image. Authors found contours from the plate's image and kept only symbols which are possibly characters (A-Z, 0-9). Next step was to enlarge the images and convert to greyscale as well increased the contrast. Subsequently, adaptive thresholding is applied to make the whole image black and white. Binary inverse can be done to get black characters on white background. The contrast helped in recognizing character boundaries. Characters other than the 36 characters (0-9 and A-Z) were removed from the plate and individual characters were cut out from the license plate. Height and width of each cropped character is increased by factor of 1.3 and 1.6 respectively and a white border is added.

4.4 Optical Character Recognition

After getting the individual character images from a license plate image, the next step is to apply OCR (Optical Character Recognition). To do this task two approaches have been tried namely, K nearest neighbour and convolutional neural networks. K Nearest Neighbours (KNN) algorithm is a well-known algorithm for regression and classification problems which is a simple algorithm that stores the spatial information of all available cases and classifies new cases based on its similarity with available examples. The similarity matrix for the algorithm depends on the problem. KNN has been implemented in Scikit learn library K Nearest Neighbor class with K as 3. As KNN implementation takes a single vector as input but input for OCR was image of a character. So, the image of shape (h,w,3) was converted to a vector of shape (h*w*3,1) and then input to the classifier for training and testing. Convolutional Neural Networks (CNN) comprise of neurons that have learnable weights and biases. Each neuron receives some inputs and performs a dot product with certain filters. Filters are 2D or 3D arrays which are used to modify an image in a desired way. Linear filtering, accomplished through an operation called convolution, is a technique in which the value of an output pixel is a linear combination of the values of the pixels in the input pixel's neighbourhood. Convolution is a neighbourhood operation in which each output pixel is the weighted sum of neighbouring input pixels. The matrix of weights is called the convolution kernel and is the filter actually.

The relation between entities were extracted using NER model class from simple trans- formers. The NER model was used with pre-trained BERT transformer. The BERT base model was used to extract relation and the version used was 'BERT-base-cased'. The inputs were converted to vectors by positional and word embedding. Positional embedding were used to evaluate the relative positions of the words in a sentence. The embedded inputs were parallely passed into the encoders where it produces some scores. The output of the encoders are passed to the feed forward neural network for further classification of the relation between the entities.

V. CONCLUSION

In this work, steps for Automatic License Plate Recognition for vehicle management have been proposed. It takes a vehicle video as input and gives the license plate number of the vehicle in text form. The license plate has been recognised using template matching technique which generated a list of possible plates in an image by matching various features like aspect ratio, area, height, width of license plate and also distance between characters, angle between them and change in area. The comparison between K Nearest Neighbours and Convolutional Neural Network showed that Convolutional Neural Network is a better alternative. Finally, 8 layered Convolutional Neural Network was used for OCR. The algorithm used in this paper not only accelerates the process but also increases the probability of detecting the license plate and extraction of characters, under certain set of constraints. Low Accuracy of classifier is mainly due to confusion between '0', 'O' and '1', 'I' in case of blurred or low-quality images. This can be improved by training theCNN classifier on largerset of varioustypes of characterimages. The template matching technique to detect licensecan be surely improved by changing the parameters according to the license plate structure ofthat country/region or using more robust methods those generalize well on new problems. Thiswill decrease the list of possible plates and thus CNN classifier will have to run on lesser num-ber of characters. The processing speeds of given ALPR system can be further improved byusing the parallelization approach for various stages of development. Two classifiers, KNN and CNN have been used for OCR. The performances of these two classifiers on the test dataset have been compared based on various metrics. So, parameter tuning was done to increase accuracy, decrease running time and improve the overall performance of the model. In classification problem, accuracy alone is not a sufficient parameter to judge the performance of the ALPR model. Sometimes accuracy can be a misleading parameter.

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