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VGG-16 CNN APPROACH FOR VEHICLE LICENSE PLATE LOCALIZATION

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Abstract

Automatic License Plate Recognition System (ALPRS) plays a major role in the area of Intelligent Transportation System (ITS). The LP detection and recognition are obtained in a two network model. In this paper, jointly trained network is used for the detection of LP. VGG-16 CNN (Convolution Neural Network) approach is used for the candidate identification. Real time capturing images are used for testing. The input image contains different environment conditions. The proposed method provides 97.13% accuracy.

I. Introduction

The number of vehicles on road is increasing in our day to day life. There is a need to improve the Intelligent Transportation System (ITS). Since the vehicle density is high, there is a need for an automatic system to monitor and control the vehicles. Automatic License Plate Recognition System (ALPRS) plays an important role in identifying vehicles by detecting its License Plate (LP) or Number Plate (NP). LP is a unique part of the vehicle

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which contains specific number to the vehicle. LP contains codes of country, state and regions [1]. Also LP contains a unique vehicle number [2, 3]. The owner of the vehicle can be identified by tracking the License Plate Number (LPN). ALPRS is used in security control, traffic monitoring control, toll gates, automatic parking system etc. The important processes of ALPRS are Image Acquisition (IA), License Plate Extraction (LPE), LP Segmentation (LPS) and Character Recognition (CR). Figure 1 shows the process of ALPR system. LPD plays a vital role in the ALPRS. The challenges in the LPD are characterized as plate variations and environmental variations [5]. Plate variation occurs due to variation of location, quantity of LP, size, color, font, occlusion and inclination. Environmental variations occur due to illumination and background.

In this paper, VGG-16 CNN approach is proposed for the detection of LP. Labeling is done for the gray scale image. The LP classification is carried out by CNN. The input images are collected under different environment conditions. The performance of the system is evaluated by LP detection accuracy. Efficiency of the detection is determined for the performance analysis.

II. Literature Survey

Artificial Neural Network (ANN) was proposed in [3] for the detection and recognition of LP. There were 300 samples taken for training and testing. It achieves 96.7% accuracy for detection and 92.2% accuracy for recognition. Local Binary Pattern (LBP) features were extracted for the detection of LP [4]. The extracted features were trained and tested using Neural Network (NN). The database contains images captured in different weather conditions. It achieves 96.7% accuracy for the detection. LP is rectangle in shape. The rectangle regions are determined from the input image using edge detection methods. The identification of LP is carried out on the selected rectangle region [6]. The aspect ratio of the LP is a unique property. Also, the vertical edges and horizontal edges of the LP are equal. The matching between horizontal and vertical edges was used to find proper rectangle region. Color feature is an important feature while detecting the LP of a vehicle [7]. The LP contains specific color combinations. Channel scale space approach was used to detect the LP based on color features. Connected Component Analysis

(CCA) is an image processing technique which is used to categorize the regions based on similar regions [8]. It is a spatial domain technique. The pixel connectivity of an image is scanned from top to bottom and similar regions are identified. Spatial image measurements like area, number of pixels, diameters is considered for the identification of the required region. The color of the characters and background of the LP are different. The texture feature is also helpful to find the LP [9]. There is a variation in character color and background color. This gray level variation provides different textures. The color transition of different regions provides texture variations. Wavelet Transform (WT) is also used for the detection of LP [10]. WT is a frequency domain image processing technique. There are four subbands in WT image. Vertical edge information is represented as HL and horizontal edge information are represented as LH. The LP is searched in HL subband. The accuracy of this method is 94.8%. Adaboost classifier was used for the classification of LP from the image [11]. The feature used for the classification in this method is Haar-like features. Gradient density is the global statistic used in Haar-like features. This technique achieved 93.5% detection rate. The color of the LP was identified by Genetic Algorithm (GA) [12]. Different threshold levels of the image regions are identified using GA. Here upper and lower threshold of LP color are identified. The regions having color within the threshold are labeled. It failed to detect the LP when the distance between camera and vehicle is more. Edge based Marker controlled watershed algorithm was used to find the location of the LP [13]. Morphological operations are performed on the input image. Watersheds are formed in the flooded regions. It achieves 96.7% accuracy for the detection. Fuzzy based method was proposed for the identification of LP color region [14]. It works well for illumination variation. HSV color model was used for the mapping of fuzzy sets. Color barycenters Hexagon model was employed for the localization [15]. RGB color model was not fit for this approach. The changes in the illumination affect the system accuracy. The Kernel Density Filter method was used for the detection of the LP [16, 21]. It performed well for the skew variations. The limited number of database was used in this work. Spatial Transformation Network (STN) was used to detect the LP along with Neural Network (NN) [17, 24]. Differential warp parameters are used for the spatial transformation. It provides better accuracy for the geometrical variations of image regions. Expectation Maximization (EM) algorithm was used to find the edge based region segmentation [18, 22]. Sets of edge regions are grouped and classified by cascaded classifiers. Line density filter approach was used to connect edge gradients [19, 23]. The sparse regions are removed in the image which helps to improve the detection rate. Sobel vertical edge detection method was used for the detection of LP [20, 25]. After analyzing the existing methods for LPL, we expect that the proposed method will provide better accuracy. The real time captured input images are used in this work. The images are captured in various environmental conditions. A VGG-16 CNN approach is proposed for the segmentation of LP regions. CNN is proposed for the classification.

III. Proposed Method

A Deep Neural Network (*D*-NN) approach is proposed in this work to detect the LP from outdoor vehicle images. Many convolution layers are used to extract the features. Low level features are extracted to detect the LP. Region of Interest (ROI) and multi-layer perceptron are used to detect the LP. Figure 1 shows the block diagram of the proposed method.

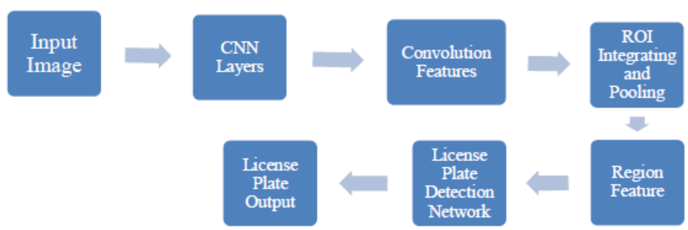

Figure 1. Block diagram of the proposed method.

For the detection of LP, low level features are extracted for CNN. VGG-16 network is used to extract features. The input RGB image is given to the convolution layers which contains many filters. Spatial padding is used to preserve the spatial resolution of the image. Spatial pooling is also carried out to reduce the spatial resolution of the feature map. It is used to reduce the computation cost. Fully Connected Layers (FCL) represents the feature vector and Rectified Linear Unit (ReLU) is used as activation function. The region of the LP is very small compared to the whole vehicle image. Therefore, two pooling layers are used.

Region Proposal Network (RPN) is used for the identification of objects.

The candidate object is identified using RPN. It is used to identify the LP object in a vehicle image. Based on the database images the aspect ratio of the LP is chosen as 5. Convolution filters are applied for the local feature extraction. Using these local features, feature vector is formed. This feature vectors are given as input to the classifier. Bounding box provides a better object detection output. Bounding box repressor is trained using fixed anchor boxes to obtain objects. The feature size is chosen as $X = 4$ and $X = 28$. Convolution layer is used for feature extraction with ReLU as the activation function. The identified LP regions are cropped and that particular region is verified. Compare to the two stage network we trained a new network which provides the LP detection and recognition in a single pass. The two stage network and the jointly trained network is shown in figure 2.

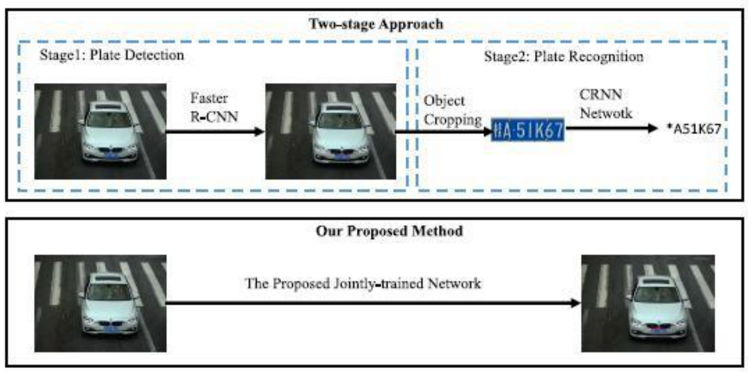

Figure 2. Two stage network and jointly trained network.

In two stage network model, the candidate region is cropped and identified using a separate block. Jointly trained network provides recognized output in a single model. In two stage network, Faster R-CNN and CRNN model are used. The proposed algorithm is implemented in images captured using surveillance camera. The sample output is showed in figure 3.

Figure 3. Sample output of jointly trained network.

Two stage networks provide a time delay to produce the output. The proposed method provides fast and efficient output. The comparison of two stage network and proposed network is listed in table 1.

Table 1. Experimental results of two stage network and jointly trained network.

Method	End-to-end Performance (%)	Detection-only Performance (%)	End-to-end Speed (per image single scale) (ms)
Ours(Jointly-trained)	**97.13**	**98.33**	**310**
Ours(Two-stage)	94.09	97.05	450

V. Conclusion

VGG-16 CNN approach is used for the detection of LP. A jointly trained network determined the LP in a single forward pass. The accuracy of the jointly trained network is best compare with two stage network. The whole network is trained to provide output in a single model. Comparison on different database shows that the proposed method provides a better output in the License Plate Recognition System. Real time capturing images are used for testing. The input image contains different environment conditions. The proposed method provides 97.13% accuracy.

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