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An Improved Compression Layer Network Structure for VLPR

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Abstract. License plate recognition is widely used in road conditions, parking, dredging traffic, etc. The license plate recognition first needs to find the specific location of the license plate and then needs to identify the content of the license plate as an image. During practical applications, main challenges of this recognition technology include the background color, size and specifications of the license plate, weather conditions, background interference, lighting, etc., which may also interfere with license plate recognition. Therefore, complex scenes and moving vehicles are two factors that need to be taken seriously. We propose an improved compression layer network structure for license plate recognition. The main way is to use a parallel structure of the compression layer network connection to alleviate errors caused by illumination, tilt and occlusion in license plate recognition. For reduce the amount of computation often pointed out in the CNN, we have tried to discard some of the parameters. Experiments have shown that this method has a lower error rate than CNN and capsule baseline, also has more advantageous in terms of time consumption.

Introduction

License plate recognition is an artificial intelligence technology that is fully utilized at home and abroad. It is widely used in automotive related fields such as traffic management, road tolls, ticket sales and charges [1]. The main techniques required for license plate recognition include segmentation, extraction and recognition of image processing techniques associated with license plates and the characters and symbols thereon.

The researchers found many different ways to position license plates. For example, vector quantization based is the main scheme of traditional signal coding. In the license plate recognition system, VQ is used as a filter to identify the license plate area in the image as an image composed of certain lines and use the accumulation function to find various maximum values for the detection of the license plate area. Another kind of fuzzy logic algorithm firstly gives the rule and uses two methods of filtering and filtering to carry out vehicle license plate detection. All of these methods still suffer from the dilemma of light and background interference. Color is a feature that is often chosen, but the background interference cannot be eliminated. The edge features may be more suitable in this case. If the edge features can be improved and combined with the above features, it can give more the result of the identification of the value.

The combination of edge and shape can be applied to extract the main area of the license plate. Experiments show that these features usually have good recognition performance [2]. Gradient and its variance are often used to identify, the main principle is that the brightness of the image in these areas is more obvious and rapid mutation. If the poor condition of illumination, occlusion, etc. interferes with the license plate, if the width and variance are added as supplementary features, the recognition performance can be further improved, and no more computing resources need to be introduced. However, this method is difficult to achieve the best results in complex road conditions or parking lots, because multiple changes in complex backgrounds in these scenes will also show rapid mutations in the image, resulting in a gradient and its variance. Increase in sex. However, this method is very suitable for real-time detection of license plates due to low computing resources and fast response.

The traditional color license plate recognition system mainly adopts the following methods [3]: preprocessing, extraction of boundaries, segmentation, recognition, and post-processing. Among them, boundary extraction usually uses shape and color and fuses or mixes both; symbol segmentation generally considers how to split symbols, including horizontal split or vertical split. For recognition, geometric or template matching can be used. For special characters that are easy to confuse, special mention and recognition are required.

Deep convolutional neural network is one of the most competitive deep learning network structure frameworks in the field of image signal processing. A large number of CNNs are applied on servers and dedicated chips. The license plate recognition system is also often designed based on the CNN method, because CNN is very good at classification of images and videos, and its classification performance is stable and excellent [4].

Literature [5] proposes a new CNN-based license plate sequence recognition system. When the lens is in a poor position, wind or jitter causes lens drift, insufficient illumination and obstacles, including the inconsistency of the license plate design specifications, Very good processing and robust. The further proposed convolutional network structure fully reduces the computational complexity, and gives the optimal conclusion of the system through multiple data sets and experimental comparison results.

There is a type of license plate recognition method that uses form sliding method, but this method has many limitations. For example, when the characters on the license plate are inconsistent with the character size in the training set, further manual intervention is needed to achieve better. The performance, such as adjusting the size of the test set characters, but this method has relatively large defects, such as the inability to know the context information of the character, only the pixel features in the region are perceived. The author of the literature [6] proposed a ConvNet-RNN method to cope with the above difficulties. First, use ConvNet to extract a round of features, and then use RNN to solve the difficulty of knowing the context information, so that the image itself can be directly input to the network without more manual participation and processing. The performance of this method was demonstrated in the experiment.

Due to the huge differences in working conditions, the key challenges of license plate recognition technology vary from application to application. Generally, license plates vary in background color, size and specifications [7]. Other obstacles include severe weather conditions, background disturbances, lighting changes, lanes, speed, distance between camera and vehicle, and other vehicles such as camera resolution and movement can also affect license plate recognition. Among the above difficulties, complex scenes and moving vehicles are two factors to be deal with in this paper.

The structure of our paper is: The second part has the basic vehicle license plate recognition method and CNN principle; then gives our improved compression structure; the fourth part details the experimental results on the general dataset; the final part is conclusion.

Vehicle License Plate Recognition and Convolutional Neural Networks

Methods Vehicle License Plate Recognition Methods

License plate recognition systems typically include: detection, segmentation and identification. These three parts are very important for license plate recognition. As noted in [8], the license plate recognition scheme includes textures, edges and color features in the image. The advantage of this method is that the bottom of the license plate usually has some relatively stable colors, such as black, white or green, and the characters above are usually fixed, such as white, black and so on. Collaboration between these colors rarely occurs in scenes of images acquired by traffic, so it is uniquely identifiable. Under some good background conditions, the license plate can be solved even with the general geometry method. The basic problem of identification. On the other hand, if the color of the bottom of the license plate is close to the vehicle or the surrounding environment, this simple method will immediately fail, it is easy to think of darkness or lack of light, and the position camera is blocked. Geometric methods will produce unfavorable results. In this case, if the texture feature is used for resolution, or the sliding window is used for area detection, the effect is stronger than the above method.

If the license plate is in a relatively simple background, the above method is more effective and correct for identifying the license plate. However, when there are many edges in the image, these methods are susceptible to noise and computationally complex. After the license plate is detected, the characters are segmented. Grayscale quantization and morphological analysis can be used to obtain candidate characters. The extracted license plate can also be rescaled to the template size, and all character positions in the template are known.

When there are some changes in the license plate, such as slight changes in angle, background, color, etc., this method cannot cope. Therefore, the algorithm is further proposed to extract the features of the license plate after various projections, to find the exact position of the license plate, and further extract the content in the license plate.

How to detect edges is the main obstacle in the boundary detection method. In literature [9], a feature transformation method was used to define two lines containing candidate regions after the edges are extracted efficiently. This method also has inherent drawbacks, the amount of calculation is too large, and the effect on non-black and white images is poor.

Deep Convolutional Neural Networks

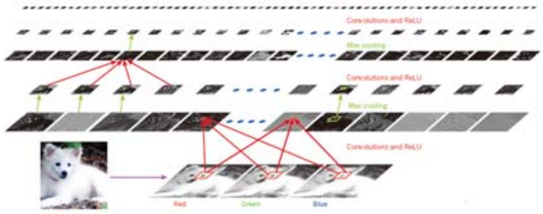

Figure 1. Convolutional network structure

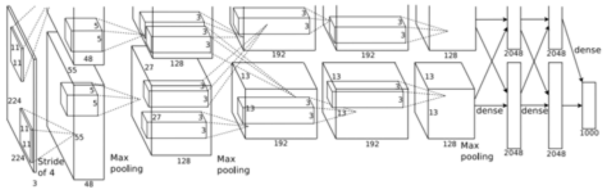

Figure 2. Architecture of CNN

The deep learning architecture is a multi-layer stack of simple modules [10]. In general, object recognition tasks are so complex that the network model should have a lot of prior knowledge [11]. Convolutional neural networks (CNN) are shown in Fig.1 and Fig.2. The rule of CNN is:

$$v_{i+1} := 0.9 v_i - 0.0005 \cdot \varepsilon \cdot w_i - \varepsilon \cdot \left\langle \frac{\partial L}{\partial w}\Big|_{w_i} \right\rangle_{D_i} \quad (1)$$

$$w_{i+1} := w_i + v_{i+1} \quad (2)$$

Convolutional Neural Networks (CNN) use translational replicas of learning feature detectors. This allows them to convert knowledge about good weight values obtained at one location in the image to other locations. However, the level of the CNN structure is too small, only the neurons, the neural network layer, and the entire neural network.

An Improved Compression Structure for VLPR

Hinton et al. [12] replaced the CNN's scalar output feature detector with a vector output capsule (shown in Fig.3) and updated the maximum pool by routing. In order to achieve this, all capsules except the last layer of capsules are convoluted. The purpose of making higher-level capsules is to cover a larger area of the image, whereas unlike max-pooling, the capsule does not discard information about the exact location of the entities in the area. For low-level capsules, the location information is "position-coded" and the capsule is active.

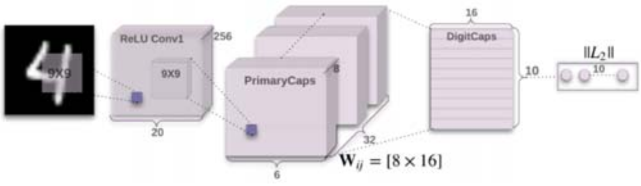

Figure 3. A simple CapsNet architecture

The main feature of the capsule structure is that the parameters of the low-level capsule output are converted into multi-dimensional predictive vectors for delivery to high-level capsules in which the high-level capsules look for the presence of a predictive compact set. In view of the advantages of capsule structure compared to CNN, we propose an improved compression structure network for license plate recognition systems. The improved compression structure network is shown in Fig.4.

When the compression layer is first generated, the parallel structure is used and the weights are shared. The volume is 9*9*3 stereo convolution kernels, and their center position and compression layer are the spatial position of a number can correspond, and in the process of transferring data to the second layer compression layer, some parameters are randomly discarded as a means of reducing the parameter amount. The second layer of compression layer also emphasizes the depth space features in the original image through convolution training, that is, the multiple change information of original image, that is, each compression layer is learned each input may occur better. Interference such as illumination, tilt and occlusion, and re-refining into features.

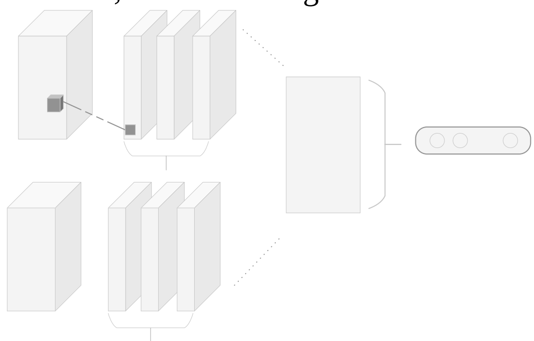

Figure 4. The improved compression structure network architecture

In the second compression layer, the first layer is weighted by weight matrix to have a prediction vector. Each input to the second compression layer is a weighted summation of this prediction vector. At this level, each compression block learns a vector, and each dimension corresponds to the spatial position, orientation and size of input image.

Experiment Results

To demonstrate the superiority of the improved compression network architecture, various experiments were conducted in the pytorch and related Python environments. Part of the experimental data comes from MNIST corpus stitching (shown in Fig.5), another part from the network, and some are randomly shot using a digital camera in an outdoor natural environment. These data have different characteristics of illumination, occlusion, tilt, blur, etc., used to train and test the robustness of our network structure. All photos are stored in JPG format and the dimensions are normalized.

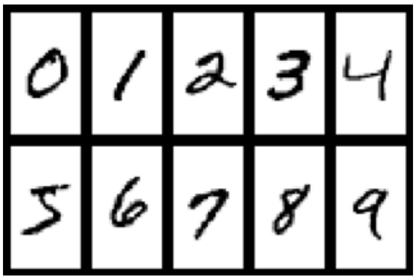

Figure 5. MNIST Example

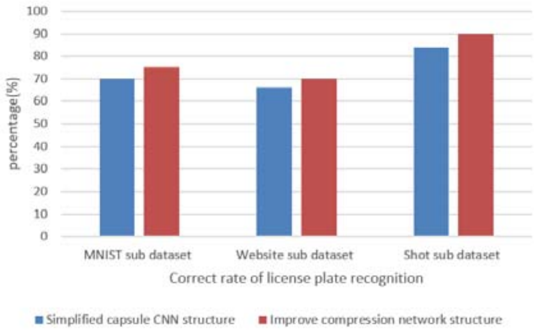

Figure 6. Correct rate of license plate recognition on three sub-data sets

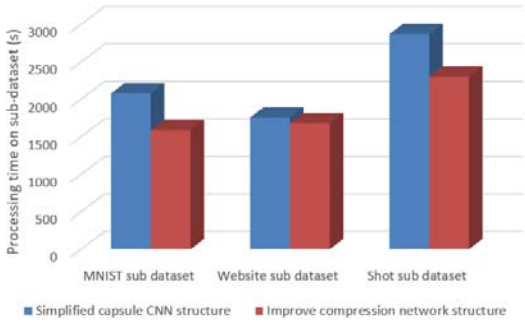

Figure 7. Processing time on test sub-dataset

First, the simplified capsule CNN structure is used as a baseline for the training data set and compared to the proposed improved compression network structure. The experimental results are in Figure 4. We divide the test data set into three sub-data sets according to different sources. On these sub-data sets, the latter has certain accuracy to improve the license plate recognition, especially on the self-timer sub-dataset. 90% of characters recognize the correct rate. In addition, we compared the time spent on CNN, baseline, and proposed methods on these sub-datasets. The results are shown in Figure 5. We observed that the benefit of CNN, baseline and proposed method consumption time on each sub-data set is gradually improved. Therefore, its compression network structure can have better robustness and high recognition accuracy.

Conculusions

We propose an improved compression layer network structure for license plate recognition. The main way is to use a parallel structure of the compression layer network connection to alleviate errors caused by illumination, tilt and occlusion in license plate recognition. For lower the amount of computation often pointed out in the CNN, we have tried to discard some of the parameters. Experiments have shown that this method has a lower error rate than CNN and capsule baseline, and have more advantageous in terms of time consumption.

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