Moving Car Detection and Model Recognition based on Deep Learning

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Abstract. Vehicle analysis is an import task in many intelligent applications, such as automatic toll collection and driver assistance systems. Among these applications, moving car detection and model recognition are a challenging task due to the close appearance between car models. In this paper, we propose a framework to detect moving cars and its model based on deep learning. We first detect the moving car using frame difference; the resultant binary image is used to detect the frontal view of a car by a symmetry filter. The detected frontal view is used to identify a car based on deep learning with three layers of restricted Boltzmann machines (RBMs). Experiment results show that our proposed framework achieves favorable recognition accuracy.

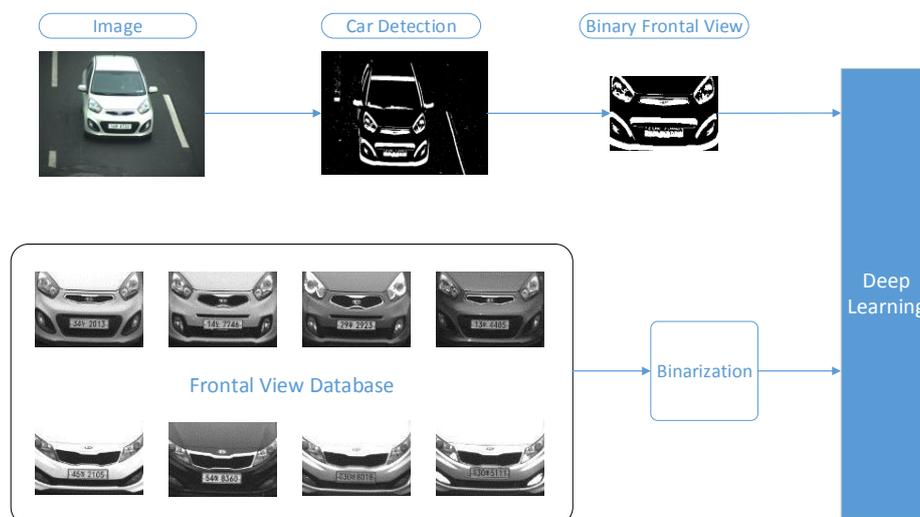**Keywords:** Moving car detection; Car model recognition; Deep Learning; Pattern recognition

1   Introduction

Driving vehicle analysis is an essential component in many intelligent applications, such as automatic toll collection, driver assistance systems, self-guided vehicles, intelligent parking systems, and traffic statistics (vehicle count, speed, and flow). There are various methods of vehicle analysis. Chen et al. [1] proposed to use Support Vector Machine (SVM) and random forests to classify vehicles on the road into four classes, namely, sedan, van, bus, and bicycle/motorcycle. Ma and Grimson [2] used edge points and modified SIFT descriptors to represent vehicles. AbdelMaseeh et al. [3] used the combination of global and local cues to recognize car model. Hsieh et al. [4] proposed symmetrical SURF for both vehicle detection and model recognition. Considering the favorable performance of deep learning [5], we apply it to car model recognition. This is the first attempt to use deep learning for car model recognition to our knowledge.

In this paper, we propose a framework to detect moving vehicles and their manufacturer model based on deep learning. The goal of this paper is to identify over 100 specific vehicle models for vehicle manufacturers. We first detect the moving car using frame difference; the resultant binary image is used to detect the frontal view of a car by a symmetry filter. The extracted frontal view is fed into an inference engine

to identify the vehicle type based on deep learning. The framework of the proposed system is presented in Fig. 1. It is noted that frontal view suffer less variances than a full car, thus, we prefer to use frontal view instead of full car in this paper.

The remainder of this paper is organized as follows. Section II describes the moving car detection and frontal view extraction method. We then introduce the car model recognition based on deep learning in Section III. Section IV applies the above algorithm to our car database, and presents the experiment results. Finally, we conclude this paper in Section V.

Fig. 1. Framework of proposed car detection and model recognition system based on deep learning.

2   Moving Car Detection and Frontal View Extraction

Moving car detection is the prerequisite of car analysis. In this paper, we use frame difference to detect the moving car on account the fact that our camera is fixed on the street. Frame difference is simple and sufficient in this scenario, which enables real time application.

It is not wise to recognize a car by its whole appearance due to its 3D characteristic. The 3D object results in large variance within one class incurred by pose changes. In this paper, we proposed to use the frontal view of a car to recognize its model. Frontal view of a car offer sufficient features to represent a car model. Also, a portion of the car image reduces the computation time than an entire car image. Furthermore, the frontal view of a car is basically symmetrical, thus, we use a symmetrical filter to detect the frontal view. After the binary image is calculated from the frame difference, a symmetrical filter is used to extract the symmetrical region of the binary image. As a result, the symmetrical region is regarded as a frontal view of the detected driving vehicle.

3   Car model recognition based on deep learning

Deep architecture is capable of learning different layers of representations of the input data. Traditional back-propagation method to learn a deep architecture suffers from the poor local optima problem as well as the long learning time. Also, labeled training data is a necessary for back-propagation, which is not always satisfied in case of small dataset. Deep learning method [5] provides a solution to address all these problems, which enable us to use unlabeled data to initialize the deep network. The idea behind the deep learning method is to learn $p(image)$ instead of $p(label|image)$, which is to maximize the probability that a generative model would have produced the input data.

As for our car model recognition, we use three layered Restricted Boltzmann machines (RBM). The binary image of frontal part of a car with size 40*50 is used as input. This binary image is unrolled into a vector with dimension of 2000. The following three RBM layers are used as pre-training to obtain an initial weight. After the pre-training by RBM, we use traditional back-propagation method to fine-tuning the deep network using the labels of 107 car models.

4   Results

To evaluate the performance of our proposed framework, we built a car database, which consists of 3210 car images with varying companies and models. These images composed of 107 car models with 30 images for each model. We are apt to use image instead of video, because it is easy to measure the accuracy. However, to use the frame difference for images, we shifted each image with 10 pixels to generate a neighboring image. The difference image was generated by an image and its shifted image.

Fig. 3 shows the frontal view detection results, which includes four car models with four companies. Left column shows the original car image with detected frontal region marked by red box. Right column shows the binary representation of frontal view. Our system is able to detect the frontal view of each car image accurately. We test the detection algorithm on all 3210 images in the system, and get 100% accuracy with regard to the detection accuracy. Thus, the detection algorithm is proved to be effective and fast in our system.

Fig. 3. Results of frontal view extraction on five car images with four companies and four models.

Once the frontal view of a car was obtained, we feed it into trained deep model as input; the output label is used to recognize the car model. We compared our deep learning method to the widely used methods as follows: local binary pattern (LBP) [6], local Gabor binary patterns (LGBP) [7], and scale-invariant feature transform (SIFT) [8]. The experimental results are shown in Table 1. In our experiments, we use 29 images of each model for training, and the left one image for testing. The results show that deep learning can achieve impressive performance compared with other methods.

Table 1. Performance comparison of car model recognition with widely used methods.

Algorithm	LBP	LGBP	SIFT	Deep Learning
Accuracy (%)	46.0	68.8	78.3	88.2

5   Conclusion

In this paper, we propose a framework to detect moving car and its model based on deep learning. We first detect the moving car using frame difference; the resultant binary image is used to detect the frontal view of a car by a symmetry filter. The detected frontal view is used to identify a car based on deep learning. Experiment results show that our proposed framework achieves favorable recognition accuracy.

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