The Precise Vehicle Retrieval in Traffic Surveillance with Deep Convolutional Neural Networks

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Abstract—This paper describes a system for precise vehicle retrieval in traffic surveillance, exploiting image representation based on Convolutional Neural Network. Our training data contains about 450k vehicle face images cropped from different scene and angle. We prepare two test datasets, one set of images all from daytime and another set of images in night scene. Experiment results on data from a real city traffic surveillance network validate and evaluate our system. We demonstrate that our CNN features have outstanding performance in both two test-sets and achieve an expected recall of 97.89% and precision of 58.22% at top100 for the first test-set and recall of 97.09% and precision 57.57% for the second one. Our work is very import especially in traffic surveillance and public surveillance to find one special vehicle.

Index Terms—Precise vehicle retrieval, convolutional neural network, siamese structure.

I. INTRODUCTION

The number of vehicles grows rapidly in cities, and the traffic surveillance system usually has tens of thousands of cameras connected into a huge network. Vehicle retrieval has received much attention in recent years. It is an important part of intelligent transportation system (ITS) or Smart City. However, it is a great challenge task due to the following difficulties.

- 1) LPR (License Plate Recognition) is a common solution for vehicle retrieval problem. However, LPR is incompetent on the situation of blurred-license cars, unlicensed and fake-license cars.
- 2) This task is on the key work “precise”, which means only the exactly same car can be identified as true positives. Others are negatives even the vehicle brand is same, which always look very similar to the query and cannot be solved by traditional methods.
- 3) Both vehicle brand and other information (interior trim, annual inspection tags and drivers, etc.) should be considered. But it’s very hard to make a common model because it is always personalized.

In computer vision field, visual image retrieval is a classical problem. It is a process of browsing, searching and retrieving images from a big image database. Image retrieval returns a list of images with the same class as query image in accordance with a given retrieval standard. Traditional and common methods of visual image retrieval utilize key representations such as texts [1], colors [2], shapes and

textures [3] to describe images and obtain certain achievements in early years.

Our retrieval task is different from the common retrieval work, which is known as a ‘fuzzy’ retrieval. As we mentioned above, vehicle retrieval is on the key word “precise”, only the exactly same car can be identified as true positives. Moreover, traditional CBIR method cannot meet the requirements of ‘precise’ in such a mass data today, so we seek a more powerful method to solve the vehicle retrieval problem.

Deep convolutional neural network have achieved a great progress in the field of computer vision, and other fields. Various work on convolutional neural networks (CNN) (Simonyan *et al.*, 2013 [4], Girshich *et al.*, 2014 [5], Chatfield *et al.*, 2014 [6], Zeiler & Fergus, 2014 [7]) have successfully demonstrated its powerful representation on visual recognition. For the visual image retrieval task, the results of researches began to announce recent two years.

Since CNN features have been proved to be effective as a state-of-the-art descriptor, we choose CNN to solve the vehicle retrieval problems. CNN feature can overcome the deficiencies mentioned above. Besides, personalized features of each vehicle such as interior trim, annual inspection tags and drivers can be captured and utilized to perform a diversified retrieval.

In 2005, LeCun *et al.*, [8], [9] published a new loss function named “contrastive loss function” in Siamese network. Siamese network is a similar with CNN, with a contrastive loss function to CNN, usually was used as verification task, such as face verification or signature verification. Recently, a lot of researchers and facilities, such as Xiaogang Wang [10], Stan Z. Li [11], Facebook [12] and Google [13] etc., used Siamese network or similar with contrastive loss function in networks for face representation system and achieved amazing results. Inspired by these works, we transplant the Siamese structure to our retrieval system for feature generation.

In this paper, we focus on the targeted traffic images retrieval, which is a very important part of intelligent transportation system (ITS) or Smart City. Our goal is to perform a precise retrieval which can find “the” car rather than “a” same car. In order to generate a robust and efficient representation to distinguish images and locate the right target, we build several powerful convolutional neural networks. Among these models, network with ‘Siamese’ architecture achieves the best descriptors. Our model performance is measured by precision, recall and AP of top N images on the rank list, and our system is validated and evaluated by the experiment results on the data which is from a real city traffic surveillance network. As the experimental results shown below, our system is robust

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enough on deformation and aberration, even on a change of license plate or car trim.

II. RELATED WORK

A. Content-Based Image Retrieval

Content-based image retrieval (CBIR) is one of the fundamental research extensively studied in computer vision community for decades. CBIR aims to search for images by analyzing their visual contents. Variety of low level feature descriptors have been proposed for image representation such as SIFT [14]. Conventional CBIR approaches usually choose rigid distance functions such as Euclidean distance or cosine similarity on some extracted low-level features.

In CBIR, the retrievals are based on matching the features of the query image to image database through some feature similarity estimation. So the selected features of images and the pattern are crucial to the image retrieval. Broadly defined, the feature of an image includes textual feature and visual feature can be distinguished as primitive feature and domain-specific feature. The former, includes color, shape and texture, represents the common features of images while the latter includes face recognition and finger prints, which form a sort of high level image description or meta-object.

As a research hot field CBIR technique has achieved great improvement, but this computer-centric query is not competent to fully satisfy the need of the researchers, since the objective description of images. This is reflected in the subjectivity and differential of human perception, and the disconnection between visual features and high-level semantic.

B. Deep Learning

Deep learning refers to a class of machine learning techniques. In deep learning methods, layers of information processing stages in hierarchical architectures.

Deep learning has a long history, and its basic concept is from artificial neural network research. Feed-forward neural networks with many hidden layers are a good example of deep architecture. Back-propagation, popularized in 1980's, has been a well-known algorithm for learning the weights of these networks. For example, LeCun *et al.* [15] successfully adopt the deep supervised back-propagation convolutional network for digit recognition. The deep convolutional neural networks (CNNs) proposed in [16] came out first in the image classification task of ILSVRC-2012. The model was trained on more than one million images, and has achieved a winning top-5 test error rate of 15.3% over 1,000 classes.

After that, some recent works get better results by improving CNN models. The top-5 test error rate decreased to 6.67% in [17] by training a 22 layers deep networks. Besides image classification, the object detection task also benefits from the CNN model, as reported in [18].

Some researchers attempt to address the long-standing fundamental feature representation problem in CBIR by using deep learning methods [19]. They investigate a framework of deep learning with application to CBIR tasks with an extensive set of empirical studies by examining a state-of-the-art deep learning method (convolutional neural networks).

III. PROPOSED METHOD

CNN has been proved to be an outstanding solution for classification task due to its strong descriptive power, hence we try to utilize CNN to solve image retrieval problems. In our early work, models were trained with ImageNet using the framework of AlexNet, and fine-tuned with our vehicle datasets. Then we simply extract the middle layer features as the vehicle representation feature vector and acquire a retrieval result by computing the distance of feature vectors of two images. The CNN model leads to breakthrough in retrieval performance, however it is still unsatisfied with our practical need. With the development of our studies on model frameworks, we believed a change of our model in framework can lead the way out.

A. CNN-P as Brand Classification

Our first try is to train a classification model using famous AlexNet framework. The retrieval performance is significantly better than the traditional methods. We then try more sophisticated models to realize the recent advances from deep learning communities.

The model which achieves good retrieval results is a CNN classification model called CNN-P model (P means precise). We remove one fully-connected layer and change the filter amount. It is constructed by combining many tricks from recent successful networks including small filter and very deep architecture [20].

The proposed network includes 10 convolutional layer, 5 pooling layers and 1 fully connected layers, the detailed architecture of which is shown in Table I. The size of all filters in the network is 3×3 that equals to the setting of [16], which achieved high performance in ImageNet 2014 challenges by a 19 layer network using small filter. We use multiple small filters to approximate large filters and remove redundant fully-connected layer to reduce the number of parameters.

The comparing structure is shown below in Table I. CNN-P is a classification model trained by more than 750 kinds of vehicle brands. The division of classes is based on the type amount of the vehicles. We use 460k images to train this model, and each class contains at least 3k images.

The experiment result, in Table II, shows that this model is excellent for classification but still insufficient for retrieval. Images in the rank list looked the same, but actually the licenses are quite different. We believed that the description ability of the model was limited by the 750+ classes, and the personalized information worked unobvious. Hence, we adopt a new label discrimination standard to overcome this problem.

B. CNN-P as Vehicle Verification

As mentioned above, the labels restrict the performance of the retrieval system. Our retrieval task can be considered as an intra-class retrieval, while classification can only maximize the inter-class distance. So a manual classification is operated on our database and more than 10K car images are collected to compose a new training set. There are about 45 images for each label, hence we have more than 450k images in training set in total, almost same as our classification dataset. Through this method, we try to eliminate the inter-class interference artificially.

We set labels as the vehicle plates instead of their brands inspired by the face verification [11]. This label pattern satisfies our need of retrieval, since we define vehicle images with the same plate as the ‘same’. We believe that vehicle verification is the right formulation for vehicle retrieval. Deep model trained on this dataset can learn efficient representation for vehicle retrieval.

We still use CNN-P as our classification model. Network configuration was exactly same as brands classification.

TABLE I: OUR MODEL (CNN-P) AND ALEXNET (CNN-A)

Layer	Filter Size/Stride	
	CNN-P	CNN-A
conv1-1	64×3×3/1	96×11×11/4
conv1-2	64×3×3/1	
pool1	2×2/2	3×3/2
conv2-1	64×3×3/1	256×5×5/1
conv2-2	128×3×3/1	
pool2	2×2/2	3×3/2
conv3-1	96×3×3/1	384×3×3/1
conv3-2	192×3×3/1	
pool3	2×2/2	-
conv4-1	128×3×3/1	384×3×3/1
conv4-2	258×3×3/1	
pool4	2×2/2	-
conv5-1	160×3×3/1	256×3×3/1
conv5-2	640×3×3/2	
pool5	7×7/1	3×3/2
fc1	10957	4096
drop1	0.5	0.5
fc2	-	4096
drop2	-	0.5

C. CNN-P with Siamese

Based on the CNN-P, we import the Siamese structure. The architecture of our Siamese network is summarized in Table I. It contains five convolutional layers and one full-connected layer. Two loss functions, a softmax loss function and a contrastive loss function, were used at the same time in the network. A contrastive loss function is employed to learn the parameters, in such a way that neighbors are pulled together and non-neighbors are pushed apart. As in [9], contrastive loss function is given by the expression:

$$L(W) = \sum_{i=1}^P L(W, (Y, X_1, X_2)^i) \quad (1)$$

$$L(W, (Y, X_1, X_2)^i) = (1 - Y)L_G(E_W(X_1, X_2)^i) + YL_I(E_W(X_1, X_2)^i) \quad (2)$$

where $(Y, X_1, X_2)^i$ is the i -th sample, which is composed of a pair of images and a label (genuine or impostor), L_G is the partial loss function for a genuine pair, L_I the partial loss function for an impostor pair, and P the number of training samples.

Samples with the same label are defined as a genuine pair in the contrastive loss, otherwise as an impostor pair. As in other CNN networks for classification, the softmax loss function followed the fully connected layer, but contrastive loss function followed the last pooling layer as the same in [11]. A comparison of AlexNet structure and our model is shown in Table I.

The framework of our network is similar with the structure in [11]. But as we are dealing with totally different data, in our model the input image size is $224 \times 224 \times 3$, cropped from 256×256 color images. The same as in face

verification problems, two cars with the same vehicle license plate are verified as the similar pair else as different non-matching pair. Alignment or mirror operation is unnecessary in our model. The difference between the CNN framework and ours is the number of the filter using in the first convolutional operation (64 filters but not 32), and before the last pooling 640 dimension features is generated. The stride in convolutional operation is 2. In the training, the learning rate was initialized at 0.001 and reduced two times prior to termination. Totally, we trained the Siamese network for about 9 epochs through the training sets before the optimization done. The CNN framework is shown in Fig. 1.

Fig. 1. Siamese architecture.

D. CNN-P for Vehicle Retrieval

Visual image feature generated by CNN models above, such as pool5 or fc1, can be considered as high dimensional feature vector in the process of measuring similarity. Therefore, we can regard image feature as a point in the n -dimensional vector space based on Vector Space Model, then describe the similarity of two vectors by computing their distance. Traditional methods for computing distance are L1 and L2 norm, Euclidian distance, Mahalanobis distance, histogram intersection and cosine similarity. In retrieval works, Euclidian distance is usually the first choice as distance measurement, however, in this paper, we adopt cosine similarity as our measurement of similarity. Euclidian is the absolute distance of the spatial feature points, which is directly related with the points coordinates. While cosine similarity measures the angles of space vectors. It focuses on the differences in direction, not position. In Fig. 2 we show the characteristics of two measurements. Therefore, cosine similarity has a strong robust on all kinds of affine transformations as well as partial shelter or missing.

The features from both fully-connected layer (fc1) and last pooling layer (pool5) are used for feature representation. Compared with the last pooling layer (pool5) in the performance of image descriptive power, we conclude that: 1) pool5 is a set of responsible node to the filters and retains location information, while fc are encoded features with semantic description. 2) Spatial features such as pool5 cannot describe images independently: pool5 represent meaningless shapes or textures that all vehicles exist. 3) Encoded features are higher level of descriptors: fc1

demonstrates that combination of spatial features with certain logistic rules can distinguish objects.

We use three judgment criteria for retrieval performance: recall (measurement of the ability of a system that can retrieve relevant information), precision (evaluation of the capacity of a system that can reject uncorrelated information) and AP (average precision). Recall and precision have opposite interdependent relationship, that means a raising recall will reduce precision, and vice versa.

Fig. 2. The first row is a subset of test 1, the second row is of test 2.

IV. EXPERIENCE RESULT

To evaluate the retrieval result, we use two networks in the experiment. AlexNet [20] that available on Krizhevsky's homepage. This network is kept intact to produce a benchmark for the evaluation of retrieval. Then we generate our network CNN-P and trained on both brand classification and vehicle verification, and the model with "Siameses" structure.

A. Preparation for Test-Data

We build two test-groups for this test. In each test 25 query images are picked from our database, each query image has more than 50 matching pairs. The difference between two tests is that query images in test-1 are composed of daytime images, while queries in test-2 are from night scene. Test-2 is more challenge than test-1. We select very common vehicles in tests in order to check whether CNN-P can extract features in high degree of distinction. Samples are shown in Fig. 3.

B. Vehicle Retrieval on Brands Classification Models

TABLE II: RETRIEVAL RESULTS OF TWO MODELS TRAINED ON BRANDS CLASSIFICATION

Model	R@K=50	P@K=50	R@K=100	P@K=100
CNN-A	63.6	63.23	82.92	45.22
CNN-P	69.70	79.52	88.46	52.08

We compare the AlexNet fine-tuned with 750+ classes as well as CNN-P, the result is shown in Table II. The difference of this two model is the parameter amount of the filters and the depth. R means recall, and P means precision. K represent the number we check from rank results. There are 5% improvement on R@K=100, and 6% on P@K=100. The result demonstrates the structure of CNN-P is more powerful and competent to our task. Results show that with much powerful model the performance is improved greatly.

C. Experiment on Vehicle Verification

In this part, we train CNN-P with different training set. A significant increase (up to 6% improvement on R@K=100) arises by adopting model from trained on brands classification to vehicle verification. That means the classification by individual vehicle can help extract pivotal and useful information which is needed in retrieval work, especially include interior trim, annual inspection tags and drivers, etc. (See Table III).

TABLE III: PERFORMANCE COMPARISON OF OUR MODEL TRAINED BY BRANDS CLASSIFICATION (CNN-P) AND VEHICLE VERIFICATION (CNN-P*)

Model	R@K=50	P@K=50	R@K=100	P@K=100
CNN-P	69.70	79.52	88.46	52.08
CNN-P*	80.73	92.02	94.95	56.10

D. Test of Performance

A comprehensive experiment is operated to verify the effect of Siamese architecture (CNN-P*S). We show the retrieval result in Table IV. Test-1 contains a group of query images from daytime, while test 2 are images from night scene, and they share the same database. We show our retrieval result of features from pool5 and fc1. Another performance argument AP is presented as a judgment to CNN-P*S, this argument can verify the top rate of retrieval results.

TABLE IV: TWO TESTS ON CNN-P* AND CNN-P*S (CNN-P* WITH SIAMESE)

Model		Feature	R@K=50	R@K=100	P@K=50	P@K=100	AP@K=50	AP@K=100
CNN-P*	Test-1	poo5	69.91	85.38	79.81	50.26	66.80	78.07
		fc1	80.73	94.95	92.02	56.10	79.43	91.53
CNN-P*S		pool5	74.62	88.87	85.17	52.49	72.82	84.11
		fc1	84.09	97.89	95.92	58.22	83.37	96.17
CNN-P*	Test-2	pool5	51.35	67.30	58.85	39.47	44.69	53.76
		fc1	71.27	88.18	81.50	52.04	67.37	79.84
CNN-P*S		pool5	58.04	73.69	67.34	43.77	53.31	63.48
		fc1	82.95	97.09	94.54	57.57	81.84	94.54

With Siamese architecture, we obtain top points among all results, and successfully cut the error rate down to the

range of 3%. We set another test to check the robustness of CNN-P*S. There is only less than 1% drop on the

performance. The exciting result demonstrates CNN-P*S have outstanding robustness on illumination. In both tests, the AP (average precision) is very high, that means our model can work stably in different situations and the target images in rank list are in very front.

We show examples of correct results and faults result in Fig. 3. The correct results demonstrate the robustness of our model in scale, rotation and illumination. The fault ones have the same brands with query image, hence the similarity is high. In normal retrieval cases the fault results can be considered as true, however to our task, these two vehicles are identified as different images.

Fig. 3. An example of retrieval result shown in the form of images.

V. CONCLUSION

This paper shows our study on precise vehicle retrieval, and demonstrates that precise vehicle retrieval is a challenge problem due to its target which should be “the” car rather than “a” same car. Powerful deep learning model can achieve better performance than traditional hand-craft feature descriptors, even when we use the “wrong” formulation (trained by brands classification). Vehicle verification can tell the subtle difference between the different car with same brands and color. Performance can be further boosted by using Siamese architecture even using night query images.

Through our study, we find that the Siamese network can imitate the behavior of human learning methods like to learn things by comparison. Our rigorous experiment results demonstrate that 1) CNN-P*S effectively reduces the intra-class distances and expands the inter-class distance. 2) The comparing learning (Siamese structure) is higher level of human learning than memorizing learning which represents the traditional convolutional neural networks, since the retrieval process itself is a kind of comparison. Therefore, the reserved correlative features from matching pairs and uncorrelated features of non-matching pairs can reveal outstanding and efficient descriptive power in retrieval tasks. 3) A combination of spatial features and semantic features is a more powerful descriptor than any of them, and qualified with complex retrieval tasks. We believe a more exciting achievement can be obtained by a further study on Siamese architecture in the future.

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