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Robust Vehicle Logo Recognition Based on Locally Collaborative Representation with Principal Components

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***Abstract*—Vehicle logo recognition (VLR) is a main issue in vehicle identification system. Logo recognition is still a challenge technique since VLR methods suffer from the large within-class variations due to the different illumination conditions, different viewpoints et al. In this paper, motivated by the excellent performance of the collaborative representation based classification (CRC), we formulate VLR problem under CRC scheme. It is noted that the performance of CRC is generally proportional to the size of the dictionary for better data representation capability. However, a large dictionary requires high computational cost. Aiming at maintaining the CRC performance but reducing the cost, the principal components analysis (PCA) is firstly employed on the class-dictionary to remove within-class information redundancy and noisy components. In addition, we introduce a new idea to code a data over a local dictionary instead of a global dictionary used in a conventional CRC, where the local dictionary is built by selecting the K-nearset neighbors of this data. As a result, a novel locally collaborative representation based classification with principal components (termed as LCRC_PC) method is systematically derived. The proposed LCRC_PC method is evaluated on two data sets. The average accuracies are 99.44% and 99.53% on a self-built data set and a public data set, respectively. Moreover, the computational cost of LCRC_PC is about a tenth of that of conventional CRC. Experimental results validate the effectiveness and robustness of our proposed LCRC_PC method.**

***Keywords*—Vehicle logo recognition; collaborative representation based classification; KNN; PCA; LCRC_PC**

I. Introduction

Vehicle identification system (VIS) is a crucial sub-system in intelligent transportation system (ITS). For vehicle identification, vehicle logo provides the most important information of its vehicle manufacturer, vehicle logo recognition (VLR) is required in VIS. However, compared with vehicle type recognition (VTR) and vehicle license plate recognition (VLPR) in VIS, VLR is a field with fewer studies in research and industry.

In general, VLR system always consists of two steps including vehicle logo detection (VLD) and vehicle logo classification (VLC). For VLD, it is a indispensable step in most VLR systems. Consequently, some approaches were proposed in [1]–[5] to address the problem. As the most primary step in a VLR system, VLC directly determine the performance of the system. In this paper, we mainly discuss the VLC step in VLR problem.

To solve the VLR problem, Lee [6] applied a three-layer neural network in VLR problem. Wang et al. [7] adopted template matching and edge oriented histogram to address VLR problem with an accuracy of 90%. Dai and Huang [8] presented a recognition method via Tchebichef moment invariants and support vector machine (SVM). Psyllos et al. [9] reported a scale invariant feature transform (SIFT) based enhanced matching scheme with a promising recognition rate and acceptable processing time, but suffered from illumination variations and various viewpoints. Huang et al. [10] proposed a convolutional neural model based method that removed the requirement for precise logo detection. They obtained an average accuracy of 99.07%, but the training phase was time-consuming.

Previous VLR methods are limited by: 1) poor illumination, low resolution and noise; 2) logo rotation and viewpoints variation; 3) high computational cost. Distinct from the previous studies, in this paper, we study the problem from a collaborative representation insight. Inspired by the collaborative representation based classification (CRC) model used in face recognition problem [11], we formulate vehicle logo recognition problem under CRC Scheme. Compared with face recognition, the interior shape of vehicle logo is more complex. Vehicle logos captured from real world are distorted by variant rotation, scale and illumination. Due to the large within-class variances, a dictionary with more atoms is needed in CRC, which means higher computational cost and more noise. Thus, principal components analysis (PCA) technique is used to reduce the dimension of each class-dictionary and remove the noise simultaneously. Furthermore, a local dictionary is built by selecting the K-nearest neighbors of a testing sample, which reduces the size of dictionary used in a conventional CRC. As a result, we code the testing sample over the new local dictionary. Experimental results show that the proposed method offers a high recognition rate and suffers low computational complexity.

The framework of the proposed VLR method is shown in Fig.1. There are three main modules in the proposed VLR method, e.g., location, preprocessing and recognition.

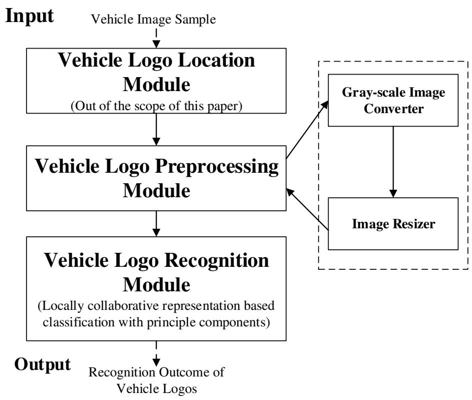

Fig. 1. Framework of the proposed VLR method.

The rest of this paper is organized as follows. A brief introduction of collaborative representation based classification is presented in Section II. The proposed locally collaborative representation based classification with principal components method is described in Section III. Experimental results are presented and discussed in details in Section IV. Finally, a conclusion is drawn in Section V.

II. Collaborative Representation Based Classification

In conventional CRC [11], a testing sample $\boldsymbol{y}$ is represented collaboratively over a global dictionary $\boldsymbol{D}$ which is constructed by all training samples.

Assume training samples are from k classes, and there are n_i samples in ith class. The dictionary is formulated as

$$\boldsymbol{D} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_k] \in \mathbb{R}^{m \times n} \tag{1}$$

where $n = \sum_{i=1}^{k} n_i$ and the ith class-dictionary is denoted as $\boldsymbol{D}_i$, namely

$$\boldsymbol{D}_i = [\boldsymbol{d}_{i1}, \boldsymbol{d}_{i2}, \cdots, \boldsymbol{d}_{in_i}] \in \mathbb{R}^{m \times n_i} \tag{2}$$

in which $\boldsymbol{d}_{ij}$ is the jth training sample in the ith class, m stands for the dimension of training sample.

In term of collaborative representation, $\boldsymbol{y}$ from the ith class can be represented by

$$\boldsymbol{y} \approx x_{i1}\boldsymbol{d}_{i1} + x_{i2}\boldsymbol{d}_{i2} + \cdots + x_{in_i}\boldsymbol{d}_{in_i} \tag{3}$$

where $x_{ij} \in \mathbb{R}, j = 1, \cdots, n_i$ is the collaborative representation coding coefficient associated with vector $\boldsymbol{d}_{ij}$. By defining the vector $\boldsymbol{x} = [\boldsymbol{x}_1, \cdots, \boldsymbol{x}_i, \cdots, \boldsymbol{x}_k]^T$ in which $\boldsymbol{x}_i$ is the collaborative representation coding coefficients of class-dictionary $\boldsymbol{D}_i$, the testing sample $\boldsymbol{y}$ can be expressed in a compact form as

$$\boldsymbol{y} \approx \boldsymbol{D}\boldsymbol{x} \tag{4}$$

The testing sample $\boldsymbol{y}$ can be also represented as $\boldsymbol{y} = \hat{\boldsymbol{y}} + \boldsymbol{e}$ where $\hat{\boldsymbol{y}} = \boldsymbol{D}\boldsymbol{x}$ is estimated testing sample and $\boldsymbol{e}$ is the residual. The collaborative representation coding coefficient $\boldsymbol{x}$ can be calculated by Eq.5:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}} \|\boldsymbol{x}\|_2 \; s.t. \; \|\boldsymbol{y} - \boldsymbol{D}\boldsymbol{x}\|_2 \le \varepsilon \tag{5}$$

where ε is a small constant. By Lagrangian formulation, the method of CRC can be generally described as

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}}(\|\boldsymbol{y} - \boldsymbol{D}\boldsymbol{x}\|_2^2 + \lambda\|\boldsymbol{x}\|_2^2) \tag{6}$$

where λ is the regularization parameter. $\hat{\boldsymbol{x}}$ can be easily obtained by

$$\hat{\boldsymbol{x}} = (\boldsymbol{D}^T\boldsymbol{D} + \lambda\boldsymbol{I})^{-1}\boldsymbol{D}^T\boldsymbol{y} \tag{7}$$

Let $\boldsymbol{P} = (\boldsymbol{D}^T\boldsymbol{D} + \lambda\boldsymbol{I})^{-1}\boldsymbol{D}^T$. Eq.7 can be denoted as:

$$\hat{\boldsymbol{x}} = \boldsymbol{P}\boldsymbol{y} \tag{8}$$

where $\boldsymbol{P}$ is independent of testing sample $\boldsymbol{y}$ so that it can be pre-calculated.

In CRC, we obtain the reconstruct testing sample by coding coefficient $\hat{\boldsymbol{x}}$. The class label of testing sample is determined with following equation:

$$identity(\boldsymbol{y}) = \arg\min_i(\|\boldsymbol{y} - \boldsymbol{D_i}\hat{\boldsymbol{x}}_{\boldsymbol{i}}\|_2/\|\hat{\boldsymbol{x}}_{\boldsymbol{i}}\|_2) \tag{9}$$

The CRC algorithm is summarized in Algorithm 1.

Algorithm 1 The CRC Algorithm

1. **Input:** a matrix of training samples

$$\boldsymbol{D} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_k] \in \mathbb{R}^{m \times n}$$

for k classes, a testing sample $\boldsymbol{y} \in \mathbb{R}^m$.

2. Normalize the columns of $\boldsymbol{D}$ to have unit l_2-norm.
3. Code $\boldsymbol{y}$ over $\boldsymbol{D}$ by

$$\hat{\boldsymbol{x}} = \boldsymbol{P}\boldsymbol{y}$$

where $\boldsymbol{P} = (\boldsymbol{D}^T\boldsymbol{D} + \lambda\boldsymbol{I})^{-1}\boldsymbol{D}^T$.

4. Compute the regularized residuals

$$r_i(\boldsymbol{y}) = \frac{\|\boldsymbol{y} - \boldsymbol{D}_i\hat{\boldsymbol{x}}_i\|_2}{\|\hat{\boldsymbol{x}}_i\|_2}$$

for $i = 1, 2, \cdots, k$.

5. **Output:** the identity of $\boldsymbol{y}$ as

$$identity(\boldsymbol{y}) = \arg\min_i r_i(\boldsymbol{y})$$

III. Locally Collaborative representation Based Classification with Principal Components

Aiming at reducing the redundant information and potential noise in each class-dictionary, we utilize principle components analysis (PCA) in each class-dictionary to get the class-dictionary more efficient and robust. Furthermore, for purpose of making full use of similar images and abandoning the redundant dissimilar images in the dictionary, locally subspace is used instead of global space as the projective space. Inspired by K-nearest neighbors (KNN) algorithm, we choose K nearest neighbors of the testing sample from training images. The labels of the K neighbors are used to select all the corresponding class-specific class-dictionaries to reconstruct a new dictionary. Then, we use the new dictionary to collaboratively represent the testing sample. Specifically, for each class i ($i \in \{1, 2, \cdots, k\}$), compute the top t principal components of $\boldsymbol{D}_i$, and modify the class-dictionary as $\boldsymbol{D}_i' = [\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p}_t]$. The dictionary is represented as $\boldsymbol{D}' = [\boldsymbol{D}_1', \boldsymbol{D}_2', \cdots, \boldsymbol{D}_k']$. Then, for testing sample $\boldsymbol{y}$, compute the K nearest neighbors $\boldsymbol{c}_j$, $j = 1, 2, \cdots, K (K \leq n)$. The labels of the K nearest neighbors are denoted by $L = \{l_1, l_2, \cdots, l_d\}$ $(d \leq k)$. Finally, take all the class-dictionary corresponding to class l_i to form a new dictionary , indicated as $\boldsymbol{D}'' = [\boldsymbol{D}_{l_1}', \boldsymbol{D}_{l_2}', \cdots, \boldsymbol{D}_{l_d}']$, and represents the testing sample $\boldsymbol{y}$ by this new dictionary. This method is named as locally collaborative representation based classification with principal components (LCRC_PC). Fig.2 shows the proposed construction method of $\boldsymbol{D}''$. The LCRC_PC algorithm is summarized in Algorithm 2.

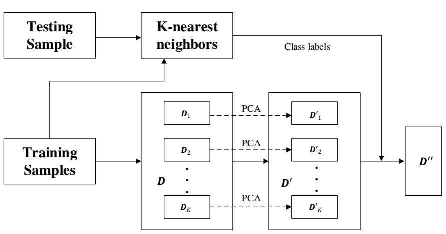

Fig. 2. Proposed construction method of $\boldsymbol{D}''$.

IV. Experiments and Results

A. Experiments With Self-built Vehicle Logo Data Set

In this part, we build a data set with 3000 vehicle logo images captured from surveillance video to assess our proposed method. The vehicle logos are precisely segmented and tagged manually. Samples in the data set are from 15 popular manufactures in China, and each has 200 images. Some sample images from the data set are shown in Fig.3. The vehicle logo images have large variations, e.g., lighting condition, image resolution, background, noise condition. In vehicle logo preprocessing module, all vehicle logo images are converted to gray-scale and resized to 32×32. In each class, 140 vehicle logo images are randomly chosen as training samples and the remaining are used as testing samples. For demonstrating that our proposed LCRC_PC method is effective, we compare LCRC_PC method with nearest neighbor (NN) method [12] and CRC method [11]. In terms of the parameters of LCRC_PC, the values of K and t are set to 15 and 30 respectively. Results are shown in Table I and Table II. It can be seen that our method performs well in the experiment, and obtains the highest accuracy of 99.44%. Besides, the time performance of the LCRC_PC method is close to NN method, and much faster than conventional CRC method. As the results, we are confident that LCRC_PC method can meet the real-time acquirement in real world applications.

Algorithm 2 The LCRC_PC Algorithm

1. **Input:** a matrix of training samples

$$\boldsymbol{D} = [\boldsymbol{D}_1, \boldsymbol{D}_2, \cdots, \boldsymbol{D}_k] \in \mathbb{R}^{m \times n}$$

for k classes, a testing sample $\boldsymbol{y} \in \mathbb{R}^m$.
2. Normalize the columns of $\boldsymbol{D}$ to have unit l_2-norm.
3. For each class i ($i \in \{1, 2, \cdots, k\}$), compute the top t principal components of $\boldsymbol{D}_i$, form $\boldsymbol{D}_i' = [\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p}_t]$,a new dictionary:

$$\boldsymbol{D}' = [\boldsymbol{D}_1', \boldsymbol{D}_2', \cdots, \boldsymbol{D}_k'] \in \mathbb{R}^{m \times tk}$$

4. Compute the K nearest neighbors of testing sample $\boldsymbol{y}$ from training samples, as $\boldsymbol{c}_j$ ($j = 1, 2, \cdots, K$). The labels of the K nearest neighbors are denoted by $L = \{l_1, l_2, \cdots, l_d\}$ $(d \leq k)$.
5. Take all atoms belong to class l_i from $\boldsymbol{D}'$ to form a local dictionary, as

$$\boldsymbol{D}'' = [\boldsymbol{D}_{l_1}', \boldsymbol{D}_{l_2}', \cdots, \boldsymbol{D}_{l_d}']$$

6. Code $\boldsymbol{y}$ over $\boldsymbol{D}''$ by

$$\hat{\boldsymbol{x}} = \boldsymbol{P}\boldsymbol{y}$$

where $\boldsymbol{P} = (\boldsymbol{D}''^T \boldsymbol{D}'' + \lambda \boldsymbol{I})^{-1} \boldsymbol{D}''^T$.
7. Compute the regularized residuals

$$r_{l_i}(\boldsymbol{y}) = \frac{\|\boldsymbol{y} - \boldsymbol{D}_{l_i}' \hat{\boldsymbol{x}_{l_i}}\|_2}{\|\hat{\boldsymbol{x}_{l_i}}\|_2}$$

for $l_i \in L$.
8. **Output:** the identity of $\boldsymbol{y}$ as

$$identity(\boldsymbol{y}) = \arg\min_{l_i} r_{l_i}(\boldsymbol{y})$$

Fig. 3. Samples of self-built vehicle logo data set.

B. Experiments With XMU Vehicle Logo Data Set

In this part, we use a more complex data set from Xiamen University [10] to assess our method. Vehicle logos in the data set are from top ten popular manufactures in China mainland. The vehicle logo images are coarsely segmented from vehicles in real surveillance video. The images are additionally treated with various distortions, e.g., noise, illumination variance, viewpoint variations. There are 11500 images from 10 manufactures with 1150 images for each manufacture.

TABLE I
CLASSIFICATION ACCURACY ON SELF-BUILT VEHICLE LOGO DATA SET.

Method	**NN** [12]	**CRC** [11]	**LCRC_PC**
Accuracy	97.22%	97.89%	99.44%

TABLE II
THE AVERAGE RUNNING TIME FOR PER LOGO ON SELF-BUILT VEHICLE LOGO DATA SET.

Method	**NN** [12]	**CRC** [11]	**LCRC_PC**
Time	22.57ms	245.73ms	25.53ms

Some example images in the data set are shown in Fig.4.

Fig. 4. Samples of XMU vehicle logo data set.

1000 images from each manufacture in the data set are used as training data, and the remaining are testing data. In vehicle logo preprocessing module, all the images are converted to gray images and normalized to 30 $\times$ 30. We compare our proposed LCRC_PC method with NN [12], CRC [11], Kernel-CRC [13], CNN and Pretraining CNN [10]. In terms of the parameters of LCRC_PC, K is set to 300 and t is set to 300. The classification accuracies are shown in Table III. We can observe that our proposed method obtains the highest accuracy of 99.53% and conventional CRC method only obtains 96.93%. The computational cost comparison is provided in Table IV. We can clearly see that our proposed method is almost 10 times faster than CRC method. The classification accuracy for the ten manufactures from LCRC_PC is shown in Table V. 7 vehicle logo images from three categories are wrongly recognized with the LCRC_PC method.

Different values of K, t are chosen in our experiments. We set up seven values (5, 15, 30, 50, 100 and 500) as K and five values (50, 100, 200, 300, and 500) as t. They are shown in Fig.5. We can clearly see that when appropriate K and t are chosen , the LCRC_PC method acts better than conventional CRC method.

TABLE III
CLASSIFICATION ACCURACY ON XMU VEHICLE LOGO DATA SET.

Method	**Accuracy**
NN [12]	96.60%
CRC [11]	96.93%
KCRC [13]	91.73%
CNN [10]	98.13%
PreCNN [10]	99.07%
LCRC_PC	99.53%

TABLE IV
THE AVERAGE RUNNING TIME FOR PER IMAGE ON XMU VEHICLE LOGO DATA SET.

Method	**Time**
NN [12]	51ms
CRC [11]	571ms
KCRC [13]	4813ms
CNN [10]	15ms
PreCNN [10]	160ms
LCRC_PC	59ms

TABLE V
CLASSIFICATION ACCURACY ON XMU VEHICLE LOGO DATA SET ACROSS DIFFERENT VEHICLE MANUFACTURES BY THE LCRC_PC.

Manufactures	**True**	**False**	**Accuracy**
Honda	150	0	100.00%
Peugeot	149	1	99.33%
Buick	147	3	98.00%
VW	150	0	100.00%
Toyota	150	0	100.00%
Lexus	150	0	100.00%
Mazda	150	0	100.00%
Chery	150	0	100.00%
Hyundai	147	3	98.00%
Citroen	150	0	100.00%
Average	1493/1500	7/1500	99.53%

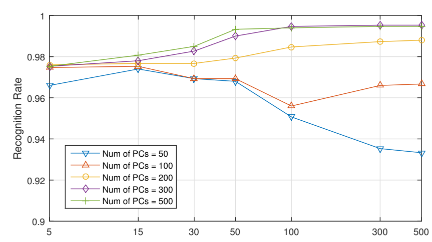

Fig. 5. Recognition rate of LCRC_PC on XMU vehicle logo data set by different settings of K and t.

From above experimental results, we can conclude that the proposed LCRC_PC method is effective to vehicle logo recognition and robust to various poor imaging situations.

V. CONCLUSION

In this paper, an effective and robust vehicle logo recognition method has been proposed. Under collaborative representation classification scheme, we proposed a new preprocessing method by employing PCA method to remove the within-class variations and noisy components meanwhile instead of using global dictionary, we code the sample data by the local dictionary which is built by K-nearest neighbor approach. It is clear that the PCA approach improves the robustness to noise and variations. It also reduces the computational cost. Besides, the local dictionary coding approach further reduce the computational cost. Experiments show that our proposed LCRC_PC method offers the best classification accuracy compared with the CRC, KNN, CNN methods. Moreover, its computational cost is less than that of CRC. In conclusion, we are confident that our proposed method can be used as a working solution for vehicle recognition in practical applications.

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