Vehicle Logo Recognition Based on Optimized Dictionary and Robust Collaborative Representation

Xinye Li, Huang Teng, Mengmeng Cao

Department of Electronic and Communication Engineering, North China Electric Power University, Baoding, Hebei 071003, China
email:799057162@qq.com

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Abstract. Recently, with the increase of the car ownership, transportation network becomes more and more complex, the traffic management system is facing a serious challenge. Therefore, vehicle recognition plays a decisive role. The vehicle logo contains information of a vehicle, so vehicle logo can be used to identify vehicle models. Considering the problem of the high calculation cost of the vehicle recognition based on sparse representation, a vehicle logo recognition method based on optimized dictionary and robust collaborative representation is proposed. This method not only has a high recognition rate but also reduces the computation time. In our method, HOG feature is selected to represent the vehicle logo image. HOG features are extracted from training samples and testing samples respectively, and then dictionary learning method based on Fisher discrimination criterion is adopted to optimize the train samples. Finally, robust collaborative representation is used to recognize the vehicle models. The experimental results show that our method achieves a high recognition rate 98.2% and reduces the computation time.

Introduction

Intelligent transportation system has become one of the important research directions of traffic management. Vehicle recognition, as an important part of intelligent transportation systems, is mainly used in highway automatic charge system, parking management system and so on. But rough classification of the vehicle has been unable to meet our requirement, we need to identify the license plate number and to determine the consistency of the license plate and models.

Scholars have done some researches on vehicle logo recognition and have developed many new logo recognition methods. Psyllos et al. [1] used SIFT (Scale Invariant Feature Transform) [2] to recognize an automobile make from its logo. Cai et al. [3] used knowledge about the body of an automobile to detect an automobile. Badura and Foltan [4] used SIFT (Scale Invariant Feature Transform) [2] and SURF (Speed up Robust Features) [5] to find interest points and generate an invariant descriptor. Liu Jiamin et al. [6] applied Hu invariant moments to the vehicle logo recognition. Li Wenju et al. [7] think that the independent component analysis (ICA) can express the logo feature better. Burkhard et al. [8] used feature descriptors and shape descriptors to recognize vehicle logos from logo images.

Sparse representation theory is applied to the vehicle logo recognition and obtains good effect. The core idea is to represent the samples to be recognized as a linear sparse combination of training samples, and then decide which category it belongs to by calculating its reconstruction error. The algorithm shows the good robustness in the experiment. It is widely believed that the good recognition effect is attributed to the constraints on the norm of sparse coding coefficient, but norm minimized problem makes sparse representation recognition algorithmic computational complexity high, which leads to bad real-time performance. With the deepening of the research, some scholars begin to ask
questions about norm minimized problem [9]. The reference [10] analyzed the basic principle of the SRC (sparse representation-based classifier) method. It means that collaborative representation plays a more important role in sparse representation than the norm sparse, and based on this, they raise the robust collaborative representation algorithm [11]. Based on the above analysis, in order to solve the problem of high time complexity of the sparse representation algorithm, this paper proposes a combination of optimized dictionary and robust collaborative representation vehicle-logo recognition algorithm, improving recognition rate and reducing the computing time.

The Vehicle Logo Feature representation

HOG feature describes the size and direction information of the local image gradient, representing the edges structure characteristic. Compared with other feature description method, the HOG feature is the structure feature edges, so it can describe the shape of the local information. Secondly it is operating on local small pieces of the image, we think that the small scale has the same illumination intensity. So it can keep good invariance of light. In addition, to some extent, in the position and direction of space quantization, it can restrain the influence of the translation and rotation. So HOG feature is more suitable for logo descriptor, therefore, this article selects the HOG features to describe the logo image.

The following is the basic implementation approach of extracting HOG features: Firstly, a gray image is divided into several small pieces, and then according to the gray scale-pixels within each piece, the gradient or edge statistics for each histogram is calculated, finally the histogram of each small piece is generated together to form the characteristics of the image descriptor. In order to get a better effect, we can use these local histogram contrast normalization in the broader area of the image, the method we used is: Calculate the density of each histogram in this region, then according to the density normalize each block in the area normalization. The normalized descriptor has the ability of resistance to illumination changes and shadow effect.

Robust Collaborative representation model

The iterative weighted collaborative representation model [12] is:

\[
\hat{\alpha} = \arg \min_{\alpha} ||P^{1/2}(y - A\alpha)||_F^2 + \lambda \|\alpha\|_1
\]

(1)

Where \( \lambda \) is a positive number and a scalar. \( y \) is a sample to be identified. \( \alpha \) is the representation coefficients of the sample \( y \), \( A = [r_1, r_2, \ldots, r_n] \), \( r_i \) is the \( i \)-th row in dictionaries. \( e = y - A\alpha \) represents the coding remainder. Define \( e = y - A\alpha = [e_1; e_2; \ldots; e_n] \), and \( e_i = y_i - r_i\alpha \). Assume that the \( e_1, e_2, \ldots, e_n \) are independent and identical distribution.

The logistic function is widely used as the weighted function,

\[
W_{ij} = w_o(e_{ij}) = 1 / (1 + \exp(\mu(e_{ij})^2 - \mu\delta))
\]

(2)

If \( W \) is given, we can deduce the answer of (1):

\[
\hat{\alpha} = (A^TWA + \lambda I)^{-1} A^TWy
\]

(3)
Finally use SRC classification method to classify $y$:

$$identity(y) = \arg \min \left\{ \|W^{1/2} (y - D \hat{\alpha}) \|_2 \right\}$$  \hspace{1cm} (4)

**Feature Dictionary Optimization Based on Fisher Criterion**

After the features of training samples being extracted, it will be constructed dictionary matrix by columns directly. Due to interference information, the dictionary cannot effectively represent the test samples and at the same time may lose many training samples hidden in the classification information. The process of optimizing the dictionary feature is called dictionary learning. The last two years many scholars have proposed some methods to learn the dictionary. The purpose is to make the training samples of the dictionary learning more conducive to be classified [13-15]. So this paper uses the dictionary learning algorithm based on Fisher criterion, and obtains the dictionary matrix which has a better ability to represent and classify the training samples.

Suppose a training sample $H = [H_1, H_2, ..., H_N]$ comprising $N$ classes feature set. $H_i$ corresponds to the $i$th type sample feature subset. Learn a structured dictionary $D = [D_1, D_2, ..., D_N]$. $D_i$ represents the $i$th type sub-dictionary. The coding coefficient of training samples in the dictionary is $X = [X_1, X_2, ..., X_N]$, $X_i$ represents the coding coefficients in the dictionary of $H_i$.

The objective function of Dictionary learning based on Fisher criterion is:

$$J(D, X) = \arg \min_{D, X} \left\{ r(H, D, X) + \lambda_1 \|X\| + \lambda_2 f(X) \right\}.$$  \hspace{1cm} (5)

$\lambda_1$ and $\lambda_2$ are adjustment coefficients, $\|X\|$ represents a sparse coefficient constraint item, $f(X)$ is the discriminating item, $r(H, D, X)$ is the dictionary fidelity term, it is written as:

$$r(H, D, X) = \|H_i - DX_i\|_F^2 + \sum_{j \neq i} \|DX_j\|_F^2.$$  \hspace{1cm} (5)

In order to make the dictionary to be discriminative, the Fisher criterion is introduced to the process of training samples:

$$S_w(X) = \sum_{i=1}^{N} \sum_{x \in X_i} (x - m_i)(x - m_i)^T$$  \hspace{1cm} (6)

$$S_b(X) = \sum_{i=1}^{N} n_i (m_i - m)(m_i - m)^T$$  \hspace{1cm} (7)

$m$ is the average value of $X$ and $m_i$ represents the average value of $X_i$. $n_i$ represents the amounts of the samples in $H_i$. The discrimination $f(X)$ is defined as:

$$f(X) = tr(S_w(X)) - tr(S_b(X)) + \eta \|X\|_F$$
Through the above description we can see that the learned dictionary ensure that the samples can be represented by the corresponding class sub-dictionary and the representation coefficients are discriminative. It is convenient for the latter classification.

Vehicle-logo Recognition based on Optimized Dictionary and Robust Collaborative Representation

We combine the dictionary learning algorithm based on Fisher criterion with the weight collaborative representation model to realize vehicle-logo recognition. The Vehicle-logo recognition steps are the following:

1) Extract HOG features from training samples to get feature set \( H = [H_1, H_2, ..., H_N] \);
2) Use Principal Component Analysis (PCA) method to reduce the dimension of feature vectors;
3) Use dictionary Optimization Based on Fisher Criterion to get optimized dictionary \( A \) of training samples;
4) Initialize the coefficient of coding vector \( \alpha^{(i)} \) and iteration number:

Because we do not know the test category, so set the \( \alpha^{(i)} \) to be \( \alpha^{(i)} = [\frac{1}{k}, \frac{1}{k}, ..., \frac{1}{k}] \), and \( k \) is the number of training samples. Set iteration number \( t = 1 \)
5) Calculate the remainder code \( e^{(i)} = y - A\alpha^{(i)} \).
6) Calculate the weighted function \( W_{(i)} = w_p(e^{(i)}) = 1/1 + \exp(\mu(e^{(i)})^2 - \mu\delta) \).
7) Calculate robust collaborative representation based on the weighted regularization \( \hat{\alpha} = \arg \min \{ ||W^{(i)}(y - A\alpha)||^2_2 + \lambda ||\alpha||_2 \} \), that is: \( \hat{\alpha} = (A^T W^{(i)} A + \lambda I)^{-1} A^T W^{(i)} y \). \( W^{(i)} \) is a diagonal weight matrix, \( W_{ii} = w_p(e^{(i)}) \) are diagonal elements .
8) Update coding coefficient matrix:

If \( t = 1 \), then \( \alpha^{(i)} = \hat{\alpha} \)
If \( t > 1 \), then \( \alpha^{(i)} = \alpha^{(i-1)} + \mu^{(i)}(\hat{\alpha} - \alpha^{(i-1)}) ; \ 0 < \mu^{(i)} < 1 \).
9) Calculate the reconstructed results of test sample \( y_{(i)} = A\alpha^{(i)} \), and make \( t = t + 1 \).
10) If condition \( \frac{||W^{(i)}(y - A\hat{\alpha})||_2}{||W^{(i)}||_2} < \epsilon \) is satisfied or the maximum number of iterations is reached, then stop the iteration, otherwise go to step 5).
11) Get recognition results: \( \text{identity}(y) = \arg \min \{ ||W_{\text{final}}^{1/2}(y - A_\hat{\alpha})||_2 \} \), \( W_{\text{final}} \) is the weight value. \( A_\hat{\alpha} \) denotes sample sub-dictionary of the \( c \) th class. The \( \hat{\alpha}_c \) is the coding coefficients of test sample on \( A_c \).
The Experimental Results and Analysis

This experiment uses MATLAB, and we use Database including Volkswagen, Hyundai, Audi and other 20 kinds of samples, the samples in each class contains 60 logo image. And we use the Database Medialab LPR Database [16], and some logo images are from intersection traffic video images segmentation. Extract HOG features in the logo image of \(64 \times 64\) pixels. The size of block is \(16 \times 16\) and cell is \(4 \times 4\). The gradient direction angle number is 9. The scanning step length on sample image is \(8 \times 8\). The dictionary learning parameters are set to be \(\lambda_1 = 0.003\), \(\lambda_2 = 0.005\). The parameters of collaborative representation are set to be \(\lambda = 0.001\), \(\varepsilon = 0.5\).

(1) First of all, in order to verify the effectiveness of our method, we compare our method with the SVM method, sparse representation classification (SRC) and collaborative classification (CRC) method. Extract HOG feature and use Principal Component Analysis (PCA) dimension to reduce the feature dimension of \(d = 50, 100, 150, 100\) respectively. The results are shown in the following table:

<table>
<thead>
<tr>
<th>feature dimension (d)</th>
<th>SVM(%)</th>
<th>SRC(%)</th>
<th>CRC(%)</th>
<th>Our Method (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>89.5</td>
<td>91.4</td>
<td>90.8</td>
<td>94.1</td>
</tr>
<tr>
<td>100</td>
<td>92.2</td>
<td>93.8</td>
<td>92.2</td>
<td>95.2</td>
</tr>
<tr>
<td>150</td>
<td>93.1</td>
<td>94.5</td>
<td>92.9</td>
<td>96.6</td>
</tr>
<tr>
<td>200</td>
<td>93.8</td>
<td>95.9</td>
<td>94.2</td>
<td>98.2</td>
</tr>
</tbody>
</table>

It can be seen from table 1 that with the increase of feature dimension, the algorithm of the recognition rate is improved, for feature dimension \(d = 200\), the recognition rate of each algorithm achieves good effect, our algorithm achieves the best recognition results.

(2) In addition to considering the recognition rate, the calculation speed is also a measure of the recognition algorithm. We also test the recognition time of each algorithm. When feature dimension \(d = 200\), the recognition time of each algorithm are shown in the table 2:

<table>
<thead>
<tr>
<th>algorithm</th>
<th>recognition time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRC</td>
<td>1.031</td>
</tr>
<tr>
<td>CRC</td>
<td>0.012</td>
</tr>
<tr>
<td>Our Methods</td>
<td>0.015</td>
</tr>
</tbody>
</table>

Summary

Classification algorithm based on sparse representation requires solving the \(l_1\) norm minimization problem. It makes the method has high computational complexity. And study based on \(l_2\) minimum norm of the collaborative representation can obtain the approximate identification effect with sparse representation, and reduces the amount of calculation greatly. Based on this situation, this paper proposes a vehicle logo recognition method based on collaborative representation with the dictionary optimization. Experiments show that this method achieves a high recognition rate and reduces the computation time.
References


