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Vehicle Logo Recognition Using Modest AdaBoost and Radial Tchebichef Moments

Kam-Tong Sam [+] and Xiao-Lin Tian

Faculty of Information Technology
Macau University of Science and Technology

Abstract. Logo recognition is a vital yet challenging task in vehicle identification system as the logo is distorted by viewpoint variation. This paper presents a solution for vehicle logo recognition using Modest AdaBoost combined with radial Tchebichef moments. Firstly, a machine learning algorithm, based on Modest AdaBoost which mostly aims for better generalization capability and resistance to overfitting, was applied to locate the vehicle logo over the input image. After normalization with shape compacting, radial Tchebichef moments were then employed to recognize the vehicle logo. The solution was tested on images captured from Macao border crossing vehicles in outdoor conditions. Experimental results show that high accuracy and efficiency were achieved by the proposed method. It overcomes the problems of viewpoint variation and non-symmetric frontal license plate location, which are limitations of many previous methods for vehicle logo recognition.

Keywords: Vehicle logo recognition, Modest AdaBoost, Radial Tchebichef moments

1. Introduction

Vehicle identification system plays an important role for law enforcement agencies. Although license plate recognition can fulfill the objective, additional vehicle attributes can contribute in sense of detecting, for instance, vehicles with cloned license plates, from comparison between collected data and the original registration record.

Being one of the vehicle attributes, logo recognition is a vital yet challenging task since the vehicle logo is distorted by viewpoint variation as shown in Fig.1. In general, there are four basic forms of shape distortion: rotation, scaling, translation and skewing. In this paper, a solution is presented for vehicle logo recognition using Modest AdaBoost in conjunction with radial Tchebichef moments. Firstly, a machine learning algorithm, based on Modest AdaBoost which mostly aims for better generalization capability and resistance to overfitting, was applied to locate the vehicle logo over the input image. After normalization with shape compacting, radial Tchebichef moments was then employed to recognize the vehicle logo.

Fig. 1: Vehicle logo distorted by viewpoint variation

The rest of this paper is organized as follows. In Section 2, related work on vehicle logo recognition is surveyed. In Section 3, the detection method based on AdaBoost classifier is presented. In Section 4, the

[+] Corresponding author. Tel.: +853-2888-1122; fax: +853-2888-0022.
E-mail address: ktsam@customs.gov.mo

recognition algorithm using radial Tchebichef moments is discussed in details. In Section 5, experimental results are presented. At last the paper is concluded in Section 6.

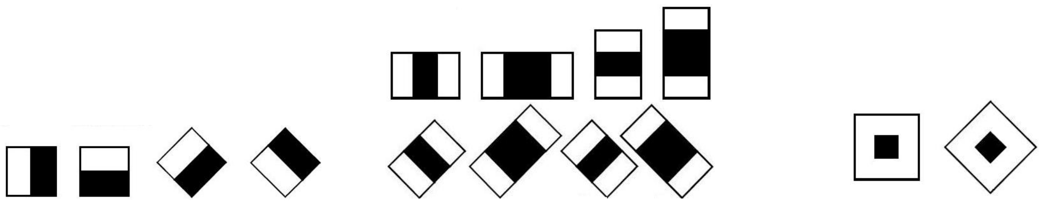
2. Related Work

Compared with other vehicle related classification, vehicle logo recognition is an area with fewer published papers. Many researchers make use of license plate location, followed by coarse-to-fine methods to identify the logo area using symmetry or edge statistics, to extract the logo area from the vehicle image. Logo recognition is then either performed through neural networks [1-2] or template matching using Scale Invariant Feature Transform (SIFT) [3]. Dlagnekov et al. [4] utilized SIFT features to identify vehicle manufacturer and model on rear-view vehicle images but the system performance did not meet real-time requirement. Psyllos et al. [5] proposed an algorithm using a SIFT-based enhanced matching scheme, which boosts the recognition accuracy compared with the standard SIFT-based feature-matching method. Wang et al. [6] presented a method for logo classification using template matching and edge orientation histograms. However, the above coarse-to-fine methods are not valid for vehicles having non-symmetric frontal license plate location. In the case where the vehicle logo has not been detected and segmented correctly, logo recognition will eventually fail.

3. Vehicle Logo Detection

3.1. Extended Haar-Like Features

For vehicle logo detection, simple but sufficient features must be extracted from logo images during learning procedure. The three types of features used by our system, i.e. edge, line and center-surround features, are shown in Fig.2. They are subset of the features proposed by Lienhart and Maydt [7], an extended set of Haar-like features which was originally introduced by Viola and Jones.



(a) Edge features (b) Line features (c) Center-surround features

Fig. 2: Features used for vehicle logo detection

Each simple feature is composed of at least two non-overlapping rectangular regions. Value of features can be calculated as the difference of the sum of the pixels of rectangular areas, and at any position and any scale in the same constant time. The computation of features can be given by:

$$F_j = \sum_{i=1}^{n} w_i \times RctSum(r_i) \tag{1}$$

where w_i denotes the weights, $RctSum(r_i)$ is the sum of the pixels of rectangular area r_i, and n denotes the number of rectangular areas.

3.2. Modest AdaBoost

The first practical boosting algorithm, called AdaBoost, was proposed by Freund and Schapire [8] in 1995. The basic idea of the Adaboost algorithm is as follows. Initially, all weights are set equally. It searches over a pool of weak classifiers to find one with the lowest classification error for the subsequent combination. Weak classifiers are only required to be slighly better than chance. In each round, the weights of incorrectly classified samples are increased so that more focus will be put on the misclassified samples on the next iteration.

Different variants of boosting are known such as Discrete AdaBoost, Real AdaBoost, Gentle AdaBoost and Modest AdaBoost. Discrete AdaBoost uses binary weak classifiers. Real AdaBoost is the generalization of a basic AdaBoost algorithm first introduced by Freund and Schapire, which should be treated as a basic fundamental boosting algorithm. Gentle AdaBoost is a more robust and stable version of real AdaBoost. As rule Gentle AdaBoost performs slighly better than Real AdaBoost on regular data but it is considerably better on noisy data, and much more resistant to outliers. Modest AdaBoost is employed in this paper because it outperforms Gentle AdaBoost in terms of generalization error and overfitting [9].

3.3. Training and Detection

A total of 500 vehicle images were used in the training procedure. The positive samples were obtained by manually cropped the vehicle logo area from the images. All samples were resized to 15x15 pixels. To generate negative samples, we extracted randomly 10 regions of 15x15 pixels from the rest of the image known not to contain vehicle logo, which resulted in 5,000 negative samples. We then applied boostrap operations where false positives obtained from test on the training data were used as additional negative samples for re-training the cascade. With the above samples, we trained 12 layers of classifier based on extended set of Haar-like features and Modest AdaBoost learning algorithm.

The detection of vehicle logo is done by sliding a sub-window across the image at multiple scales and locations. Scaling is achieved by changing the detector itself. The features can be evaluated at any scale at the same computational cost. The initial size of the detector is 15x15 and then, after each sliding over the whole image, the detector window is scaled at 1.2. Using the cascade classifier obtained in the previous training phase, it can decide whether an image region at certain location is classified as vehicle logo or non vehicle logo, as shown in Fig.3.

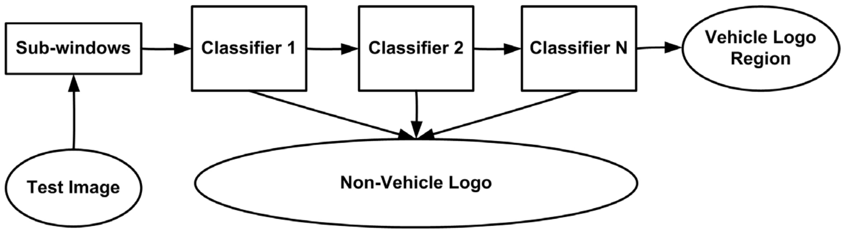


Fig. 3: Vehicle logo detection with cascade classifier

4. Vehicle Logo Recognition

4.1. Radial Tchebichef Moments

Moments have been extensively employed as invariant global features of images in pattern recognition because they are robust to noise and shape distortions such as objects with holes, partially-occluded objects, and complex objects consisting of multiple disconnected regions. Using moments as image descriptor was pioneered by Hu [10]. After that, numerous derived moments were consecutively introduced including Legendre moments, Zernike moments and Tchebichef moments. Since the discrete orthogonal Tchebichef polynomials satisfy perfectly the orthogonal property in the discrete domain of image coordinate space and the computation of Tchebichef moments does not require any discrete approximation, these properties make them superior to the conventional continuous orthogonal moments in terms of image representation capability [11]. In this study, we use radial Tchebichef moments, which was intoduced by Mukundan [12] and posses rotational invariance property, as shape descriptor of vehicle logos.

The scaled orthogonal Tchebichef polynomials for an image of size *N x N* are defined according to the following recursive relation:

$$
\begin{aligned}
&t_0(x) = 1;\\
&t_1(x) = (2x - N + 1)/N;\\
&t_p(x) = \frac{(2p-1)t_1(x)t_{p-1}(x) - (p-1)\left\{1 - \frac{(p-1)^2}{N^2}\right\}t_{p-2}(x)}{p}, \qquad p > 1.
\end{aligned}
\tag{2}
$$

and the squared-norm $\rho(p,n)$ is given by:

$$\rho(p,N)=\frac{N\left(1-\frac{1}{N^2}\right)\left(1-\frac{2^2}{N^2}\right)\cdots\left(1-\frac{p^2}{N^2}\right)}{2p+1}, \qquad p=0,1,\ldots,N-1. \tag{3}$$

The radial Tchebichef moment of order p and repetition q is defined as:

$$S_{pq}=\frac{1}{2\pi\,\rho(p,m)}\sum_{r=0}^{m-1}\sum_{\theta=0}^{2\pi}t_p(r)e^{-jq\theta}f(r,\theta) \tag{4}$$

where m denotes $(N/2)+1$, both r and θ take integer values. The mapping between (r,θ) and image coordinates (x,y) is given by:

$$x=\frac{rN}{2(m-1)}\cos(\theta)+\frac{N}{2};$$
$$y=\frac{rN}{2(m-1)}\sin(\theta)+\frac{N}{2}. \tag{5}$$

It can be shown that the magnitudes $|S_{pq}|$ are invariant to rotation.

4.2. Shape Normalization

An algorithm called shape compacting [13] is used to normalize the segmented vehicle logos before feature computation. For a given logo, we first compute its dispersion matrix. Then we shift the origin of the coordinate system to the center of the logo and rotate the coordinate system according to the eigenvectors of the dispersion matrix. At last, we change the scales of the two axes according to the eigenvalues. After normalization, the moment-based shape descriptor will effectively be invariant to scaling, translation and skewing in addition to rotation.

4.3. Classification

Different vehicle logos were enrolled with one image each, of which feature extraction and computation were done in advance. We compared test and registration samples with the euclidean distance measure. The identity of the test sample was then determined using the nearest neighbour rule.

5. Experimental Results

The solution described in this paper was tested on Macao border crossing vehicles captured from different viewpoints in outdoor conditions, consisting of 200 vehicle images at a resolution of 640 x 480 pixels, of which some have non-symmetric frontal license plate location.

In our experiment, among the 200 test images, 184 images were recognized successfully as shown in Tab.1 while 16 images were classified mistakenly, of which 4 were because of logo detection failure. The test system processes a 640 x 480 pixel image in 2.2 seconds with MatLab on Intel Core2Duo processor at 2.66GHz and 2GB RAM. The results show that an accurate recognition rate of 92% was obtained with the proposed solution.

6. Conclusion

This paper presents a solution for vehicle logo recognition using Modest AdaBoost and radial Tchebichef moments. A machine learning algorithm based on Modest AdaBoost with extended set of Haar-like features was applied to locate the vehicle logo over the input image. Thanks to the invariance property of radial Tchebichef moments, we have successfully applied it to vehicle logo recognition. The solution was tested on Macao border crossing vehicle images taken from different viewpoints in outdoor conditions. Experimental results show that high accuracy and efficiency were achieved by the proposed method. It overcomes the problems of viewpoint variation and non-symmetric frontal license plate location, which are limitations of many previous algorithms for vehicle logo recognition.

However, our prototype system is in its preliminary development. Further improvement is necessary to increase detection rate as well as the recognition rate. One possible approach is to study the alternative features instead of extended Haar-like features for detecting vehicle logos.

Tab. 1: Logo recognition rate

Manufacturer	Correct	Mistaken
Audi	20	0
BMW	16	4
Honda	19	1
KIA	17	3
Mazda	18	2
Mitsubishi	20	0
Nissan	17	3
Suzuki	18	2
Toyota	19	1
Volkswagen	20	0
Total	184	16

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