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Wavelet Moment and Improved Adaboost Application to Vehicle-logo Location

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***Abstract*—In this paper, we firstly describe improved Adaboost algorithm,and then introduce wavelet moment, which has rotation, shift, scale moment invariants and multi-resolution characteristic, and which can not only extract image local feature, but also can extract global feature. so it is more stronger to oppose noise. This paper proposes dynamic pyramid changing idea of detector scale. A cascade classifier was trained based on wavelet moment and improved Adaboost to detect Vehicle-logo. The experiment proved that it was real-time and had quite a high rate of detection.**

***Index Terms*—wavelet moment, moment invariants, Adaboost, cascade classifier, vehicle-logo**

I. INTRODUCTION

Specialists in the world pay close attention in the recognition of vehicle size and shape to coarsely classify vehicle. With the development and requirement of society, it is more important to accurately classify vehicle. vehicle-logo is the key information for accurately recognizing vehicle, the biggest difficulty is to locate vehicle-logo in natural image.

Detection image which is usually acquired from surrounding is easily influenced by illumination and the shake of camera and so on, so it is usual to result in the distortion of image zoom and(or) rotation. The methods based on energy enhancement[1][2] or Haar feature[3] likely lead to the missing of image information, for they only describe the location features. This paper select the wavelet moment proposed by Shen[4] which has rotation, shift, scale moment invariants and multi-resolution characteristic, a cascade classifier[3] was trained by improved Adaboost algorithm to achieve vehicle-logo detection.

II. IMPROVED ADABOOST ALGORITHM STEP AND ANALYSIS

A. Improved Adaboost algorithm step

(1) Given training sample images (x1, y1), (x2, y2), ... , (xn, yn), yi={0, 1}, i=1, 2, ... , n. 0 substitute negative sample, 1 substitute positive sample.

(2) Initialize weights, $\omega_1(i) = \{\frac{1}{2m}, \frac{1}{2l}\}$ for yi=0, 1 respectively, where m and l are the number of negative and positive samples respectively.

(3) Select T weak classifiers

For t=1 ,2, ... , T do

(a) Normalize the weights

$$\omega_t(i) = \frac{\omega_t(i)}{\sum_{j=1}^{n} \omega_t(j)} \tag{1}$$

so that ω_t is a probability distribution.

(b) For each feature j train a weak classifier $h_j(x)$ which is restricted to using a single feature.

$$h_j(x) = \begin{cases} 1 & f_j(x) \leq \theta_j^{min} \text{ or } f_j(x) \geq \theta_j^{max} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The weight error of each feature is evaluated with respect to

$$\varepsilon_j = \omega_t(i)|h_j(xi) - yi| \tag{3}$$

(c) Choose the classifier $h_t(x)$ with the lowest weight error ε_t. The weight sum of positive sample which is correctly classified is evaluated with respect to

$$R_t = \sum_{yi=1, h_j(xi)=1}^{n} \omega_t(i) \tag{4}$$

(d) update samples' weight

$$\omega_{t+1}(i) = \omega_t(i) \times \begin{cases} e^{-\alpha_t} & h_t(xi) = yi \\ e^{\alpha_t} & h_t(xi) \neq yi \end{cases} \tag{5}$$

where, $\alpha_t = \ln \frac{1-\varepsilon_t}{\varepsilon_t} + k * e^{R_t}$, k is a const.

(4) The final strong classifier is

$$h(x)=\begin{cases}1 & \sum_{t=1}^{T}\alpha_t h_t(x)\geq\frac{1}{2}\sum_{t=1}^{T}\alpha_t\\ 0 & \text{otherwise}\end{cases} \tag{6}$$

B. Improved Adaboost algorithm Analysis

Adaboost algorithm was proposed by Yoau Freund and Robert E.Schapire in 1995, it can not only select feature to achieve dimensionality reduction, but also can achieve classifier and target detection. It was successfully applied to face detection by Poul Voil and Michael J. Jones, the first real-time face detection system[3] in the world was developed in 2001.

The fatal disadvantage of traditional Adaboost algorithm is the training speed of weak classifier, see Step (3)-b). This paper adopt a fast training method which was proposed by WANG Han-Chuan etc.[5][6]. The time Complexity of traditional Adaboost is O(m×n) for training weak classifier, every feature value is used as forecast threshold, it is accurate to select threshold, but its generalization capabilities is bad. To improve generalization capabilities, space of feature value is divided into L equal parts,in other words, $\triangle j$=$(max(h_j(xi))-min(h_j(xi)))/L$, i=1, 2, ... , n, forecast threshold is evaluated with respect to $min(h_j(xi))+k*\triangle j$(k=1, 2, ... , L) respectively. The time Complexity of training weak classifier is only O((m+n)×L) in this way. We also discovered that the wavelet moment distribution of negative and positive vehicle-logo was bipolar by experiment, see Fig. 1.

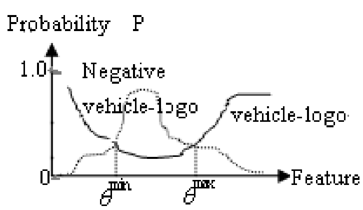

Fig. 1. The wavelet moment distribution of negative and positive vehicle-logo

In view of Fig. 1, this paper adopted the dual-threshold judgement[6] in weak classifier, see equ.(2), it can enhance the precision of detection, at the same time, it can also enhance the speed of training and location. Search process of dual-threshold following,

(1) Firstly, we get distribution curves of feature value of vehicle-logo and negative vehicle-logo which are signified by logo(x) and neglogo(x) respectively. x is feature value of wave moment.

(2) Calculate $logo(x)-neglogo(x)$ respectively for every x.

(3) x' is evaluated with respect to, $max(logo(x)-neglogo(x))$.

(4) θ^{min}, θ^{max} are searched from both side of x' respectively, in other words, $logo(\theta^{min})-neglogo(\theta^{min})$=0 and $logo(\theta^{max})-neglogo(\theta^{max})$=0

In fact, a weak classifier of double-threshold corresponds to two single-threshold weak classifier, so a strong classifier can be constructed by less weak classifier so that the training speed is improved. The accurate of recognition is also improved when it is used to object detection or classifier. It is specially applicable to the questions that bear a resemblance to Fig.1.

Negative and positive samples are treated equally and the sample weight update is based on the smallest weight error in traditional Adaboost algorithm. Negative and positive vehicle-logo are asymmetric, in case, there are excessive representative or rare negative vehicle-logo in training samples, it will result in adapting to negative sample in excess. To attach importance in positive sample and enhance the correct detection rate of positive sample, this paper adopt diffident impact factor α_t[7] of weak classifier, the value is more higher, it shows that the classification capacity of classifier is more stronger.

III. WAVELET MOMENT

Wavelet moment has not only rotation, shift, scale moment invariants, but also has multi-resolution characteristic of wavelet. It is not sensitive to noise, it can extract image local feature and global feature so that it can describe the fine information of image. So this paper adopts wavelet moment.

Wavelet basic function set, see equ.(7).

$$\psi^{a,b}=\frac{1}{\sqrt{a}}\psi(\frac{r-b}{a}) \tag{7}$$

Where, a∈R^+ is phase factor, b∈R is displacement. In the experiment, it is the form of binary wavelet,a=1/2^m,b=n*a, m=0,1,2,3,4. n=0,1,2,3,...,2^m-1.

So wavelet basic function set, see equ.(8).

$$\psi_{m,n}(r)=2^{\frac{m}{2}}\psi(2^m r-n) \tag{8}$$

Wavelet moment is evaluated with respect to

$$\|F_{m,n,q}\|=\|\int s_q(r)\psi_{m,n}(r)rdr\| \tag{9}$$

where, $s_q(r)=\int f(r,\theta)e^{jq\theta}d\theta$

Discrete wavelet moment is evaluated with respect to

$$\|F_{m,n,q}\|=\sum_{r=0}^{1}\sum_{\theta=0}^{2\pi}f(r,\theta)\psi_{m,n}(r)e^{jq\theta}r \tag{10}$$

Two adopted wavelet basic functions following:

(1) Shannon function

$$\psi(r)=\frac{\sin(\pi r/2)}{\pi r/2}\cos(3\pi r/2) \tag{11}$$

(2) 3rd B-spline function

$$\begin{aligned}\psi(r) &= \frac{4\alpha^{n+1}}{\sqrt{2\pi(n+1)}}\sigma_w\cos(2\pi f_0(2\pi-1))\\ &\quad\times\exp(-\frac{(2r-1)^2}{2\sigma_w^2(n+1)})\end{aligned} \tag{12}$$

where, n=3, α=0.677066, f_0=0.409177, σ_w^2=0.561145.

IV. Experiment and Analysis

In this paper, the study is limited to ten Categories of vehicles, they are Volkswagen, Honda Motor, Logo car, Kia Motors, Mazda Motor, Hyundai Motor, Mercedes-Benz, Lexus car Mercedes-Benz, and Chery Automobile respectively.

There are 1000 vehicle-logo and negative vehicle-logo respectively in training samples.

Vehicles-logo samples were cut along the external rectangular of vehicles-logo in vehicle image, negative vehicle-logo samples were randomly cut in vehicle image. All samples was normalized to gray image of 72 by 48 pixels after they were in histogram equalization. Because the size of vehicle-logo is not unified, this paper adopted pyramid idea[8][9][10] to detect and locate vehicle-logo. The detector window was zoomed by pyramid idea so that vehicle-logo can be even accurately located.The factor of zoom was 1.15 by 1.13. Dynamic changing idea of detector scale based on pyramid method, see Fig. 2.

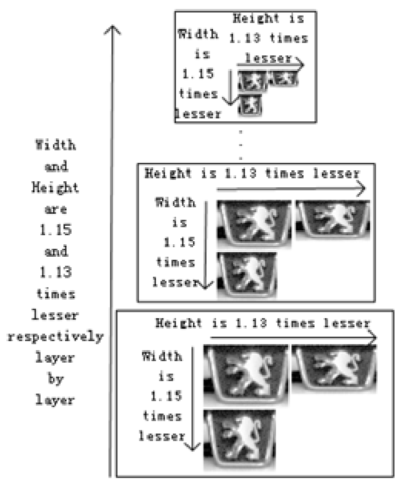

Fig. 2. Dynamic pyramid changing idea of detector scale. There is approximately regarded as a pyramid respectively along every arrowhead. The zoom scale of detector(detection window) have already been signed near arrowhead. Width or/and height is/are 1.15 or/and 1.13 times lesser respectively layer by layer.

To achieve real-time detection and high detection rate, it is prerequisite to train a cascade classifier based on Adaboost algorithm. The negative set for training subsequent layers is obtained by collecting all false detections found by running the current detector on a set of images which do not contain any instances of the object, the vehicle-logo set in each layer is always initial. Theory shows that the construction complexity of detector is in the control of feature dimension, the more higher that feature demotion, the more complex that the construction of detector, the more higher that detection rate, but the more lower that detection speed.

The principle of training cascade classifier following:

The construction of subsequent layers are more and more complex(the feature dimension is more higher layer by layer). At the same time, it requests that the correct rate of negative

TABLE I
The results of cascade detector

Detector	Feature Dimension	Vehicle-logo Correct Detection Rate (percent)	Negative Vehicle-logo Correct Detection Rate (percent)
Layer1	4	100.00	60.14
Layer2	11	99.89	62.19
Layer3	19	99.64	67.35
Layer4	24	99.73	72.43
Layer5	29	99.52	63.20
Layer6	43	98.94	78.19
Cascade	110	97.73	99.8942

vehicle-logo is not less than 60 percent and the correct rate of vehicle-logo must be 100 percent in the first layer, the most of negative vehicle region will be removed in the first layer so that the region scanned by subsequent layers is greatly reduced, so the detection rate is enhanced. Because it is increasingly difficult to distinguish between vehicle-logo and negative vehicle-logo in the subsequent layers, the correct detection rate of vehicle-logo can be appropriately reduced.

Experiment showed that six layers had already been suitable. See Fig. 3, the construction of cascade detector.

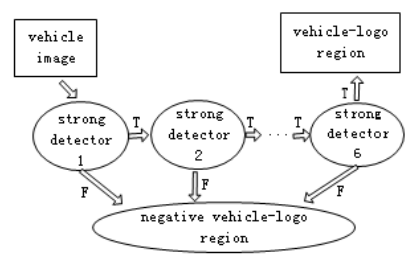

Fig. 3. Schematic depiction of a the detection cascade. The region detected negative vehicle-logo (signed 'F') is excluded and the region detected vehicle-logo(signed 'T') are put into subsequent detector. The region which can finally pass through the sixth detector is the vehicle-logo that is expected.

According to wavelet moment, there are a total of 186 features. Finally, the results of every layer, see TABLE I.

1000 testing samples are color images of 768 by 576 pixels, they were grayed before they were detected. The detector is also scanned across all testing image. Subsequent location was obtained by shifting the window $\triangle$ pixels. The choice of $\triangle$ affects the speed of the detection as well as detection accuracy. Experiment showed that $\triangle$ equaled 2 was suitable. see Figure 4, experiment results.

V. Conclusion

Figure 4 shows that vehicle-logo region finally detected is not accurately coincide with external rectangular of vehicle-logo and experiment also shows that there are less region which were undetected or were not correctly detected. The first reason

(a) (b)

Fig. 4. The results of vehicle-logo detection

is that the number of training sample is not enough or the representativeness of training samples is not greatly strong, the second reason is that vehicle-logo size and texture are not unified, it is extremely difficult to accurately choose the size of shifting window(detector) or the zoom proportion of pyramid. But experiments proved that it was very high real-value to further study the application of wavelet moment and Adaboost algorithm to target detection or recognition.

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