An Improved Algorithm Based on AdaBoost for Vehicle Recognition

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***Abstract*—An Improved algorithm based on AdaBoost is proposed to solve the problem of much time consumed for training AdaBoost classifier as well as the problem of performance and storage space based on SVM (Support Vector Machines) and NN (Neural Networks) classifiers in vehicle recognition. Experimental results demonstrate that the proposed approach has better performance than the traditional methods and has less time comsuming in training process than traditional AdaBoost algorithm and shows promising perspective.**

Keywords-vehicle recognition; machine learning; AdaBoost algorithm; haar-like feature

I. INTRODUCTION

Machine learning is becoming an area of active research for simple operation, good performance and robustness in vision based vehicle detection. In [1] [2] PCA was used to extract features and SVM/NN was for classification. Goerick et al. [3] used a method called Local Orientation Coding (LOC) to extract edge information. The histogram of LOC within the area of interest was then fed to a NN for classification. Papageorgiou et al. [4] detected vehicles and pedestrians with over-complete wavelet features and SVM. Schneiderman et al. [5] detected vehicles using the truncated wavelet coefficients for feature extraction and SVM for classification. Sun et al. [6][7] utilized Gabor filters to extract moment features or combined Gabor features with wavelet features and then preformed SVM for classification. [8][9] introduced a method with Adaboost classifier for vehicle recognition.All above methods achived good effects in some aspect, but they have their own weakness in classification. For the method based on SVM or neuronal network classifier: For one,feature extraction is time consumed, and can't represent the vehicle image effectively,and the ability needs to be improved. For another, using RBF-SVM although do well in classification, the optimal parameters selection is complicated.While NN classifier overrely on expert knowledge and easy to fall in local minimum. And there exists time consuming problem while training AdaBoost classifier. Based on the success in human face rocognition by using Haar-like feature and AdaBoost classifier[10][11][12], an algorithm based on haar-like features and improved AdaBoost classifier is proposed to solve the time consuming and ability problem. Experimental results have shown that the proposed approach has better performance than traditional methods.

II. ALGORITHM DESCRIPTION

In this section, the traditional AdaBoost algorithm is firstly analysed, then an improved algothm based on AdaBoost is proposed to deal with the problem of much time consumed and the performance needs to be improved.

A. *AdaBoost Classifier*

AdaBoost algorithm is proposed by Freund & Schapire[13] as a self-adapted Boost algorithm, it shows good performance compare to SVM and NN algorithms.Its principle is to give a same initial weights to all samples. In every training iteration a weak classifier (better than random guess) with the least error is constructed, then the old weights are updated, that is, the weights of the samples which being classified incorrectly are increased, or else, the weights will be decreased. Final the classification error will be near to zero after several iterations, and the AdaBoost classifier can be generated by these weak classifiers and being applied to vehicle detection. However, there are two shortages in this algorithm: first, there are too many candidate classification locations while selecting the best location with the least error, they need much computing resources and lead to time consuming. Second, the construction process of weak classifiers is not effective. So an improved AdaBoost algorithm is proposed to deal with these problems.

B. *Improved AdaBoost algorithm*

The improved AdaBoost algorithm includes two steps : First, generating candidate classification location set corresponding to every haar-like feature by combining; Second, constructing weak classifier with least error from the candidate classification location set. These two steps will be introduced in the following respectively.

For explaining conveniently, assume matrix A denotes the set of all haar-like feature values computed on training samples according to the literatures [10][11][12].

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$$A=\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{21} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} \quad (1)$$

n denotes the number of training samples, m is number of the haar-like feature getting from a 32 × 32 grayscale image, $a_{ij}\,(i\in\{1,2,\cdots,m\}, j\in\{1,2,\cdots,n\})$ denotes the i th haar-like feature on the j th sample.

Take the example of constructing the weak classifier from the i th haar-like feature on samples S(corresponding to i th row on A), Vec is the value vector, w_i is the weight of x_i samples, y_i ($y_i\in\{-1,+1\}$) denotes the label (vehicle or non-vehicle) of this sample. $Vec[i]$ is the feature value on sample x_i.

(1) Sorting the eigenvector. Sorting all elements in Vec by ascending to get new vector $VecSort$, and Lab denotes the label vector of $VecSort$.

(2)Obtaining candidate classification location set L. In traditional method, it generates L only consider the feature value, so there are too many candidate classification locations to be considered while select a classification location with the least classification error. An improved method is proposed to generate L by combining feature values to the labels corresponding to the samples. The method is as follows: observe on all changed location-pairs with different labels from left to right, check wether its feature values are same,if not,put the first location of the pairs into L,otherwise, look up a different feature value from left, judge wether the location of the feature value belongs to L, if not,add this location to L,then look up the first feature value different from the same feature value from right.The following steps are similar to the operation from left. Finally a candidate classification location set can be obtained: $L=\{l_1,l_2,\cdots,l_k\}$.

(3)Constructing weak classifier. select a classification location with the least classification error from L obtained by step (2).The method is as follows: $\forall l_s\in L$, l_s is the selected classification location, then the classification results of these samples corresponding to $l_1,\cdots,l_s$ are same, make it $\lambda(\lambda\in\{-1,+1\})$, and the results of those samples corresponding to $l_{s+1},\cdots,l_n$ are $-\lambda$, AdaBoost error compute formula can be changed as:

$$\varepsilon_i=\frac{1}{4}\sum_{j=1}^{n}w_j\left(f_j-y_j\right)^2 \quad (2)$$

Where j is subscript of $VecSort$, n is the number of samples, w_j is the weight of the j th sample, $f_j\in\{-1,+1\}$ is the classification result of j th sample, $y_j\in\{-1,+1\}$ is the real label of j th sample. So

$$\begin{aligned}\varepsilon_i&=\frac{1}{4}(\sum_{j=1}^{n}w_j\left(f_j-y_j\right)^2)\\&=\frac{1}{4}(\sum_{j=1}^{l_s}w_j\left(\lambda-y_j\right)^2+\sum_{j=l_s+1}^{n}w_j\left(-\lambda-y_j\right)^2)\\&=\frac{1}{4}\sum_{j=1}^{n}w_j\left(\lambda^2+y_j^2\right)^2+\frac{1}{2}\lambda\left(\sum_{j=l_s+1}^{n}w_jy_j-\sum_{j=1}^{l_s}w_jy_j\right)\end{aligned} \quad (3)$$

As w_j and y_j have been known, so $\sum_{j=1}^{n}w_jy_j$ is also known. According to

$$\sum_{j=1}^{n}w_jy_j=\sum_{j=1}^{l_s}w_jy_j+\sum_{j=l_s+1}^{n}w_jy_j \quad (4)$$

and

$$\lambda^2=y_j^2=1,\sum_{j=1}^{n}w_j=1 \quad (5)$$

It can be concluded

$$\begin{aligned}\varepsilon_i&=\frac{1}{4}\sum_{j=1}^{n}w_j\left(\lambda^2+y_j^2\right)+\frac{1}{2}\lambda\left(\sum_{j=1}^{n}w_jy_j-2\sum_{j=1}^{l_s}w_jy_j\right)\\&=\frac{1}{2}+\frac{1}{2}\lambda\left(\sum_{j=1}^{n}w_jy_j-2\sum_{j=1}^{l_s}w_jy_j\right)\end{aligned} \quad (6)$$

Let's discuss two different label for λ.

(a)When $\lambda=1$, (6) turns to

$$\varepsilon_i=\frac{1}{2}+\frac{1}{2}\left(\sum_{j=1}^{n}w_jy_j-2\sum_{j=1}^{l_s}w_jy_j\right) \quad (7)$$

So comupte $\min(\varepsilon_i)$ means to comupte $\max(\sum_{j=1}^{l_s}w_jy_j)$.

As $w_j>0$, $\sum_{j=1}^{l_s}w_jy_j$ gets the maximum if and only if $y_{l_s}=1$ and $y_{l_s+1}=-1$. Then some locations meet to this condition can be found from $L=\{l_1,l_2,\cdots,l_k\}$, assume find p locations, and $\tau1=\{s_1,s_2,\cdots,s_p\}\subseteq L$ denotes these locations, lets

$$e_1 = \sum_{j=1}^{s_1} w_j y_j \tag{8}$$

$$e_r = e_{r-1} + \sum_{j=s_{r-1}+1}^{s_r} w_j y_j , r = 2,3,\cdots, p \tag{9}$$

Then:

$$\max(\sum_{j=1}^{l_s} w_j y_j) = \max\{e_1, e_2, \cdots, e_p\} \tag{10}$$

(b)When $\lambda = -1$, (6) turns to

$$\varepsilon_i = \frac{1}{2} - \frac{1}{2}\left(\sum_{j=1}^{n} w_j y_j - 2\sum_{j=1}^{l_s} w_j y_j\right) \tag{11}$$

So comupte $\min(\varepsilon_i)$ means to comupte $\min(\sum_{j=1}^{l_s} w_j y_j)$. $\sum_{j=1}^{l_s} w_j y_j$ gets the minimum if and only if $y_{l_s} = -1$ and $y_{l_s+1} = 1$. Then some locations meet to this condition can be found from $L = \{l_1, l_2, \cdots, l_k\}$, assume find q locations, and $\tau 2 = \{s_1, s_2, \cdots, s_q\} \subseteq L$ denotes these locations, similar to (8)(9), it can be concluded

$$\min(\sum_{j=1}^{l_s} w_j y_j) = \min\{e_1, e_2, \cdots, e_q\} \tag{12}$$

Assume the least errors are ε_1 and ε_{-1} when $\lambda = 1$ and $\lambda = -1$ respectively, then the classification direction symbol and error corresponding to the t th iteration and i th haar-like feature are:

$$p_i = \begin{cases} 1, \lambda = 1 \\ -1, \lambda = -1 \end{cases} \qquad \Omega_i = \min(\varepsilon_1, \varepsilon_{-1}) \tag{13}$$

Lets $\tau \in L$ denotes the location with least classification error,then compute classification threshold with traditional method:

$$\theta_i = \frac{VecSort[\tau] + VecSort[\min\{(\tau+1), n\}]}{2} \tag{14}$$

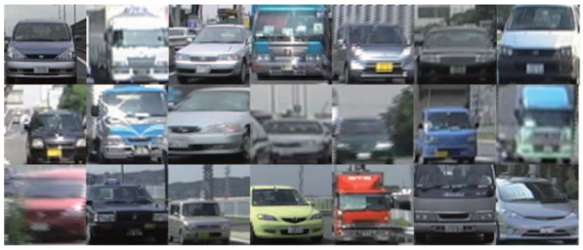
Similarly to above method, the classification direction symbols,errors and classification thresholds corresponding to the t th iteration and the other haar-like features can be obtained. So the all classification direction symbols,errors and classification thresholds for the t th iteration are:

$$P = \{p_1, p_2, \cdots, p_j, \cdots\} \qquad \Omega = \{\Omega_1, \Omega_2, \cdots, \Omega_j, \cdots\} \qquad \theta = \{\theta_1, \theta_2, \cdots, \theta_j, \cdots\} \tag{15}$$

Finally, according to the define of AdaBoost algorithm, combining all constructed weak classifiers to a strong classifier for future vehicle existence detection.

III. EXPERIMENT RESULTS AND ANLYSIS

In order to compare the performance of several monocular-vision based recognition methods for rear-vehicle static images, we adopt our method as well as the methods in the literature. The simulating environment is Matlab 7.1. ROIs were extracted based on shadow underneath the vehicles and aspect ratio [15][16]. We collected a total of 17,647 samples for training which include 8774 vehicle sub-images (positive samples) and 8873 non-vehicle sub-images (negative samples). There are 6040 testing samples, including 4266 vehicle samples and 1774 non-vehicles. Fig.1 shows the training examples of vehicle and non-vehicle images.



(a)

(b)

Fig.1 Examples of training samples. (a)vehicle samples (b) non-vehicle samples

To evaluate the performance of the approaches, the true positive rate (or vehicle detection) t_p and false positive rate f_p were recorded. They are defined as follows.

$$t_p = \frac{N_{TP}}{N_{TP} + N_{FN}}, \quad f_p = \frac{N_{FP}}{N_{FP} + N_{TN}} \tag{16}$$

Where N_{TP}, N_{FP}, N_{TN} and N_{FN} are the number of objects identified as true positives, false positives, true negatives and false negatives respectively.

The evaluation result of 6 recognition methods is listed in Table I. We can see that the proposed algorithm has the highest positive rate and the lowest false positive rate, and the storage space size which the proposed algorithm needed is just more than that of the algrithm based on cascading AdaBoost classifiers, and much less than that of the other four recognition methods. Although the algrithm based on cascading AdaBoost classifiers has obtained successful application in human face recognition, but it can't meet the requirements of real-time and low false positive rate in vehicle detection system.

From TABLE II, the training time consumed by the proposed approach is decreased about 13.3% than traditional AdaBoost.

Finally, apply the proposed approch to the road object detection system based on monocular-vision, the average recognition ratio reached 98.20%, false alarm rate is 1.44%, the average detecting time is about 32ms/frame.

TABLE I RESULTS OF 6 RECOGNITION METHODS

Recognition methods	t_p	f_p	**Model Size （KB）**
PCA +SVM[1] [2]	96.95%	6.14%	3,233
Gabor +SVM [6]	96.13%	6.54%	3,458
Wavelet +SVM [5]	96.34%	6.43%	11,954
Wavele+ Gabor +SVM [7]	96.81%	5.64%	21,464
Haar-like feature+CascadeA daBoost [12]	97.09%	13.19%	14
Haar-like feature+Proposed method	97.43%	4.33%	244

TABLE II TRAINING TIME OF 2 ALGORITHMS

Algorithm	**Training time (hours)**
Traditional AdaBoost	116.59
improved method	101.08

IV. CONCLUSION

The paper proposed an improved algorithm based on AdaBoost algorithm for vehicle recognition.The improved algorithm includes two aspects: first, an improved method is proposed to produce candidate classification locations, that is, combining feature value and the label of every samples to generate candidate classification locations, this method can greatly decrease the number of candidate classification locations than traditional method. Second, an improved method is proposed to speed up the acquisition of weak classifier. Experimental results have shown that the proposed approach has better performance than traditional methods in vehicle recognition.

In future, we will do further research on different AdaBoost versions such as Modest AdaBoost, Gentle AdaBoost etc. in this field to improve the performance of the detection system.

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