Vehicle Identification Based on Haar-Like Compression Feature

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Abstract: The traditional haar-like feature extraction algorithm is a method based on integral image to help extract image features with different feature modules. However, there are many problems with this kind of method: there are too many features extracted, there is redundant information and the expression of the target information is not enough. In view of these shortcomings, the paper adopts the improved active appearance model (AAM) to extract the image features, and compresses the multidimensional feature information by using the compression sampling method. The recognition classification uses the Adaboost classifier training method to the compressed feature space. Experiments show that the training time required by the classifier is reduced by compressing the extracted eigenvalues, and the recognition performance is also better than the traditional algorithm.

Key Words: haar-like features, AAM, Adaboost, vehicle recognition

1 Introduction

In the field of pattern recognition, due to its outstanding identification performance and easy operation, machine learning method is widely applied in intelligent transportation systems, object recognition, etc. So far, studies on this method are mainly focused on object recognition and non-object recognition. References [1] and [2] introduced an improved ASM(Active Shape Model) algorithm that realizes feature extraction, vehicle identification and gray image feature extraction based on PCA. In reference [3], features of Interceptive Wavelet Coefficients are combined with SVM for vehicle recognition. The authors of references [4] and [5] proposed a multi-scale Gabor filter bank which can increase the stability of the extracted features and keep the scales invariant. References [6] and [7] studied the application of the cascade AdaBoost classifiers and haar features in pedestrian detection and vibration damper recognition.

All of these above-mentioned algorithms have good performance in terms of object recognition, but there still exist some deficiencies:

(1) Recognition training based on classifiers like SVM or neural networks is faced with many problems, for example, the feature extraction process can be really complex and time-consuming; hence, it needs to be further improved.

(2) In regard to the Adaboost classifier, the real time performance is better and recognition rate is higher; however, it requires a huge number of positive and negative samples that lead to a large amount of computations in the training process.

Given that the combination of Haar-like features with Adaboost classifiers have achieved satisfactory results in face recognition, this paper puts forwards a type of algorithm based on compressed haar-like features for vehicle recognition. The structure chart of this algorithm is shown in Figure 1.

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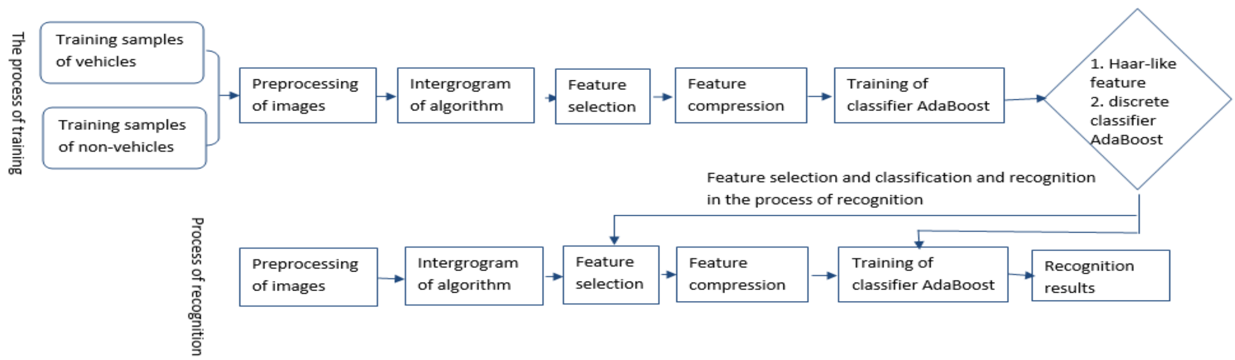

Fig 1 Structure chart of the algorithm

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This paper has improved on the traditional feature extraction method. Through the improved algorithm, the number of features in the feature space is deceased to a certain extent, which results in less training time and thereby reducing the time complexity of the traditional algorithm. This improved algorithm is applied in vehicle recognition in this paper, which can efficiently increase the accuracy rate and decrease the false alarm rate compared with traditional algorithms.

2Haar Feature Extraction Algorithm and Its Improvement

The theory of Compressive Sensing(CS)[9] points out that when signals are sparse, a sparse matrix can be adopted to extract features with a discrete sampling method; afterwards, a nonlinear image reconstruction algorithm can be used to reconstruct the signals. Given the enormous quantity of the extracted haar-like features in this study and their lack of features of the target information, it is possible to choose a measurement matrix that is applicable to sparse signals but irrelevant to the sparse space of the extracted haar-like features, so as to eliminate the redundant information in the extracted haar-like features.

The compressed sampling process is displayed in Figure 2: when signal X is compressed with measurement matrix A, we get the compressed signal Y. Suppose X is the feature space after haar-like features are extracted and A is a M×N sparse matrix (M rows; N columns); Y=A×X, Y is called the measured signal.

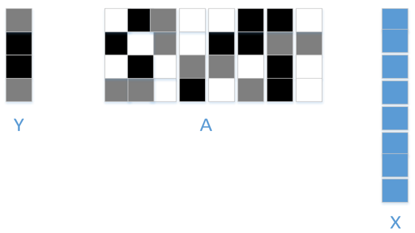


Fig 2 Compressive sensing process

Due to the huge number of the extracted haar-like features and the presence of redundant information, when a small number of features are missing, a few codes can be used to refer to their feature space. Therefore, when a spare matrix that is in consistent with the Johnson-Lindenstrauss[10] theorem is used to measure the signals, not only is error of the reconstruction of X minimized, but the information of the original signal is also kept intact.

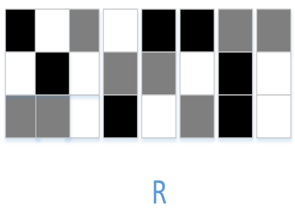
2.1 Feature Extraction and Compression

Measurement matrices can be classified into two kinds: random ones and deterministic ones. Normally, measurement matrices include Gaussian random measurement matrix and Bernoulli matrix. For the former one, the matrix element rij∈N(0～1)[11]. If the matrix is not sparse and matrix series is relatively large, the cost of storage and calculation of the measurement matrix would be very high. In order to avoid the high cost, a very sparse matrix is adopted in this paper. The definition of its element is shown by formula (1):

$$r_{ij} = \frac{1}{\sqrt{s}} \times \begin{cases} 1 & (p = \frac{1}{2s}) \\ 0 & (p = 1 - \frac{1}{s}) \\ -1 & (p = \frac{1}{2s}) \end{cases} \qquad (1)$$

During the feature extraction process, the extracted features' description of the object can directly affect the accuracy rate of the recognition. When most of the elements are "0"in the measurement matrix, a lot of calculations can be omitted and simplified, thus enhancing the performance of the algorithm. Haar features can be viewed as a set of pixel sums of various rectangular frames. In the traditional haar feature extraction algorithm, black and white rectangular frames are used to form different templates for feature extraction. The value of the haar-like features equals the difference value between the pixel sums of different rectangular frames[12]. Haar-like features are an extension of the concept of Haar features.

Traditional feature extraction algorithm uses the compressed domain to construct AAM of the extracted features. When calculating the feature values, this algorithm only considers the difference of different pixel sums of the rectangular frames. In the formed feature space, the dimensionality of the feature vector is very high, thus affecting the performance of the algorithm. In this paper, the compressive sampling method is adopted, a proper measurement matrix is selected so as to reduce the dimensionality of the feature space. The dimensionality reduction process is displayed in Figure 3:



$$\times \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \\ x_m \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \\ v_m \end{bmatrix}$$

Fig 3 Feature compression

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R (M rows; N columns) is a measurement matrix; "M" refers to the the total sum of different features in different rectangular frames; $(x_1, x_2, x_3,\ldots, x_m)^T$ is the original high-dimensional feature space. By multiplying the sparse measurement matrix with the original high-dimensional feature space, we get a low-dimensional feature space $v=\{v_1, v_2, v_3,\ldots, v_n\}^T$.

2.2 The Improvement of the Haar Feature Extraction Algorithm

The selection of the AAM directly influences the amount and quality of the extracted features. In the traditional haar-like feature extraction process, rectangular features are randomly selected among all samples. Although this method can guarantee the randomness of the rectangular features, the samples selected under this random fashion may not be able to appropriately express thefeatures of the object to be identified, which will cause inaccurate recognition. This paper adopts a new method to select the rectangular frames: sample images are divided into differentareas; then rectangular frames are selected respectively in differentareas. As seen in Figure 4, the gray rectangular frame is the selected area. By dividing the sample images into different sections, we can not only guarantee the randomness of the rectangular frames and, at the same time, ensure that different information of the sample images is selected. But it is worth noting that when selecting the gray area, there should be an overlapped area so as toguarantee that random selection will not result in localized expression of the extracted features.

Within the gray section, randomly select a rectangular frame which is similar to the one used to extract haar-like features. The selected area is colored in black, as seen in Figure 4. The position and size of the black rectangular frames should be restricted within the gray area. A computation method similar to the haar-like feature extraction algorithm is then adopted: section 2 and section 3 in Figure 4 are viewed as black rectangular frames while section 1 is the white one; let the pixel sum of the black rectangles in section 2 and 3 minus that of the section 1, the difference is the features generated by the improved AAM, which are regarded as a one-dimensional vector in the feature space. i.e. $F=f_3+f_2-2f_1$; the Feature Space={F1, F2, F3, …, Fm}. The feature space has large series and high dimensionality; if it were applied in object recognition, it would result in a curse of dimensionality. Here in this paper, the aforementioned compressive sampling theory is combined with a properly selected sparse measurement matrix to reduce the dimensionality which, according to the theory, can keep the majority of feature information in the images intact.

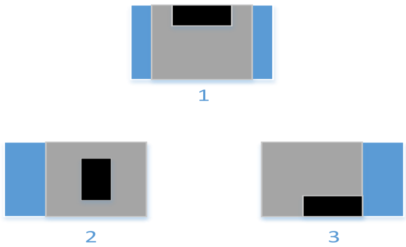
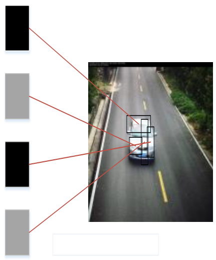


Fig 4 Image regional division

As seen in the sparse measurement matrix in Figure 3, the black, gray and white rectangular frames respectively refer to the feature coefficient –1, +1 and 0. The process of feature extraction is shown in Figure 5:



$$\left.\begin{array}{l} x_1 \times \omega_1 \\ x_2 \times \omega_2 \\ x_3 \times \omega_3 \\ x_4 \times \omega_4 \end{array}\right\} v_1 = \sum_{i=4}^{4} x_i \times \omega_i$$

Fig 5 Feature extraction process

From the feature space of the input image samples, randomly select S rectangular frames. As seen in Figure 5, the left is non-zero elements in sparse measurement matrix. Here, 4 non-zero elements are selected as examples. Their corresponding feature values are X_1,X_2,X_3andX_4, respectively and the corresponding weightsareω_1, ω_2, ω_3 and ω_4, among which $\omega i \in\{$ s, 0, +s $\}$, i={1,2,3,4}. The generated feature value is the sum of the products of the selected rectangular features multiplying their corresponding weights, which is seen in formula (2):

$$v_1 = \sum_{i=1}^{4} x_i \times \omega_i \qquad (2)$$

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With the same method, we get n features from the other feature vectors in the feature space and the feature space generated by the improved AAM: v ={v1, v2, v3,…, vn}^{T}. In this way, with the compressive sampling method, the high dimensionality of the feature spaceis reduced; since the features extracted with the new AAM are very sparse, it is still possible to reconstruct the signal after compression with little information missing.

3 The Recognition Process Based on AdaBoost Algorithm

Many kinds of classifiers are available in the field of image recognition, for example, decision tree and selection tree classifiers, evidence classifiers, SVM, etc. With comprehensive consideration of the calculating cost and the difficulty level of algorithm realization in the designing process, AdaBoost algorithm[13] is adopted in this paper to realize the classification of features. For any input sample, after processed by the improved haar-like feature extraction algorithm, the generated feature space can be indicated as F={F_1, F_2, F_3........F_n}^{T}. Here the training process of the AdaBoost algorithm is only briefly introduced. The generation process of the strong and weak classifiers is described as follows:

(1) Determine the initial weight w_1,i= D(i);

(2) For t =1.2.3......T,

1. Normalize the initial weight:

$$q_{t.i} = \frac{w_{t,i}}{\sum_{j-1}^{n} w_{t,j}}$$

2. For each feature vector in the feature space, train a weak classifier h(x, f, p, q), calculate the error rate β_f through weighted summation:

$$\beta_f = \sum_i q_i \left| h(x_i, f, p, \theta) - y_i \right|$$

3. Classifiers with the lowest error rate perform the best.

Based on this principle, select the best classifier $h_t(x)$:

$$\beta_t = \min_{f,\ p,\ \theta} \sum q_i \left| h(x_i, f, p, \theta) - y \right|$$
$$= \sum_i q_i \left| h(x_i, f_t, p_t, \theta_t) - y_i \right|$$
$$h_t(x) = h(x, f_t, p_t, \theta_t)$$

4. Adjust the weight based on the selected weak classifier:

$$w_{t+1,i} = w_{t,i} \alpha_t^{1-e_i}$$

When $e_i = 0$, it suggests that the corresponding feature X_i is correctly classified; when e_i= 1, it is the other way around.

$$\alpha_t = \frac{\beta_t}{1-\beta_t}$$

(3) Eventually, the strong classifier is generated:

$$C(X) = \begin{cases} 0 & \\ 1 & \sum_{t=1}^{T} \mu_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \mu_t \end{cases}$$

$$\mu_t = \log \frac{1}{\alpha_t}$$

The whole object recognition process is composed of three steps: image pre-processing (the main purpose to obtain the integrogram of the images); extraction of Haar features with the improved AAM and the compressive sampling of these features; classification and recognition of the features in the compressed feature space with the selected AdaBoost classifier. Through the calculation of the integrogram, computation in the feature extraction process is greatly reduced. The extracted features are used to form feature vectors and classifiers are used for object recognition of the images to be detected.

4 Experimental Result

In this part, the algorithm in this paper is applied in vehicle recognition for static images of these vehicles. The experimental data were obtained from the project of road tunnels monitoring system on Bayi Road in Wuhan. All of the collected image samples are chosen from the video clips in this monitoring system and most of them are pictures of front the vehicles. From all of these images, 13647 are selected as training samples, among which 6873 are positive samples and 6774 are negative samples; 5040 are selected as test samples, including 3766 vehicle samples and 1274 non-vehicle samples. In order to ensure the

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diversity of the samples, various types of vehicle are covered in the vehicle samples, including compact cars, large trucks, etc. For non-vehicle samples, image samples which may cause interference are selected, for example, street lamps, road pavement, etc.

Fig 6 positive samples

Fig 7 negative samples

In the testing process of the experiment, the performance of the algorithm is evaluated by the accuracy rate a_p and the false alarm rate b_p of the detection result. The two indexes are defined in formula (3):

$$a_p = \frac{N_{AP}}{N_{AP}+N_{BN}} \qquad b_p = \frac{N_{BP}}{N_{BP}+N_{TN}} \qquad (3)$$

In this formula, NAP, NBP, NTN and NBN respectively refer to the number of vehicles that are correctly detected by the algorithm, the number of non-vehicles that are recognized as vehicles, the number of non-vehicles that are detected correctly and the number of vehicles that are recognized as non-vehicles in the test samples. The following 2 experiments are conducted:

Experiment 1: The performance of the improved algorithm is compared with the traditional algorithm in terms of time complexity. The experiment result is displayed in Form 1:

Form 1: Comparison of results before and after feature compression

Algorithm	Training hours(H)
Traditional algorithm	113.9
Improved algorithm	102.5

Experiment2: In order to prove the effectiveness of the improved algorithm in the paper, it is compared with some classical recognition algorithms in the field of image recognition. The test result is seen in Form 2:

Form 2: Comparison among several recognition methods

Recognition method	a_p	b_p
PCA + svm	96.95%	6.14%
Cabor + svm	96.13%	6.45%
Wavelet + svm	96.34%	6.43%
Wavelet+Cabor+svm	96.81%	5.64%
Haar feature+ Cascade Adaboost	97.09%	13.19%
Method in this paper	97.47%	7.23%

Form 1 shows that after compressing the haar-like features with a new AAM under the guidance of the compressive sampling theory, the improved algorithm saves over 10 hours compared with the traditional algorithm. This reduces the time complexity of the traditional algorithm to some extent. As seen in Form 2, the recognition rate of the improved algorithm is higher than many other recognition algorithms available. As to the recognition methods of the AdaBoost cascade classifiers, they are generally applied in face recognition and have witnessed a good momentum of development in this field. However, when training weak classifiers into strong classifiers, this method has very strict

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criteria in terms of sample selection; when it decides that a sample is not the object of recognition, it discards it directly, which will result in the missing of some samples that contain the features of the object and lead to high false alarm rate as well. The method in this paper has somewhat improved on the basis of the traditional haar feature extraction algorithm and AdaBoost cascade classifiers. However, due to the special nature of cascade classifiers, compared with classifiers like SVM, the false alarm rate of this algorithm still needs to be further reduced.

When it comes to the evaluation of the overall performance and complexity of the algorithm, suppose the selected sample image for training is N and the number of the extracted Haar features is M. The complexity of the method based on the traditional feature extraction algorithm and Adaboost classifiers can be indicated as O (M×N) and that of the improved method based on the compressive sampling theory can be expressed as O (1/s×M×N). Here S refers to the ratio by which the original haar features are compressed. From this we can see that the improved algorithm is better that the traditional method.

5 Conclusions

This paper advances a type of vehicle recognition algorithm based on compressed haar-like features. In order to deal with the rapid increase and the high dimensionality of the features, this paper adopts a new AAM to extract features and the compressive sampling method to compress the features and reduce the dimensionality with the help of a very sparse measurement matrix. After running a test on the selected dataset, we can see from the experimental result that the method proposed in this paper has a better performance in the aspect of training time and recognition accuracy rate compared with the traditional recognition methods.

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