BOOSTING GABOR FEATURE CLASSIFIER FOR FACE RECOGNITION USING RANDOM SUBSPACE

Yong Gao, Yangsheng Wang, Xuetao Feng and Xiaoxu Zhou

Institute of Automation, Chinese Academy of Sciences,
Beijing 100080, China
email: {yong.gao, yangsheng.wang}@ia.ac.cn

ABSTRACT

Gabor feature has been widely viewed as a good representation method for face recognition. AdaBoost is an excellent machine learning technique. Learning Gabor feature based classifier using AdaBoost is one of the best face recognition algorithms. However, dimensionality of Gabor feature space usually is very high, which makes the training program need huge memory or else take a very long time to run. In this paper, we propose a method which not only can solve the problem but also can improve recognition accuracy. Several subspaces with moderate size are randomly generated from original high dimensional Gabor feature space. Then strong classifier is trained in every random subspace [1] respectively and the outputs of multiple classifiers are combined in the final decision. Experimental results demonstrate that the method saves a great amount of training time, and achieves an exciting recognition rate of 97.91% on the FERET Fb test set.

1. INTRODUCTION

Motivated by its scientific significance and potential wide application, face recognition has drawn more and more attention in recent years. As a typical pattern recognition problem, face recognition has to deal with two main issues: (i) what features are used to represent face, and (ii) how to classify face based on the chosen representation. Gabor feature has been used as face representation by many famous recognition algorithms, such as Gabor Fisher Classifier (GFC) [2], Elastic Bunch Graph Matching (EBGM) [3] and Gabor Wavelet Networrks (GWN) [4]. Boosting (Freund and Schapire, early 1990's) has been proposed in the machine learning community as a technique for generating and aggregating multiple classifiers. In a number of applications, such as face detection [5], it has been found to produce excellent predictions. It is not surprising that the algorithm [6], AdaBoost combined with Gabor feature, achieved good recognition accuracy on FERET database.

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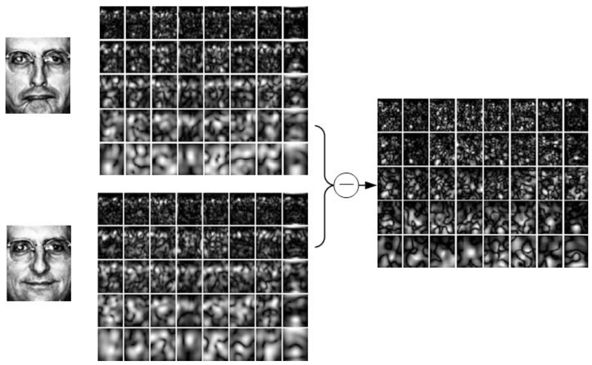
However, the dimensionality of Gabor feature space used in face recognition is very high. For a 50×60 face image, if using Gabor kernels with 5 scales and 8 orientations, there will be $120,000$ features. Whereas, to extract enough discriminative features, we usually hope to use face image with larger size, which will further increase the dimensionality. For boosting algorithm, high dimensional data means the need of large memory or long training time. Let's take training on FERET standard training set as an example. If all features are precalculated, more than 4 Gb memory is needed for the training program. If only part of the features are precalculated, the remainder will be calculated in every round of calling the weak learner, which will increase training time. The time needed by the weak learning algorithm is also proportional to the dimensionality of feature space.

In this paper, we use the random subspace method to solve the above problem, meanwhile improve the recognition accuracy. Moderate number of features are randomly selected from original Gabor feature space to form random subspace, Gabor feature classifier is learned using AdaBoost from each subspace. In recognition, input face image is fed to the multiple boosted Gabor feature classifiers and the outputs are combined using sum rule to make the final decision.

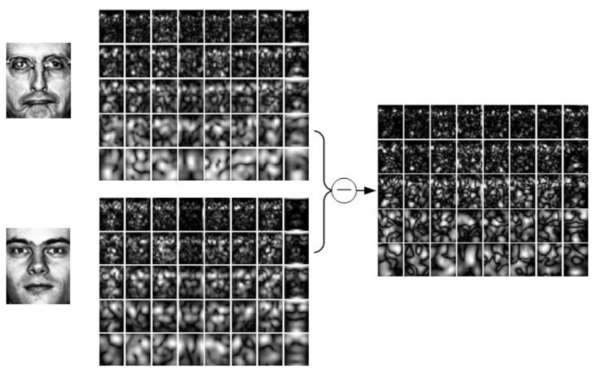
The remainder of this paper is organized as follows: in section 2, we briefly introduce the boosting Gabor feature classifier algorithm; Our proposed random subspace method is presented in section 3; The next section details the comparison experiments, followed by the conclusion in section 5.

2. LEARNING GABOR FEATURE CLASSIFIER

Using the concepts of Intra-personal Variation and Extra-personal Variation proposed by Moghaddam and Pentland [7], face recognition is converted from a multi-class pattern recognition problem into a two-class one. The variation in different images of the same individual forms the intra-personal space, while the variation in different images of different individuals forms the extra-personal space. The intra-personal and extra-personal Gabor face representations are illustrated in Fig.1. AdaBoost is used to learn Gabor feature classifier, which make two-class classification between intra-personal and extra-personal Gabor representation.



(a) Intra-Personal Gabor face representation



(b) Extra-Personal Gabor face representation

Fig. 1. Intra-personal and Extra-personal Gabor face representation.

2.1. Gabor Feature Representation

Gabor feature representation is computed by convoluting face image with a bank of Gabor filters (kernels, wavelets), which have been found to be a good approximation to the filter response profiles of simple cells of mammal's visual cortex. Gabor filters can be defined as follows:

$$\Psi_{\mu,\nu}(z) = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{-\frac{\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}} [e^{ik_{\mu,\nu}z} - e^{-\frac{\sigma^2}{2}}] \qquad (1)$$

where $k_{\mu,\nu}$ is the wave vector and defined as $k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$, $k_\nu = k_{max}/f^\nu$ and $\phi_\mu = \pi\mu/8$. k_{max} is the maximum frequency, and f is the spacing factor between kernels in the frequency domain. k_ν and ϕ_μ specify the frequency and orientation respectively. The parameters of Gabor filters at five scales, $\nu \in \{0,\ldots,4\}$, and eight orientations, $\mu \in \{0,\ldots,7\}$, are commonly as follows: $\sigma = 2\pi$, $k_{max} = \pi/2$ and $f = \sqrt{2}$. These Gabor Kernels form a bank of 40 different filters which exhibit desirable characteristics of spatial frequency, spatial locality and orientation selectivity. On the other hand, the dimension number of Gabor feature representation is 40 times that of the original image.

2.2. Feature Selection and Classifier Learning

The intrinsically low dimensional face appearance pattern means that the fully extracted Gabor feature set is over-complete and contains much redundant information. AdaBoost is employed to select discriminative features from the feature set and construct weak classifiers using the selected features, then combined the weak classifiers into a strong classifier. Pseudocode for AdaBoost is given in Fig. 2, in the slightly generalized form given by Schapire and Singer [8].

Given:$(x_1, y_1), \cdots, (x_m, y_m)$ where $x_i \in X, y_i \in Y = \{-1, +1\}$
Initialize $D_i(i) = 1/m$.
For $t = 1, \cdots, T$:

Train base learner using distribution D_t.
Get base classifier $h_t : X \to \mathcal{R}$.
Choose $\alpha_t \in \mathcal{R}$
Update

$$D_{t+1}(i) = \frac{D_t(i)exp(-\alpha_t y_i h_t(x))}{Z_t}$$

where Z_t is normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final classifier:

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

Fig. 2. The boosting algorithm AdaBoost.

3. BOOSTING IN RANDOM SUBSPACE

As mentioned in section 2, though Gabor wavelets can extract discriminative information from face image effectively , dimensionality of the feature space is very high. On the other hand, AdaBoost is a learning algorithm that repeatedly calls a weak learner using same sample set but with different distributions. To avoid unnecessary repetition of feature calculation, the best way is to precalculate all features. However, high dimensional Gabor feature data make this optimization almost impossible for many desktop and server nowaday. A compromise is to precalculate a portion of the total features, and the remainder is still repeatedly calculated every round. This will result in intolerable long training time. To cope with this problem, we propose a method which run boosting algorithm in several moderate size random Gabor feature subspaces which are generated from original high dimensional space. Experimental results in section 4 demonstrate that the method not only greatly reduces training time, but also achieves a promising recognition accuracy improvement.

3.1. Training in Gabor Feature Random Subspace

The original random subspace method [1] directly samples feature space, our Gabor feature random subspace is not fully random. Gabor feature is a kind of local feature (related to position). So we divide the face region into several windows, then randomly sample Gabor features in every window to construct a random subspace. In our experiments, the original face image size is 50×60 pixel, we divide the face image to 3×2 windows uniformly, as shown in Fig. 3. For a M dimensions subspace, we will randomly select $M/6$ features in every window.

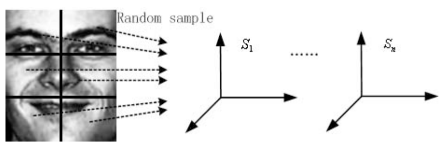


Fig. 3. Generation of Gabor feature random subspace.

The dimension of each random subspace M is mainly decided by the size of memory that training computer can afford to precalculated features, such that no features will be calculated repeatedly in every round of calling the weak learner. Another important point is how many random subspaces need to be generated? Let N denote the number of dimensions of original Gabor feature space. The number of random subspaces n should satisfy $nM > N$, which ensures that almost all features will be evaluated by weak learner.

After random subspaces are generated, Gabor feature Classifier is learned in each feature subspace, as illustrated in Fig. 4. We can found that the AdaBoost training programs can run parallel and further shorten total training time. This is another merit of the proposed method.

3.2. Decision Fusion

We assume that $H_i(x)$ is the output of Gabor feature classifier trained in random subspace i. We use simple sum rule to combine the n classifiers. The final output is defined as:

$$S(x) = \sum_{i=1}^{n} H_i(x), \tag{2}$$

where x is the difference of Gabor representation of two images (Intra-personal or Extra-personal Gabor representation). The value $S(x)$ indicate similarity of the two face images.

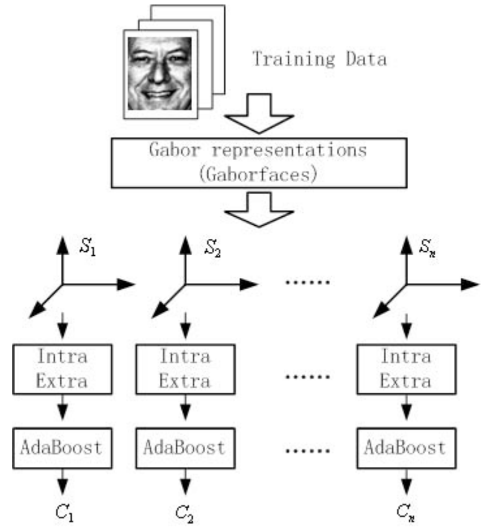


Fig. 4. Training Gabor classifiers in random subspaces. C_i is the Classifier trained from random subspace S_i.

4. EXPERIMENTS

We conducted a series of experiments on the FERET face database [9] to compare performances of direct training method (DTM) and our proposed random subspace training method (RSM). The training set includes 736 images of 314 subjects, which yields 592 intra-personal pairs and $269,888$ extra-personal pairs. All images are cropped and rectified according to the manually located eye coordinates. The normalized face images are 60 pixels high by 50 pixels wide. At any time, all 592 intra-personal pairs and 4000 extra-personal pairs are used for training. A new set of 4000 extra-personal pairs is selected by re-sample method [10] after a stage of AdaBoost has finished.

Total number of Gabor features is $120,000$ ($50 \times 60 \times 5 \times 8 = 120,000$). Considering the memory size of our training computer, we selected $30,000$ as the number of dimensions of random subspace. Totally 6 Gabor feature random subspaces were generated. In each training, a 3-stage strong classifier was learned.

4.1. Training Time Comparison

On a platform with P4 3.2GHz CPU, 2Gb memory, we compared the training time of RSM and DTM. Tab. 1 shows the results. The second column, Mem. Allocated, denotes the memory allocated for precalculated features. For RSM, the 1.2Gb memory is not fully used, and all $30,000$ features are precalculated. Running AdaBoost in a random subspace needs about 2 days. For DTM, almost all the 1.2Gb memory is used, and $34,200$ features (about one fourth of the whole features) are precalculated. The training time is intolerable long, about 38 days. Explicitly RSM is time saving, besides

Method	Mem. Allocated	Precal. Num	Time
DTM	1.2 Gb	34,200	38 days
RSM	1.2 Gb	30,000	6×2 days

Table 1. Training time comparison.

Algorithm	GFC	Bayesian	EBGM	RSM
Recog. Rate	0.964	0.82	0.90	0.9791

Table 2. Compare recognition accuracy of RSM with other methods on FERET Fb test set.

the training can run parallel in multiple computers simultaneously, which will further shorten the training time.

4.2. Recognition Accuray Comparison

On FERET Fb test set, the rank-1 recognition rates of these classifiers, including the combined one, are shown in Fig. 5. Although recognition accuracy of individual classifier trained in random subspace is not as good as that of the directly trained Gabor feature classifier, the combined Gabor feature classifier that achieves recognition rate 97.91% is better than the directly trained one. On other FERET test sets, this relationship also keeps. A comparison with other algorithms on Fb test set is also reported in Tab. 2.

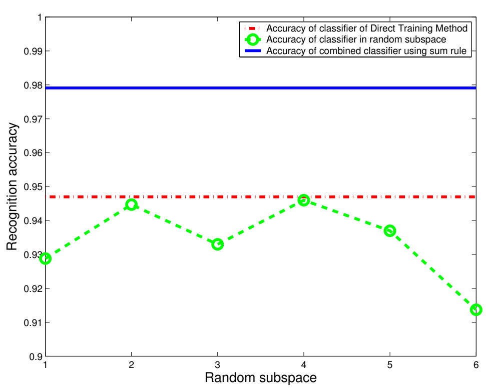


Fig. 5. Rank-1 Recognition Rates comparison.

The number of Gabor features used by different classifiers is listed in Tab. 3. There is no significant difference.

5. CONCLUSION

Complexity and accuracy are two important factors for machine learning algorithms. Usually there is only a tradeoff between them. In this paper, we proposed a novel method that generates several random subspaces with moderate size from high dimensional Gabor feature space, then runs AdaBoost in each subspace, which greatly reduces computational complexity. Using simple sum rule, the last combined classifier achieves better recognition rate than directly trained classifier. Therefore, the method not only lowers complexity but also improves accuracy of the original boosting algorithm. More detailed experimental results and discussions will be given in forthcoming papers.

DTM	RSM0	1	2	3	4	5
138	150	172	142	140	140	138

Table 3. Feature number used by trained classifiers.

6. REFERENCES

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