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Multi-channel Gabor Face Recognition Based on Area Selection

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Abstract: A face recognition method is presented We select the best area of face according to relative entropy of each face type in each channel, extract selected area's multi-channel Gabor feature and distribute weights to different results recognized by disparate Gabor channel according to relative entropy criterion. Experimental results was showed that comparing with integer Gabor token method and method using one best separability channel, the proposed method has high recognition rate and meanwhile has strong anti-noise ability.

Key words: Multi-channel Gabor, area selection, face recognition, ensemble Gable

INTRODUCTION

Face image recognition is a matching process. The identity of the face can be determined by comparing this face image with all samples in face database. A face recognition system can contain multiple components: face detection, face tracking, face correction, facial feature extraction and face features classification. But face recognition uses the characteristics of images to complete matching process. Therefore, the final recognition result will be affected greatly by the face features extracted. Currently, the face features for identification include geometric features, wavelet features, statistical features and intelligent information (Jafri and Arabnia, 2009). Gabor wavelet is a method for extracting wavelet feature. This method can be used to simulate the human visual system to capture the characteristics with different spatial location and directions. The recognition results are robust for the light and attitudes, so it has wide application prospects (Vinay and Shreyas, 2006).

Currently, Gabor wavelet applications in face recognition have two directions: (1) how to select areas in which Gabor features are extracted; (2) how to handle results from multiple Gabor filters. In region selection, common methods are to extract Gabor wavelet features in all pixels on the face images. Dimension curse often happens after Gabor filtering in this method. If image size is 100*100, 64 filters (8 scales and 8 directions) are often used. The number of features in this image is more than 640,000 after filtering. Generally, Gabor features extracted in all pixels on the face needs to be compressed. Literature (Liu *et al*., 2004; Wang *et al*., 2008) use principal component analysis and enhance linear discriminant model to effectively reduce the feature dimension. But such methods of linear transformation may miss very important details and identification features for classification. Literatures (Struc *et al*., 2006; Serrano *et al*., 2010; Wang *et al*., 2009a) proposed elastic graph matching method. Representative feature points are used to replace the entire face area for Gabor filtering, which reduces the number of face features. However, it is difficulty to solve how to dynamic adjust positions of feature points. Literatures (Liu and Wechsler, 2002; Liu, 2004) used critical feature points for face segmentation. Region segmentation in these methods is too small, which is suitable for face expression analysis and not good for feature extraction. In the expression of filtering results, the method combining all the filtering results on one face is called ensemble Gabor face representation. The method parallel processing all the filtering results is called multi-channel Gabor face representation (Fan *et al*., 2004). Ensemble Gabor face representation described in literature (Fan *et al*., 2004) retains all the local details in different filters. Literature (Fana *et al*., 2010) pointed out Gabor wavelet filters with different scales and frequencies are non-orthogonal and there is redundancy between

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different filters. So ensemble Gabor face representation also needs to consider how to reduce redundant information and reduce the feature dimension. Multi-channel Gabor face representation in literature (Wang *et al*., 2009b; Zhou *et al*., 2003) can recognize human faces in different scales and directions. But it still need to be discussed how to select the representative face region to ensure that characteristics extracted in this region are easy to be classified and how to handle multi-channel filtering results according to the contribution of each filter to the final recognition results.

In this study, we study on how to choose filtering are a in multi-channel and how to deal with different filtering results. A face recognition method is presented: in the same channel, we select face areas of each face type. These face areas have smaller relative entropy than other face area. Then we extract Gabor features in face are a for certain face type.When testimage is for recognition in different Gabor channels, recognition results are weighted and integrated in accordance with relative entropy criterion of each face type in different channels. The face type that has the largest total weighted value in all channels is selected as the final recognition results. In addition, before are a selection and Gabor feature extraction, Fourier transform is used for light pretreatment on the sample images and test images. After the inputimageis transformed into the frequency domain, phase information is preserved and the average gray degree of this image is modified for reducing the light impact.

Experiments are in the different test sets as AR, ORL, YaleB and CAS-PEAL-R1. Results show that face areas selected in our paper include facial features which are useful for recognition. These faceareas areless affected by light, and reduce training and testing time of unnecessaryareas. Our method takes good advantage of different filters and features of different face type and to a certain extent, solves how to select Gabor filter areas and how deal with different results in multi-channel Gabor filtering. Compared with the method that extracts features in the over all facial image and the Ensemble Gabor Face Representation, our method has a higher average recognition rate and has less effected by several common noise as well as increases on both accuracy and efficiency.

WEIGHTED MULTI-CHANNEL GABOR FACE REPRESENTATION

Gabor wavelet transformation: Gabor wavelet transform is Fourier transform, which can obtain image features with different spatial locations and directions in spatial domain and frequency domain. It is widely used in image feature extraction and face recognition etc. (Zhou *et al*., 2003). Discrete two-dimension Gabor filter can be defined as:

$$g_{\mu,v}(z) = \frac{{k_{\mu,v}}^2}{\rho^2}\exp(-\frac{{k_{\mu,v}}^2(x^2+y^2)}{2\rho^2})[\exp(i\,k_{\mu,v}\begin{pmatrix}x\\y\end{pmatrix}) - \exp(-\frac{\rho^2}{2})] \quad (1)$$

where, μ and ν control the direction and scale of one filter. ϕ_μ represents the direction and k_v represents the frequency. $k_{\mu,v} = k_v e^{i\varphi\mu}$ is the center frequency of the filter. Literature gives the common Gabor filter parameters. The DC component exp $(-p^2/2)$ in the formula is subtracted to reduce the impact of filtering results affected by light. Gabor feature of the input image after convoluting the filter and the input face region with formula (2) is called Gabor "characteristic face".

$$O_{\mu,v} = X * g_{\mu,v} \quad (2)$$

X can be a whole face image, selected feature regions, feature vectors, feature points, etc. $O_{\mu,v}$ is a characteristic face after **X** uses filter $g_{\mu,v}$.

MULTI-CHANNEL GABOR FACE REPRESENTATION

The characteristic face set that is obtained by the convolution of all the samples in sample set and the same filter is called one channel Gabor. Sets that are obtained by the convolution with a series of Gabor filters consisted of different μ and v are called multi-channel Gabor, ormulti-channel Gabor representation. If the sample set contains 100 samples, after they are filtered by 64 filters, each sample has a characteristic face in every 64 channel and each channel contains 100 characteristic faces.

Characteristics in different channel are different. This difference is determined by the scale and direction of the certain Gabor filter. Direction of a filteris more sensitive to ward the texture edge in the input image, while scale of a filte rcontrols the filter with range. Gabor filters with different directions have varying intensity in response of the input image's edges with different directions. A filter has a strong response of characteristics that have the same texture directionas the filter. So the horizontal filter is able toextract the information of eyes and mouth and the vertical filter retains the information of nose. As shown in Fig. 1, characteristic face O_1 that is obtained by the convolution of the horizontal filter g_1 and face image retains more information in eyes and mouth, while characteristic face O_2 that is obtained by the convolution of the vertical filter g_2 and face image retains more vertical

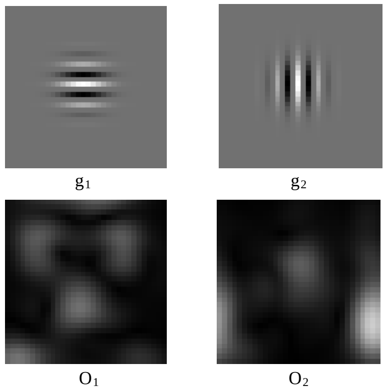

Fig. 1: Filters with the same scale and different directions and the features extracted by them

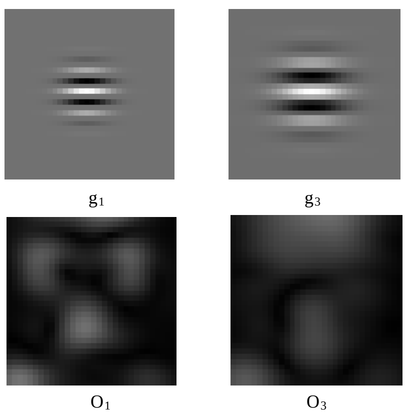

Fig. 2: Filters with the same direction and different scales and the features extracted by them

information in nose, cheeks and face borders with background. Filters with different scales have different filtering ranges. When convolution is done, the radiuses around region impacted by these filters are different. As shown in Fig. 2, characteristic face O_1 is obtained by the convolution of the small-scalefilterg_1 and face image. Each point in O_1 is impacted by a smaller area around it. Sophisticated information is extracted in O_1. Characteristic face O_3 is obtained by the convolution of the large-scalefilterg_3 and face image. Each point in O_3 is impacted by a larger area around it. Rough information is extracted in O_3.

WEIGHTED MULTI-CHANNEL GABOR FACE REPRESENTATION BASED ON RELATIVE ENTROPY

We present weighted multi-channel Gabor face representation based on relative entropy. Entropy is a measure of uncertainty. It can measure the degree of separation between categories. The smaller relative entropy between two categories, the greater difference between these two categories and the more easily these two categories can be classified. Each sample corresponds to a characteristic face in each channel. Discretion in the distribution of all characteristic faces in each channel decides characteristics importance in this channel for classification. Thus, in a channel, we calculate relative entropy of one face category relative to others, and then average the relative entropy. We can determine the separation of this face category relative to others. The smaller the relative entropy, the better the separation of this face category in this channel and the more accurate recognition results of test images in this face category in this channel will be.

Relative entropy distribution matrix between face category i and j can be calculated according to formula (3):

$$R(i,j) = -\sum p\log p - \sum q\log q + \sum p\log q + \sum q\log p \tag{3}$$

p, q refer to eigenvalues of any two normalized elements in category i and j. p and q are equivalent. That is, the entropy of q relative to p = the entropy of p relative to q. Any different elements p and q in category i and j will be executed in this algorithm. $\sum$ refers to the sum of all elements in these two category i and j. R (i, j) refers to the degree of separable uncertainty between category i and j. Thus, in the kth channel, we calculate relative entropy distribution matrix of the face category i relative to all other face categories and then average it, which is:

$$\tilde{R}^k(i) = \frac{\sum_{j=1}^{num} R^k(i,j)}{num}, \qquad j \neq i, num \tag{4}$$

Num refers to number of face categories. Then we trace this matrix. The criterion based on relative entropy of category i in the kth channel:

$$J^k(i) = \mathrm{trace}(\tilde{R}^k(i)) \tag{5}$$

Finally, we normalize this criterion based on relative entropy within the kth channel. Weights based on relative entropy of category i in the kth channel:

$$W^k(i) = \frac{J^k(i)}{\sum_{i=1}^{num} J^k(i)} \tag{6}$$

Therefore, we take the relative entropy as the criterion and distribute weights for every face category. In one channel, the lower value of relative entropy of a face category, the higher recognition result in this category accounts for the final recognition result.

When test image is for recognition, firstly the results in each channel are obtained, respectively and then weights of the same recognition results in a total of 64 channels are summed up. Finally, recognition result with the weight that is summed up and has minimum value will be the final result. Our method will achieve weighted integration of the recognition results for different channels. Weights of each Gabor channel can be dynamically adjusted when training sets are different. The first experiment in our paper can confirm that recognition rate of the recognition results on weighted multi-channel Gabor method is higher than the method that does not distinguish the different importance of each channel.

ADAPTIVE FACE AREA SELECTION

The importance of face area selection: The amount of information contained in face areas can be analyzed from both the relative entropy criterion and the recognition rates, which shows the importance of face area selection.

The face area is sub-blocked at different levels. The relative entropy in these areas with blocks is calculated. The values of relative entropies in these areas at different levels are compared to determine which areas contain the more clearly category boundaries. Face images with 120*120 are sub-blocked at different levels. They are divided into 4, 9, 16 and 25 blocks in the first layer, the second layer, the third layer and the forth layer, which are shown in Fig. 3. The average relative entropies of face samples in different channels, different face categories and different blocks are calculated according to formula (3) and (4). The results are shown in Table 1.

As shown in Table 1, the average relative entropies of face samples in face areas with blocks have a great range and a big difference. The separability in face areas such as eyes and mouth is good, while the separability in cheeks is bad.

Face recognition in each block area is done respectively in these Gabor channels with 120*120, 60*60, 40*40, 30*30, 24*24. The average values of recognition rates in these different blocks are compared. The results are shown in Table 2.

As shown in Table 2, when face areas in different blocks are for recognition, final recognition rates have a big difference. The recognition rates in face areas such as eyes and mouth are higher.

The relative entropies and the recognition rates at different blocks are sorted. It can be seen that, the areas with low relative entropies and high recognition rates mostly locate in the areas such as eyes, nose and mouth. These selected areas can reduce unnecessary information, increase the training speed and test speed, as well as contain more information that is useful to recognition.

Adaptive face area selection algorithm: Because each channel is independent, face area selection between different channels does not relate to each other. Even the same face category in different channels has their different relative entropies and recognition rates. In a channel, the intuitive method is that the shared area should be selected for all face samples in this channel. Feature extraction of every face category is done on it. However, the selected areas of different face categories in the same channel should be the same. Of course not,

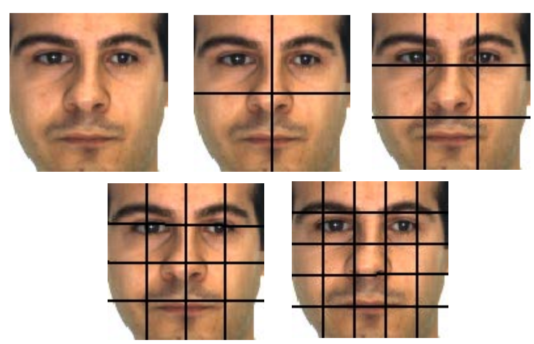

Fig. 3: The face images with different blocks

Table 1: The average relative entropies in face areas with blocks

									0.28846	0.70178	0.86876	0.97037	0.46621
					0.30438	0.67991	0.90231	0.47845	0.12495	0.33902	0.23342	0.45491	0.25513
		0.31905	0.56642	0.47631	0.10897	0.19569	0.30617	0.20689	0.075926	0.13548	0.21056	0.23756	0.16464
0.26209	0.40931	0.12799	0.2171	0.23256	0.22284	0.22927	0.33969	0.37848	0.4757	0.18736	0.43748	0.29568	0.53909
0.45273	0.66037	0.72333	0.3835	1.0152	1.1272	0.25449	0.40133	1.4706	1.6098	0.16694	0.65388	0.30138	1.0998

Table 2: The average recognition rates in face areas with blocks

									0.54833	0.625	0.5667	0.60833	0.5033
					0.69167	0.7516	0.75833	0.68	0.475	0.575	0.5983	0.56667	0.51
		0.76	0.79833	0.80333	0.53667	0.74	0.78167	0.56333	0.175	0.4717	0.4583	0.48833	0.2016
0.26209	0.40931	0.6167	0.76167	0.61833	0.30667	0.615	0.67833	0.3467	0.23833	0.5	0.47	0.54	0.5583
0.45273	0.66037	0.3767	0.70333	0.39667	0.24333	0.5216	0.545	0.2783	0.2	0.2367	0.3833	0.245	0.3716

especially when different face categories in the same channel have these area selection situations such as the different face shapes, the different face positions (that are the front face, left (right) side faces, the upper (lower) side faces), the different face expressions, the different illumination and the different (or improper) pretreatment.

Thus, different face areas of different face categories in the same channel should be selected to improve recognition rate. We propose multi-channel Gabor face area selection algorithm based on relative entropy, which is denoted algorithm*. In the kth channel, algorithm* is done for all face categories to get the area $mask^i_k$ of face category i.

Algorithm*:

Step 1: O^i_n refers to characteristics faces of all face samples in face category i. N refers to the n^{th} sample in this category. The whole face area is divided into M*N. For each small area in the kth channel, formula (3) and (4) are used to obtain the average relative entropy of this face category relative to others.

Step 2: This is a cyclical process: we combine two blocks in the same layer to be one block with larger area, and retain these blocks $\check{R}^k(i)$ of which do not reduce. We select blocks here $\check{R}^k(i)$ of which do not to reduce rather than increase. The reason is when the number and types of test samples are so single that their $\check{R}^k(i)$ do not change, we should combine blocks as much as possible to increase the amount of information.Pay attention that $\check{R}^k(i)$ of the current face category is calculated in selected face area, while $\check{R}^k(i)$ of the non-current face category is calculated in whole face area. And again we combine two blocks in the same layer, until combination can not go on or $\check{R}^k(i)$ of all combined blocks, do reduce. When combination is finished, the block with minimum value of $\check{R}^k(i)$ is the selected area of this face category. Note that the same blocks should be removed in this process

EXPERIMENT AND ANALYSIS

Matlab 7.0 in a PC with performance of Intel^R Core^{TM}2 E7400 CPU and 0.98 GB RAM is selected for experiments. Test set is in ORL face database, AR face database, Yale-B face database and parts of the CAS face database.

- Four hundred face images in ORL face database of 40 people with different poses and expressions are selected. 5 images in each people are randomly selected to create samples database. Other 5 images are selected to create test database
- Six hundred face images in AR face database of 100 people with different expressions and illumination are selected as samples database. After a period of time, another 600 face images with different expressions and illumination in different expressions are selected as test database
- Seventy face images in Yale-B of 10 people with dramatically changing in illumination are selected. 4 images in each people are randomly selected to be training images. Other 3 images are selected to be test images
- Four hundred face images in CAS-PEAL-R1 face database with different expressions and illumination are selected to be training samples and another 400 face images are selected to be test samples.When doing the recognition rates, all images need to be corrected in their location and reduced to 32*32

Recognition rates in several face recognition methods that use Gabor filters are tested in experiments:

- Algorithm 1 is based on characteristics in single channel. The highest recognition rate in different channels is recorded
- Algorithm 2 is multi-channel Gabor face representation, in which the weight in each channel is the same. We select the sample with the maximum number of occurrences in results as the final result
- Algorithm 3 is weighted multi-channel Gabor face representation
- Algorithm 4 improves Algorithm 3 to extract Gabor features in selected area
- Algorithm 5 is the traditional ensemble Gabor face representation. It expands all Gabor characteristic faces at row or column to be the ensemble characteristic face, does PCA in it and after reducing dimensions uses Euclidean distances to match the result
- In the basis of the algorithm 3, Algorithm 6 uses Fourier transform for light pretreatment
- Algorithm 7 is the method in our study

Different samples databases and test databases in ORL, AR, Yale-B and CAS-PEAL-R1 are reduced to 32*32. The average recognition rate is selected in several tests.

The recognition rates of algorithm 1, algorithm 2 and algorithm 3 are compared in Experiment 1, which verifies the importance of weighted multi-channel face representation. The results are shown in Table 3.

As seen in Table 3, comparing algorithm 1 and algorithm 2, the recognition rates of multi-channel. Gabor face representation in all databases are greater than recognition rates of in single channel, which means

Table 3: The comparison of recognition rates in Algorithm 1, 2 and 3

	Algorithm 1: results in best single channel	Algorithm 2: multi-channel Gabor face representation	Algorithm 3: weighted multi-channel Gabor face representation
ORL	0.86	0.915	0.95
AR	0.77333	0.89167	0.90167
Yale-B	0.60	0.60	0.66667
CAS-PEAL-R1	0.7375	0.95	0.96

Table 4: The comparison of recognition rates in 3, 4 and 5

	Algorithm 3: weighted multi-channel Gabor face representation	Algorithm 4: weighted multi-channel Gabor face representation based on area selection	Algorithm 5: ensemble Gabor face representation
ORL	0.95	0.96	0.915
AR	0.90167	0.95333	0.90167
Yale-B	0.66667	0.50	0.50
CAS-PEAL-R1	0.96	0.9675	0.975

Table 5: The comparison of recognition rates in Algorithm 3, 4, 6 and 7

	Algorithm 3: weighted multi-channel Gabor face representation	Algorithm 4: weighted multi-channel Gabor face representation based on area selection	Algorithm 6: FFT weighted multi-channel Gabor face representation	Algorithm 7: FFT weighted multi-channel Gabor face representation based on area selection
ORL	0.95	0.96	0.975	0.975
AR	0.90167	0.95333	0.90333	0.95333
Yale-B	0.66667	0.50	0.50	0.50
CAS-PEAL-R1	0.96	0.9675	0.965	0.9675

Table 6: The comparison of recognition rates in several algorithms with different noises

AR-600	Algorithm 5: ensemble Gabor face representation	Algorithm 7: FFT weighted multi-channel Gabor face representation based on area selection
	0.90167	0.95333
Salt and pepper noise	0.69	0.7133
Gaussian white noise	0.865	0.89833
Speckle noise	0.75667	0.77833
Poisson noise	0.85833	0.89167

information extracted in multi-channel is more. Comparing algorithm 2 and 3, the average recognition rate of weighted multi-channel Gabor face representation is higher than that of the method that does not take into account the weighted, which proves the importance of weighting.

The recognition rates of algorithm 3, 4 and 5 are compared in Experiment 2, which verifies features extracted in selected area using weighting are more effective. The results are shown in Table 4. As seen in Table 4, the recognition rates of multi-channel Gabor face representation based on area selection are higher than them of the Gabor representation in the entire face area. The recognition rate increases 5.17% especially in AR database. Besides, the recognition rates of multi-channel Gabor face representation based on area selection in ORL and AR increase obviously than them of ensemble Gabor face representation, by 4.5 and 5.17%, respectively. Experiments prove that features extracted in selected area are more effective.

The recognition rates of 3, 4, 6 and 7 are compared in Experiment 3, which verifies effectiveness of our method. The results are shown in Table 5.

As seen in Table 5, when selected area or FFT light pretreatment is used alone, the recognition effect enhances. Our method combines advantages of algorithm 4 and 6. Its recognition rates are high in several face databases.

The noise sensitivity is tested in experiment 4. There are usually a variety of noises in face images. In test images that are added several common noises, the comparison in recognition rate of our Algorithm and traditional ensemble Gabor face representation is shown in Table 6.

As seen in Table 6, although, the recognition rates in these two methods decline in the presence of noise, the recognition rate of our method is still higher than the recognition rate of ensemble Gabor face representation, which proves our method has good stability.

CONCLUSION

By analyzing the relative entropies of characteristics face categories generated by different Gabor filters, we introduce the method in weighting the results in different channels and propose multi-channel Gabor face representation by the importance of each channel. We analyze features extracted in different levels and different areas, their importance for classification and their stability for illumination changes. Finally, we propose FFT weighted multi-channel Gabor face representation based on area selection. Experiments in AR face database, ORL face database and CAS-PEAL-R1 face databases, show that our method has higher recognition rate. It is robust for illumination changes in some test database, such as AR.

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