FACE RECOGNITION USING HISTOGRAM OF CO-OCCURRENCE GABOR PHASE PATTERNS

Cong Wang, Zhenhua Chai, Zhenan Sun

Center for Research on Intelligent Perception and Computing (CRIPAC), National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences (CASIA)

ABSTRACT
The fusion of Local Binary Patterns (LBP) and Gabor magnitude features has been demonstrated to be one of the most successful descriptors for face recognition. Recently, several Gabor phase based features like Histogram of Gabor Phase Patterns (HGPP) and Local Gabor XOR Patterns (LGXP) also show competitive results and complementary attributes to Gabor magnitude based features. However, in these two typical Gabor phase based approaches only the binary relationship between neighboring Gabor phases is used, which may lose some discriminative information. To investigate the potential of Gabor phase features for robust face recognition, this paper proposes a novel local descriptor, named Histogram of Co-occurrence Gabor Phase Patterns (HCGPP). In HCGPP, Gabor Phase features are first extracted and quantized into different ranges. Second we estimate the histograms of co-occurrence Gabor phase patterns in each face region. Finally, a nearest-neighbor classifier with the dissimilarity measure $\chi^2$ is used for classification. Extensive experimental results on FERET and AR databases show the significant advantages of the proposed method over the state-of-the-art ones in terms of recognition rate.

Index Terms— Face recognition, feature extraction, local descriptor, Gabor phase, HCGPP

1. INTRODUCTION
Face recognition has been widely applied in many fields, such as access control, video surveillance and human-computer interaction etc [1]. However, face recognition is still a very challenging task. The appearance of the same person can change dramatically due to the variations of expression, illumination and occlusions. Therefore, how to extract robust and discriminative features is of vital importance to a face recognition system. In the literature, the main approaches for feature extraction can be divided into two categories: subspace based holistic methods and local feature based methods [2]. The typical ones of the former kind include principal component analysis (PCA) [3], linear discrimination analysis (LDA) [4] and independent component analysis (ICA) [5] etc, which can be unified into a general framework known as graph embedding [6]. However, the performance of this kind of approaches depends greatly on the training set. And it is easily affected by the misalignment. On the other side, local feature based methods have several advantages, and they are more stable to different facial variations. Gabor wavelets [7] and LBP [8] are two representative local features. Based on the success of these two local features, a series of improved methods have been proposed (e.g. [9, 10, 11, 12, 13, 14]) for better face representation. One representative work is local Gabor binary pattern histogram sequence (LGBPHS) [11]. Recently, there are also several Gabor phase based approaches like HGPP [12] and LGXP [10], which also show competitive performances. However, only the binary relationship between the neighboring Gabor phases is used, thus we believe there is still a space to be improved. To investigate the potential of Gabor phase features for robust face recognition, histogram of co-occurrence Gabor phase patterns (HCGPP) is proposed in this paper by exploiting the co-occurrence Gabor phase information. Experiments on FERET and AR databases show the proposed method can achieve comparable and even better performance in comparison with the state-of-the-art methods.

The rest part of this paper is organized as follows: In Section 2 the details of the proposed method HCGPP is described. Then experimental results are shown in Section 3. Conclusions and future work are given in Section 4.

2. HCGPP: HISTOGRAM OF CO-OCCURRENCE GABOR PHASE PATTERN
Our proposed method HCGPP is motivated by the fact that in most existing Gabor phase based approaches only the binary relationship between neighboring Gabor phases is used for local pattern coding. In this way, some discriminative information for face recognition may be neglected. Generally speaking, our HCGPP is based on the statistics of the co-occurrence relationship of Gabor phase patterns. The details of the main three steps are explained in each of the following subsections.
2.1. Gabor phase feature extraction

The first step of HCGPP is to extract Gabor phase features. The 2D Gabor wavelets [7] can be defined as follows:

\[
\psi_{\mu,\nu}(z) = \frac{|k_{\mu,\nu}|^2}{\alpha^2} e^{-\frac{|k_{\mu,\nu}|^2|z|^2}{\alpha^2}} \left[ e^{ik_{\mu,\nu}z} - e^{-z^2/2} \right]
\]

where \( \mu \in \{0, \ldots, 7\} \) and \( \nu \in \{0, \ldots, 4\} \) determine the orientation and scale of the Gabor filters and \( z = (x, y) \) represents the spatial position. The wave vector \( k_{\mu,\nu} = k_\nu e^{i\phi_\mu} \) has a magnitude \( k_\nu = k_{\max}/\lambda^\nu \), where \( \lambda \) is the frequency ratio between filters and \( \phi_\mu = \pi \mu/8 \).

The Gabor transformation of an image \( I(z) \) is defined as its convolution with the Gabor kernel at scale \( \nu \) and orientation \( \mu \):

\[
G_{\mu,\nu}(z) = I(z) * \psi_{\mu,\nu}(z).
\]

(2)

The Gabor wavelet coefficient \( G_{\mu,\nu}(z) \) is a complex with two parts, i.e., real part \( \text{Re}_{\mu,\nu}(z) \) and imaginary part \( \text{Im}_{\mu,\nu}(z) \). Based on these two parts, Gabor phase \( \Phi_{\mu,\nu}(z) \) can be computed by Equation (3).

\[
\Phi_{\mu,\nu}(z) = \arctan(\text{Im}_{\mu,\nu}(z)/\text{Re}_{\mu,\nu}(z))
\]

(3)

2.2. Co-occurrence Gabor Phase Patterns (CGPP)

In the second step of HCGPP, Gabor phases are firstly quantized into different ranges, and then co-occurrence matrix statistics is applied to the quantized Gabor phase map. Pairs of quantized Gabor phases at a fixed distance and along a specified direction can be considered as different co-occurrence phase patterns. We denote it as \( CGPP(i, j) \), where \( (i, j) \) is the pair of quantized Gabor phases. It is easy to understand \( CGPP(i, j) \) and \( CGPP(j, i) \) are the same pattern.

Similar to the traditional GLCM [15], co-occurrence statistics of quantized Gabor phases can also be denoted as a matrix. Each element in the matrix can be calculated as follows:

\[
P_{CGPP_{\mu,\nu,\delta}(i,j)} = \begin{cases} 
\sum_{z \in R, z + \delta \in R} \delta_s(z, i, j) + \delta_s(z, j, i) & \text{if } i \neq j \\
\sum_{i+j} \delta_s(z, i, j) & \text{if } i = j
\end{cases}
\]

(4)

\[
\delta_s(z, i, j) = \begin{cases} 
1 & q(\Phi_{\mu,\nu}(z)) = i, q(\Phi_{\mu,\nu}(z + \delta)) = j \\
0 & \text{else}
\end{cases}
\]

(5)

where \( \mu \) and \( \nu \) denote the orientation and scale of the Gabor phase map respectively. \( z = (x, y) \) denotes the pixel position. And \( \delta \) is an offset vector defining the neighbor pixel \( (z + \delta) \) of reference pixel \( z \) along a direction. In this paper, there are four different directions to be considered (as shown as in Figure 1). \( q() \) denotes the quantization operator, which calculates the quantized code of phase according to the number of phase ranges. The formula can be written as follows:

\[
q(\Phi_{\mu,\nu}(z)) = \begin{cases} 
i & 360*\frac{\alpha}{b} \leq \Phi_{\mu,\nu}(z) < 360*(i+1) \\
0 & \text{else}
\end{cases}, \quad i = 0, 1, \ldots, b - 1
\]

(6)

where \( b \) denotes the number of phase ranges.

Fig. 1. The four co-occurrence directions of Gabor phases.

Based on the above description, it is easy to understand that each element in a co-occurrence matrix of quantized Gabor phases corresponds to the frequency of a \( CGPP_{\mu,\nu,\delta}(i, j) \) pattern and the matrix is symmetric. Therefore, we only need to calculate the top half of the matrix.

2.3. Histograms of Co-occurrence Gabor Phase Patterns

Based on the frequency of each CGPP with a fixed distance and along a specified direction, we can obtain a histogram of co-occurrence Gabor phase patterns (HCGPP) (one example is shown in Figure 2).

Fig. 2. Example of HCGPP method where Gabor phase map is quantized into four ranges.
Each Gabor phase map is divided into \( m \) non-overlapping blocks. And the histograms of all Gabor phase map blocks with multiple scales and orientations are concatenated together to form the final HCGPP descriptor of a face image, which can be expressed as:

\[
H = [HCGPP_{\mu_0,\nu_0,1}, \ldots, HCGPP_{\mu_0,\nu_0,m};
HCGPP_{\mu_{-1},\nu_{-1},1}, \ldots, HCGPP_{\mu_{-1},\nu_{-1},m}]
\]

where \( HCGPP_{\mu,\nu,i} = [HCGPP^{h_1}_{\mu,\nu,i}, HCGPP^{h_2}_{\mu,\nu,i}, \ldots, HCGPP^{h_K}_{\mu,\nu,i}] \) denotes the concatenated histograms of the \( i^{th} \) block of Gabor phase map with scale \( \mu \) and orientation \( \nu \), and \( \delta_k (k = 1, 2, \ldots, K) \) denotes the \( k^{th} \) direction of phase co-occurrence. In all, the dimension of HCGPP descriptor which captures co-occurrence information in multiple directions is equal to \( K \times (1 + b) \times b/2 \) in each block of Gabor phase map.

Previous work has shown that different face regions are of different importance for face recognition [16]. Therefore, it is easy to understand that the final performance of face recognition can be improved by setting different weights to HCGPP descriptors extracted from different blocks. Then, the dissimilarity measure between two HCGPP descriptors can be computed as follows:

\[
D(H^1, H^2) = \sum_{\mu=\mu_0}^{\mu_{-1}} \sum_{\nu=\nu_0}^{\nu_{-1}} \sum_{i=1}^{m} w_{\mu,\nu,i} \chi^2(H^{1}_{\mu,\nu,i}, H^{2}_{\mu,\nu,i})
\]

where \( \chi^2 \) dissimilarity is defined as:

\[
\chi^2(h^1, h^2) = \sum_{l=1}^{L} \frac{(h^1_l - h^2_l)^2}{(h^1_l + h^2_l)}
\]

where, \( L \) is the number of histogram bins.

In this paper, we use Fisher criterion to set the weights to different facial regions similar to [11]. Given a train set, we can compute the weight for each block as follows:

\[
w = \frac{(m_i - m_c)^2}{\sigma_i^2 + \sigma_c^2}
\]

where \( m_i \) and \( \sigma_i \) denotes the mean and variance of the intra class (the same person) dissimilarity respectively, \( m_c \) and \( \sigma_c \) denotes the mean and variance of the extra class (different person) dissimilarity respectively.

3. EXPERIMENTS

In this section, we conduct several experiments on two public face databases FERET [17] and AR [18] to evaluate the effectiveness of the proposed method. First, we show the influence of different parameters on the performance of HCGPP descriptor. And then we present the best results of the HCGPP in comparison with the related state-of-the-art methods on all subsets of FERET. Besides, we also validate HCGPP on AR. For the Gabor filters, in this paper, we use the empirical five scales and eight orientations filter banks.

3.1. Experimental results on FERET database

FERET database has been widely used to evaluate face recognition algorithms. In our experiments, we follow the standard FERET evaluation protocol. Fa containing 1196 frontal face images of 1196 subjects is used as gallery set, while Fb (1195 images of expression variations), Fc (194 images taking under different illumination conditions), DupI (722 images taken later in time) and DupII (234 images, a subset of DupI) are the probe sets. Besides, there are 1002 images used as training set. All the images are normalized to \( 96 \times 96 \) according to the eye positions (Figure 3). Similar to other work, we empirically divide the image into \( 8 \times 8 \) blocks.

![Fig. 3](image)

Sample images from FERET database. Gallery images are listed in first row while images in second row are from probe sets.

3.1.1. Parameter Evaluation

There are mainly three free parameters in HCGPP: the number of phase ranges \( b \), the number of blocks per Gabor phase map \( m \) and the co-occurrence distance of CGPP \( d \). In this experiment, we evaluate how these parameters of HCGPP influence its performance.

The parameter \( b \) determines the number of CGPPs. A smaller \( b \) (a coarser division on phase space) makes the HCGPP more robust to facial variations and lower feature dimension, but at the same time it will make it less expressive. The parameter \( m \) stands for the number of space division of a face image. The parameter \( d \) makes HCGPP capture the co-occurrence relationship of quantized Gabor phases at different co-occurrence scales.

Based on the above analysis, we test the parameter \( b \) within \([2, 4, 6, 8, 10]\) and the parameter \( d \) ranged from 1 to 5. In our experiment, equal error rate (EER) is used as a stable index for parameter evaluation on FERET training set. A smaller value of EER means a better performance. From Figure 4(a) we can find how EER varies with different \( b \) at different
Gabor scales $\nu$ and eight Gabor orientations, when $m = 8 \times 8$ and $d = 3$. It can be seen that the best result is achieved when $b = 8$, thus we also use it in the rest experiments.

Fig. 4. The influence of different parameters of HCGPP descriptor $b$ and $d$ on the performance by the EER index on FERET training set.

Figure 4(b) shows how EER varies with different $d$ at different Gabor scales $\nu$ and eight Gabor orientations, when $m = 8 \times 8$ and $b = 8$. It can be seen that for five Gabor scales, the first two scales are more expressive than others. In order to keep a balance between computational cost and recognition accuracy, we only extract HCGPP feature from the first two scales of Gabor phase maps in all our experiments. And the best result can be achieved when $d_{v_0} = 5$, $d_{v_1} = 5$.

3.1.2. Evaluation of the proposed method on FERET

In this part, we evaluate our method on the four FERET probe sets, and make a detailed comparison with some state-of-the-art descriptors. Based on the former experiments, the parameters of HCGPP are as follows: $m = 8 \times 8$, $b = 8$, $d_{v_0} = 5$, $d_{v_1} = 5$. Like almost other descriptors in the Table 1, weighting strategy is used in the experiment. From the Table 1, the following observations can be gained: first, the proposed method outperforms other ones in almost all cases; second, we only use two scales of Gabor phase maps, thus the final dimension is reduced obviously; besides, the performance of the proposed method can be further improved when the appropriate preprocessing method (like [19]) is applied.

3.2. Experimental results on AR database

Our descriptor is also tested on AR database. The AR database consists of more than 3,200 images of 126 subjects, including 70 males and 56 females. The images were taken in two sessions. Each session has 13 images per person with variations in expression, illumination conditions and occlusions. To compare with previous works fairly the same protocol is used in our experiment: we randomly selected 90 different subjects (45 male and 45 female), the neutral images in two sessions (180 images) are used as gallery set and the images with variations in expression and occlusions are used as probe sets (expression, sunglasses and scarf occlusions) respectively. All the images are normalized into $80 \times 80$ according to the eye positions.

For HCGPP, we use the same parameters as in FERET. Considering that the images in the three probe sets vary with drastic expression and occlusions, weighting strategy is not suitable for these special cases. Then unweighted $\chi^2$ measure is used in the experiment. The recognition rates of different descriptors are listed in Table 2. We can find that the proposed HCGPP outperforms all the rest methods, especially on both occlusion sets.

Table 1. Top rank recognition rates on FERET database.

<table>
<thead>
<tr>
<th>Method</th>
<th>$F_b$</th>
<th>$F_c$</th>
<th>DupI</th>
<th>DupII</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBP [20]</td>
<td>97.0</td>
<td>79.0</td>
<td>66.0</td>
<td>64.0</td>
</tr>
<tr>
<td>LGBPHS-M [11]</td>
<td>98.0</td>
<td>97.0</td>
<td>74.0</td>
<td>71.0</td>
</tr>
<tr>
<td>LGBPHS-P [9]</td>
<td>96.0</td>
<td>94.0</td>
<td>72.0</td>
<td>69.0</td>
</tr>
<tr>
<td>HGPP [12]</td>
<td>97.5</td>
<td>98.9</td>
<td>79.5</td>
<td>77.8</td>
</tr>
<tr>
<td>E-GV-LBP-P [12]</td>
<td>97.8</td>
<td>97.4</td>
<td>80.4</td>
<td>78.6</td>
</tr>
<tr>
<td>E-GV-LBP-M [12]</td>
<td>98.4</td>
<td>98.9</td>
<td>81.9</td>
<td>81.6</td>
</tr>
<tr>
<td>HOGOM [14]</td>
<td>99.2</td>
<td>98.9</td>
<td>77.0</td>
<td>80.3</td>
</tr>
<tr>
<td>LGXP [10]</td>
<td>98.0</td>
<td>100</td>
<td>82.0</td>
<td>83.0</td>
</tr>
<tr>
<td>HCGPP</td>
<td>99.4</td>
<td>100</td>
<td>83.8</td>
<td>83.3</td>
</tr>
<tr>
<td>PS [19] + HCGPP</td>
<td>99.3</td>
<td>100</td>
<td>85.9</td>
<td>84.6</td>
</tr>
</tbody>
</table>

Table 2. Top rank recognition rates on AR database.

<table>
<thead>
<tr>
<th>Method</th>
<th>Expression</th>
<th>Sunglasses</th>
<th>Scarf</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBP</td>
<td>87.0</td>
<td>34.6</td>
<td>47.0</td>
</tr>
<tr>
<td>LGBPHS</td>
<td>86.1</td>
<td>37.5</td>
<td>82.5</td>
</tr>
<tr>
<td>GV-LBP-TOP-M</td>
<td>90.5</td>
<td>53.8</td>
<td>87.4</td>
</tr>
<tr>
<td>E-GV-LBP-M</td>
<td>90.9</td>
<td>47.2</td>
<td>82.7</td>
</tr>
<tr>
<td>HOGOM</td>
<td>82.7</td>
<td>82.2</td>
<td>95.0</td>
</tr>
<tr>
<td>HCGPP</td>
<td>92.5</td>
<td>99.2</td>
<td>99.4</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

In this paper, we exploit the potential of Gabor phase features by using the co-occurrence information. The proposed histogram of co-occurrence of Gabor phase patterns (HCGPP) is extensively tested and compared with previous methods on the FERET and AR databases. And all the experimental results indicate that our method is comparable and even better than the state-of-the-art ones in terms of recognition rate.

However, the proposed descriptor HCGPP has a drawback of high dimensionality. How to reduce the feature dimension and at the same time to get a better performance will be considered in our future work.
5. REFERENCES


