Face Recognition Based on Phase-Feature

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***Abstract*— Gabor wavelets (GWs) have been commonly used to extract local features for various applications. Because extracting the Gabor features is computationally intensive, the simplified GW (SGW) has been proposed. In this paper, we propose a novel face recognition algorithm based on the histogram of the SGW phase. In our algorithm, we employ the affinity propagation method to cluster face images for classification. When compared to other conventional face recognition methods, our proposed method can achieve a better performance in terms of both recognition accuracy and tolerance to illumination variations.**

I. Introduction

The principal task of face recognition is to generate a decision concerning the class of a query face image. Some classic techniques, such as the geometrical-measurement method [1], eigenface [2], manifold learning algorithms [3], and elastic graph matching [4], have been used. These approaches have provided reasonably good performances under well-controlled conditions.

Gabor filters are now being used extensively and successfully in various computer-vision applications, including face recognition and detection, due to their biological relevance and computational properties [5]. However, the Gabor features used usually consider the magnitude part only, while ignoring the phase part. Oppenheim *et al*. [6, 7] have shown that, given only the phase spectrum of an image, one can reconstruct the original image up to a scale factor. Thus, phase information is important in representing a 2D signal in the Fourier domain.

In this paper, we will propose a novel face recognition algorithm based on the histogram of Gabor phases. In our algorithm, the normalized cumulative histogram of the SGW phases is then used as the feature to distinguish different human faces for recognition. The use of the normalized cumulative histogram can most effectively represent the characteristics of the histogram for Gabor phase information. In order to describe a histogram as accurately as possible, we present a novel "overall-feature" for the histogram. We also employ affinity propagation to cluster the face images, so as to achieve a more efficient and accurate classification result. Experimental results show that our algorithm can achieve a superior performance as compared to other face recognition algorithms, and can tolerate lighting variations.

II. The Overall Features of the Histogram of Simplified Gabor Phase

Before two face images are compared, a pre-processing step to normalize and align the images is necessary in our proposed algorithm. This step allows us to measure the phase difference between the two faces being compared more accurately. Hence, after aligning two faces based on their eye positions, our algorithm uses the Hausdorff distance [8] to further refine the alignment of the two faces. In this section, we will first introduce the Gabor phase and illustrate its tolerance to variations in illumination, and then introduce the simplified Gabor phase. Finally, an overall feature based on the difference between the Gabor phases of two images is presented.

A. Gabor Phase and Simplified Gabor Phase

In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave, as follows:

$$G(x,y)=\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\exp\left[j\omega(x\cos\theta+y\sin\theta)\right], \quad (1)$$

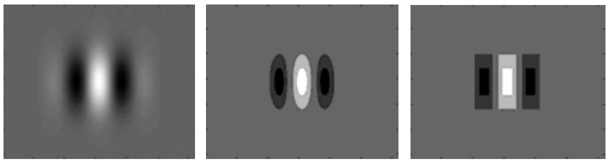
where σ is the standard deviation of the Gaussian function in the x and y directions, and ω denotes the spatial frequency. With an input image $I(x, y)$, the output, $\phi(x, y)$, of the Gabor filter is computed as follows:

$$\phi(x,y)=G(x,y)\otimes I(x,y), \quad (2)$$

where $\otimes$ denotes the two-dimensional convolution operation. The Gabor phase Θ can be described as follows:

$$\Theta=\tan^{-1}\left(\mathrm{Im}(\phi)\big/\mathrm{Re}(\phi)\right). \quad (3)$$

Although (1) can be computed using FFT, the required computation is still intensive. To reduce the computation, simplified versions of the Gabor functions [9] are considered for extracting the phase information. Fig. 1(a) shows an example of the real part of a GW, with the gray-level intensities representing the magnitudes of the wavelet. To simplify it, its values are quantized to a certain number of levels, as shown in Fig. 1(b). Then, the quantized contours are approximated by rectangles, as shown in Fig. 1(c). The imaginary part of a SGW can be constructed similarly. The experimental results in [9] have shown that the use of the simplified Gabor features can achieve a similar performance level to that of the Gabor features, but with a speedup of 3 to 4 times for feature extraction.



(a) (b) (c)

Fig. 1 (a) The values of the real part of a GW, (b) the quantized contours, and (c) the rectangles that approximate the elliptical quantized contours.

B. A Normalized Cumulative Histogram of Gabor Phase Difference

The images of two persons under two different illuminations are shown in Fig. 2. We calculate the corresponding phase images of the four face images, based on a Gabor filter of horizontal direction and at a particular scale. The histograms of the phase-difference images of the same person under different illuminations and those of different persons under the same illumination are illustrated in Fig. 3. In order to manifest the differences between the histograms, the *x*-axis is represented in log scale. The range of the Gabor phase is [0^{o}, 179^{o}], so this is the range of the Gabor-phase difference. Hence, each histogram has 180 bins.

(a) (b) (c) (d)

Fig. 2 Four images from the Yale database.

Fig. 3 shows that a unique maximum will locate near 0 in the histograms of those phase-difference images of the same person, and the maximum is followed by a sharp reduction. This means that the phase differences between the two images are very small. In other words, the phase images of the same person under different illuminations are very similar. However, the histograms of the phase-difference image of two different persons will have the maximum farther away from 0, and the slope after the maximum is not as sharp as that for the case of the same face. This also means that the phase differences of two different persons are more random. In other words, the patterns of the phase-difference images of the same person and of different persons are distinctly different. Therefore, our algorithm uses phase information to form an illumination-insensitive measurement for face recognition.

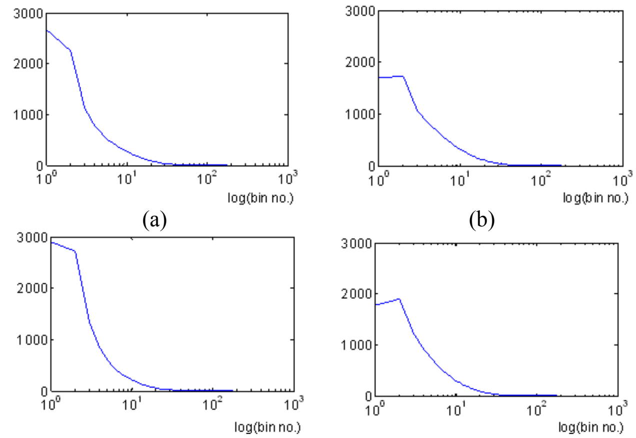


Fig. 3 The corresponding Gabor-phase difference histograms between: (a) Fig. 2(a) and Fig. 2(b); (b) Fig. 2(a) and Fig. 2(c); (c) Fig. 2(c) and Fig. 2(d); and (d) Fig. 2(b) and Fig. 2(d).

Based on the property of the Gabor phase-difference histograms, the details and the steps of our phase-based face recognition algorithm are given as follows:

Step1: Suppose p_i and p_j are the Gabor phase images of the i^{th} and the j^{th} face images in a dataset to be compared. These phase images are computed by using the simplified Gabor wavelets. The Gabor phase difference P_{ij} of these two images is then given as follows:

$$P_{ij} = \left| p_i - p_j \right|. \tag{4}$$

Step 2: The histogram of the Gabor phase difference is constructed as follows:

$$H_{ij} = hist(P) \rightarrow \{h_0, h_1, \ldots, h_{179}\}, \tag{5}$$

where h_k (k = 0, …, 179) is the k^{th} bin of the histogram H_{ij}, which counts the number of pixel positions having their absolute phase difference equal to k.

Step 3: The cumulative histogram of H_{ij} is constructed:

$$CH_{ij} \rightarrow \{cn_0, cn_1, cn_2, \ldots, cn_{179}\}, \tag{6}$$

where $cn_l = \sum_{k=0}^{l} h_k$.

Step 4: The normalized histogram of CH_{ij} is constructed:

$$NCH_{ij} \rightarrow \{ncn_0, ncn_1, ncn_2, \ldots, ncn_{179}\}, \tag{7}$$

where $ncn_k = \dfrac{cn_k}{cn_{179}}$, $k = 0, \ldots, 179$.

Step5: The characteristics of the normalized cumulative histogram NCH_{ij} are described by using two features in [10], which are the mean and derivation of the histogram, and the "overall-feature". These three features are given as follows:

(a) The mean of the histogram:

$$\mu_{ij} = \sum_{i=0}^{179} ncn_k \Big/ 180. \quad (8)$$

(b) The deviation of the histogram:

$$\sigma_{ij} = \frac{1}{180} \sum_{k=0}^{179} \left| ncn_k - \mu_{ij} \right|. \quad (9)$$

(c) The "overall-feature" used to distinguish the two face images is:

$$F_{ij} = \mu_{ij} + \frac{1}{\alpha \cdot \sigma_{ij}}, \quad (10)$$

where α is a weight used to adjust the contribution of the derivation in computing the "overall-feature" of the histogram. In our experiments, we found that setting $\alpha = 10$ can provide the best recognition performance. The formulation of F_{ij} is based on the fact that the mean of the NCH_{ij} will be large, while the deviation will be small if the two face images are of the same person; and vice versa if the two faces are of different persons. This overall feature is then used in the matching of the two face images. If the two images to be compared are of the same person, the overall features F_{ij} will have a large value. But if they are of two different persons, the value of this feature will be small.

III. CLUSTERING FACE IMAGES BY AFFINITY PROPAGATION

In Section 2, we have presented an "overall-feature" F_{ij}, which is then used for face recognition. In our algorithm, we employ a more effective clustering approach, based on affinity propagation [11], for face-image classification.

Brendan [11] has proposed a clustering approach based on affinity propagation, which simultaneously considers all the data points as potential exemplars. Considering each data point as a node in a network, the clustering algorithm recursively transmits real-valued messages along edges of the network until a set of good exemplars and their corresponding clusters emerges. In the algorithm, $s(i, k)$ denotes the similarity between the image i and image k, and we set $s(i, k) = F_{ik}$ in our algorithm. Hence, $s(i, k)$ indicates how well the image k is used as an exemplar for image i. There are two kinds of messages exchanged between the different images, which are "responsibility" and "availability", and each of these messages also takes into account a different kind of competition. The responsibility $r(i, k)$, sent from image i to candidate exemplar image k, reflects the accumulated evidence for how well-suited image k is to serve as the exemplar for image i, taking into account other potential exemplars for image i. The availability $a(i, k)$, sent from candidate exemplar image k to image i, reflects the accumulated evidence for how appropriate it will be for image i to choose image k as its exemplar, taking into account the support from other images that image k should be an exemplar. The responsibility is computed as follows:

$$r(i,k) = s(i,k) - \max_{k' s.t. k' \neq k} \{a(i,k') + s(i,k')\}, \quad (11)$$

where $a(i,k')$ is initially set to 0. This update of the above responsibility will allow all candidate exemplars to compete for ownership of the image i. The following update of the availability $a(i, k)$ gathers evidence from all images as to whether the candidate exemplar k will be a good exemplar.

$$a(i,k) = \min\left\{0, r(k,k) + \sum_{i' s.t. i' \notin \{i,k\}} \max\{0, r(i',k)\}\right\}. \quad (12)$$

The self-availability $a(k, k)$ is updated in a different way, as follows:

$$a(k,k) = \sum_{i' s.t. i' \neq k} \max\{0, r(i',k)\}. \quad (13)$$

For the image i, the image k that maximizes $a(i, k) + r(i, k)$ will be identified as its exemplar. The message-passing procedure may be terminated either after a fixed number of iterations, or after the changes in the messages are lower than a threshold, or after the local decisions remain unchanged for a certain number of iterations.

IV. EXPERIMRNTAL RESULTS

In this section, we will evaluate the performance of our algorithm. First, we will test the performances of the proposed method with different values of α in (10), with the use of the SGW in terms of recognition rate. Second, we will test the effectiveness of using the affinity-propagation approach for image classification. Finally, we will compare our proposed method with other face recognition algorithms.

A. Face databases and experimental set-up

The standard face databases used in the experiments include the Yale database, YaleB database, and AR database. The images in both the Yale and AR databases have variations in facial expression, while the images in YaleB database have large variation in lighting. Each face image is normalized to a size of 64×64. In order to enhance the global contrast of the images and to reduce the effect of uneven illuminations, histogram equalization is applied to all images. The GW and SGW adopt 3 to 5 center frequencies with 4 orientations. The performance of the SGWs depends on the number of quantization levels used; however, more quantization levels will increase the runtime required for extracting the SGW features. Therefore, as a compromise, the number of quantization levels used is 5.

B. The performances of the proposed method with different values of α

The parameter α in (10) controls the relative importance of the mean and deviation of the histogram in computing the overall feature, which will therefore directly affect the performance of the algorithm. In this section, we will measure the performances of the proposed methods with different values of α. Table 1 shows the face recognition rate when α =

{1, 10, 20}. The best performance is achieved with the different databases when α is about 10. Therefore, in the following experiments, we set $\alpha = 10$.

TABLE I
FACE RECOGNITION RATES WITH DIFFERENT VALUES OF α.

	Recognition rate (%)		
	Yale	YaleB	AR
$\alpha = 1$	63.10	70.28	62.57
$\alpha = 10$	92.68	97.03	91.28
$\alpha = 20$	92.71	95.58	89.89

C. The Performance When Using Affinity Propagation

In this section, we use the clustering method based on affinity propagation and the *K*-means clustering algorithm [11] for face recognition using the phase feature. From the recognition rates shown in Table 2, the affinity-propagation approach can achieve a better performance.

TABLE II
COMPARISON OF THE PERFORMANCES OF OUR PROPOSED ALGORITHM USING AFFINITY PROPAGATION AND THE *K*-MEANS CLUSTERING ALGORITHM.

	Recognition rate (%)		
	Yale	YaleB	AR
Affinity propagation	92.68	97.03	91.28
K-means algorithm	89.21	93.87	89.10

D. Comparison with Other Conventional Face Recognition Methods

In order to demonstrate the performance of our proposed method, we compare its recognition rate with other face recognition algorithms: HGPP [12], eigenface [2], and SGW [9]. We can see that our method significantly outperforms the HGPP, the eigenface, and the SGW methods for the Yale database and the YaleB database. This shows that our algorithm is more robust to illumination variations. With the AR database, the performance of our algorithm is very similar to the HGPP and SGW algorithms.

TABLE III
THE PERFORMANCES OF OUR PROPOSED ALGORITHM AND OTHER CONVENTIONAL FACE RECOGNITION METHODS.

	Recognition rate (%)		
	Yale	YaleB	AR
The proposed method	92.68	97.03	91.28
HGPP	89.32	93.76	91.65
Eigenface	75.60	76.38	55.36
SGW	82.00	94.69	91.74

V. CONCLUSIONS

In this paper, we have proposed an efficient algorithm for face recognition, which uses a histogram to represent the phase difference between two face images and the "overall-feature", derived from the mean and the deviation of the phase histogram in matching the two images. To classify a query face, we propose to use the affinity-propagation clustering method to identify the best exemplar for the query image. Experimental results show that our algorithm significantly outperforms the HGPP, eigenface, and SGW methods when the face images are under lighting variations. For images with variations in facial expression, the performance of our proposed algorithm outperforms all the other algorithms in the experiments.

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