Face Recognition under Varying Lighting Based on the Probabilistic Model of Gabor Phase

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Abstract

This paper present a novel method for robust illumination-tolerant face recognition based on the Gabor phase and a probabilistic similarity measure. Invited by the work in Eigenphases [1] by using the phase spectrum of face images, we use the phase information of the multi-resolution and multi-orientation Gabor filters. We show that the Gabor phase has more discriminative information and it is tolerate to illumination variations. Then we use a probabilistic similarity measure based on a Bayesian (MAP) analysis of the difference between the Gabor phases of two face images. We train the model using some images in the illumination subset of CMU-PIE database and test on the other images of CMU-PIE database and the Yale B database and get comparative results.

1. Introduction

There are still many challenges to overcome in face recognition and illumination variation is one of them [2][3].

To deal with the problem of varying illuminations, there are many methods developed, which can be categorized into three fundamental kinds: invariant features, canonical forms, and variation-modeling [4]. The invariant feature is simpler for it needs no prior knowledge and preprocessing.

This paper is trying to find an illumination-tolerant feature for face recognition under varying illuminations. Invited by the work in Eigenphases [1], which used the phase spectrum of face images as illumination tolerant invariant feature, we use the phase information of the multi-resolution and multi-orientation Gabor filters instead. We believe that the phase information of Gabor filters is more discriminative than that of the phase of FFT for its multi-resolution and multi-orientation. Though the magnitude of the Gabor filters has been used in face recognition systems [5][6], the phase information has little been used except in [7] as we known, where the phase is quantized into binary pattern. The phase information has also been successfully used in Iris recognition systems [8].

Though the phase spectrum is tolerant to illumination variations to some extent, there is still some difference between different images of the same person. Then we build a probabilistic similarity measure based on a Bayesian (MAP) analysis of the difference between the Gabor phases, which is similar with the probabilistic measure in [9] and [10], though the feature are different.

The rest of the paper is organized as follows. The details of the proposed probabilistic model based on Gabor phase are presented in section 2. We show the experimental results of the proposed method in section 3. Finally the conclusions are given in sections 4.

2. Probabilistic model of Gabor phase

We first introduce the Gabor phase and show its tolerance to variations in illumination, and then a probabilistic measure based on the difference between the Gabor phases of two images is presented.

2.1. Gabor phases

The 2D Gabor wavelet form can be defined as follows [11]:

$$g(x,y) = e^{-\pi\left((x-x_0)^2/\alpha^2+(y-y_0)^2/\beta^2\right)} e^{-2\pi j\left(u(x-x_0)+v(y-y_0)\right)}, \quad (1)$$

where (x_0, y_0) specifies wavelet position, (α, β) specifies effective width and length, and (u, v) specifies a modulation wave-vector which can be interpreted in polar coordinates as spatial frequency $\varpi = \sqrt{u^2+v^2}$ and orientation $\theta = \arctan(v/u)$. In this

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paper, five spatial frequencies and eight orientations Gabor wavelets are used. The Gabor representation of a face image can be derived by convolving the face image with the Gabor filters. Let $f(x,y)$ be the face image, its convolution with a Gabor filter is defined as follows

$$C(x,y)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x,y)f(x,y)dxdy\ . \qquad (2)$$

The images of two persons under two different illuminations are shown in Figure 1 (a). The corresponding visualization of the phase images of the horizontal direction of the largest scale Gabor filters of the face images are shown in Figure 1 (b). The difference images of the phase images of the same person under different illuminations and those of the different person under the same illumination are shown the Figure 1 (c). Finally the histograms of the four difference images are given in Figure 1 (d). The Gabor phases' range [0^o, 360 ^{o}] are quantized uniformly as 256 bins ([0, 255]), and [illegible] absolute value of the difference is 0~127.

There is a unique maximum near 0 in the histograms of the difference images of the phase images of the same person and then there is a sharp reduction, which means that the phase images of the same person under different illuminations are almost the same (The difference is very small and near 0). While in the histograms of the difference images of the phase images of the difference persons, the maximums are far away from 0 and the reduction is not so sharp, which means that the differences between the phase images of two persons are more random. In other words, the patterns of the difference images of the same person and the different persons are prominently different. Then it can be concluded that the Gabor phase is tolerate to illumination variations while remains the discriminative ability. Therefore the phase information could be used as an illumination insensitive measure for face recognition because the differences of the Gabor phases between the same person are less than those of the different persons, which differs from that of the differences of the intensity of the images [12].

2.2. Probabilistic model

The Gabor phase is not illumination invariant, though it is tolerate to illumination variations to some extent. One possible way to improve this is to model the difference between the Gabor phases of two images using a probabilistic similarity measure similar with that in [9]. Let Δ be the Gabor phase difference between two images, Ω_I be the intrapersonal

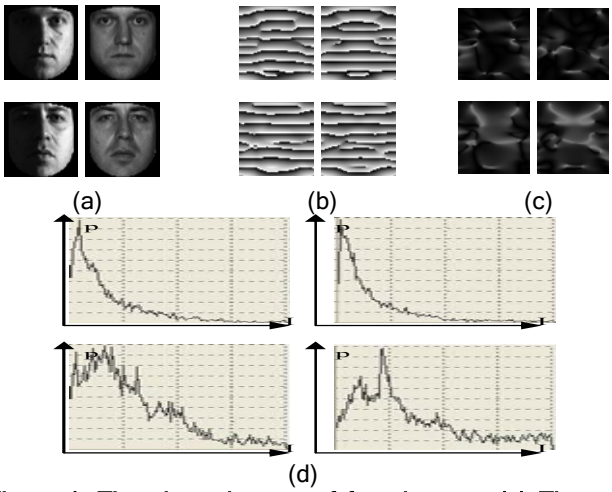

Figure 1. The phase images of face images. (a) The images of two persons under two different illuminations. The row is the same person and the column is the same illumination. (b) The phase images of the horizontal direction of the largest scale Gabor filters of the face images in (a). (c) The difference images of the phase images in (b). The first row is the same person and the second row is the same illumination. (d) The histograms of the images in (c).

variations of the Gabor phases and Ω_E be the extrapersonal variations, the similarity is then expressed in term of probability using the MAP rule as

$$S(I_1,I_2)=P(\Omega_I\mid\Delta)$$
$$=\frac{P(\Delta\mid\Omega_I)P(\Omega_I)}{P(\Delta\mid\Omega_I)P(\Omega_I)+P(\Delta\mid\Omega_E)P(\Omega_E)}. \qquad (3)$$

The next step is then how to compute the likelihood $P(\Delta\mid\Omega_I)$ and $P(\Delta\mid\Omega_E)$, and the prior $P(\Omega_I)$ and $P(\Omega_E)$. To circumvent this difficulty and for pragmatic reasons, we assume that $P(\Omega_I)=P(\Omega_E)=0.5$, and the pixels in the images are independent, ignoring correlations arising from spatial proximity. The Eq. (3) is written as

$$S(I_1,I_2)=\frac{P(\Delta\mid\Omega_I)}{P(\Delta\mid\Omega_I)+P(\Delta\mid\Omega_E)}$$
$$=\prod_{i\in M}\frac{P(\Delta_i\mid\Omega_I)}{P(\Delta_i\mid\Omega_I)+P(\Delta_i\mid\Omega_E)}. \qquad (4)$$

We estimate the density $P(\Delta_i\mid\Omega_I)$ and $P(\Delta_i\mid\Omega_E)$ in Eq. (4) by the histograms of the differences between the Gabor phases of every two images of the same person and different persons, respectively. The probability density of $P(\Delta_i\mid\Omega_I)$ and $P(\Delta_i\mid\Omega_E)$ of the phase images of the horizontal direction of the largest scale Gabor filter is shown in Figure 2 as an example. As expected, the distribution has the similar shape depicted in Figure 1 (d). The

phase images of the same person under different illuminations are almost the same, while the differences between the phase images of two persons are more random.

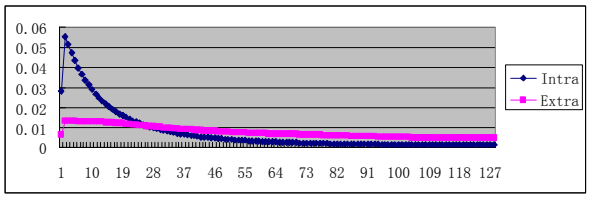

Figure 2. The density of $P(\Delta_i|\Omega_I)$ and $P(\Delta_i|\Omega_E)$ of the phase images of the horizontal direction of the largest scale Gabor filter.

3. Experimental results

We apply the proposed scheme to face recognition. In the experiments, each image is convolved with the 40 Gabor filters and then the Gabor phase information is used in computing similarity between two images as in the Eq. (4).

We select the frontal images with lighting variations from two publicly available face databases, the CMU-PIE face database [13] and the Yale B face database [14], for our experiments. There are 21 flashes (02-21) and the background light to illuminate the face in CMU-PIE database. The images are captured under the background light off (the illumination subset) and on (the light subset), resulting in 43 different conditions. There are total 68 persons included in the database. Some examples of the facial images under different illuminations are shown in Figure 3. For more details about the CMU-PIE face database, please refer to [13]. The Yale face database [13] contains images of 10 people under 64 illuminations. Figure 4 shows some of the images used in our experiments. The face images are extracted and normalized for scale using the locations of the two eyes provided with the database. The resulting images used in our experiments are of size 64×64.

Figure 3. The images of one person in the illumination set in the CMU-PIE database and the image under the background lighting (the last one).

In the experiments, the train set is composed of 34 persons (the even ID), 21 images per person from the illumination set from the CMI-PIE face database. Then we get the intra-face variation model $P(\Delta_i|\Omega_I)$ and the extra-face variation model $P(\Delta_i|\Omega_E)$ of the Gabor phase. The test sets include the images of the left 34 persons in the illumination set and the light set of CMU-PIE database and all the images in the Yale B database. For each test set, the images under the frontal lighting are used as gallery. Therefore there is no intersection between the training set and the test sets.

The Gabor phase method is compared with the other angle features that are declared as illumination invariant, the gradient angle [10], the FFT Phase [1] and the intensity of the images. The probabilistic similarity measures for these features are trained using the same training set in the same process as described in the up paragraph. Some examples of these features are visualized in Figure 4.

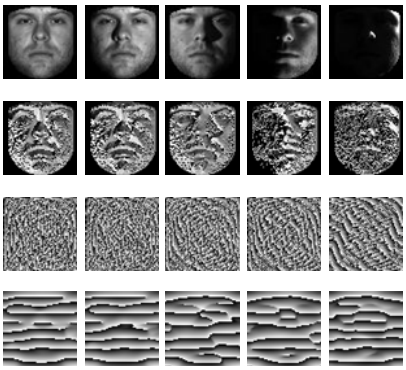

Figure 4. The images of one person in the Yale B database (the first row) and the corresponding images of the gradient angle (the second row) and the images of FFT phase (the third row) and images of the Gabor phase (the last row) .

Table 1 shows the results of face recognition test and compares it to other methods on the CMU-PIE database.

Table. 1. Error rate comparisons between different features on the CMU-PIE database.

Method	Error rate (%)	
	Illumination set	Light set
Intensity	4.0	0.0
Gradient Angle	0.0	0.0
FFT Phase	5.7	0.0
Gabor Phase	0.0	0.0

The experimental results of face recognition on the Yale B face database are given in Table 2. The Gabor phase is more robust to illumination variations than the

gradient angle and the FFT Phase. The experimental results are a little better than the complex model based on the harmonic model in [15], though a little less than that of the illumination cone considering cast shadow, which needed 7 images for gallery and complex computing. When check the images which are identified to error class, we can see that these images are difficult to distinguish even for the human beings.

Table. 2. Error rate comparisons between different features on the Yale B database.

Method	Error rate (%) Subset No.				
	1	2	3	4	5
Gradient Angle	0.0	0.0	0.0	6.4	11.6
FFT Phase	0.0	2.5	2.5	26.4	69.5
Gabor Phase	0.0	0.0	0.0	2.8	4.7
Cones-cast [14]	0.0	0.0	0.0	0.0	-
Harmonics [15]	0.0	0.0	0.0	3.1	-

4. Conclusions

We present a probabilistic similarity measures based on the Gabor phase information for face recognition under varying illuminations. We have shown that the Gabor phase of the face images is a representation relatively invariant to illumination variations. The experimental results on the CMU-PIE database and Yale B database are encouraging.

There are still several ways to improve the work. The phase information is sensitive to the alignments between images; therefore the results are not expected to so good as in the above experiments in more general cases where the images are not aligned exactly. One possible method is the more delicate local models which parts the image into multi-regions and model the intra-variations and extra-variations of each region. The dimension of Gabor phases is very high and we hope to remedy this by exploring the technique for dimension reduction to reduce the computation and the storage. The Gabor phase of face images may be encoded like Quad Phase as in the Iris recognition [7] or binary phase in face recognition [5] and combined with the probabilistic similarity measure.

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