# Discriminant Analysis with Gabor Phase for Robust Face Recognition

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## Abstract

*This paper presents an occlusion robust image representation method and apply it to face recognition. Inspired from the recent work [15], we propose a Gabor phase difference representation for occlusion robust face recognition. Based on the good ability of Gabor filters to capture image structure and the robustness to image occlusion shown in this paper, Gabor phase features are expected to be discriminative and robust for face representation in occlusion case. Besides, we adopt spectral regression based discriminant analysis with the extracted Gabor phase features to find the most discriminant subspace to classify different faces. In this way, an occlusion robust face image discriminant subspace is derived. Extensive experiments with various occlusion cases show the efficacy of the proposed method.*

## 1. Introduction

Image occlusion is a great challenge for face recognition. Although face recognition in good condition has been well addressed, its performance in uncontrolled environment like occlusion is still an open problem. There are mainly two categories to deal with face occlusion problem. One is to extract occlusion robust face representation, and the other is to design robust classifier or apply partial matching mechanism.

Most existing methods fall into the latter category. That is, they are pursued to find robust face matching method to deal with face recognition with occlusion. Park et al. [12] proposed a face representation structure ARG (attributed relational graph) containing all the geometric quantities and the structural information. In testing phase, a face is represented by the ARG structure, and the partial ARG matching

is processed for the holistic matching. Kim et al. [6] proposed LS-ICA method that uses locally salient information of important facial parts to make full use of the recognition-by-parts way. It imposes additional localization limitation while computing ICA architecture I basis images to create part-based local basis images. Zhang et al. [19] divided the images into local regions, and the Kullback-Leibler divergence (KLD) is used to estimate the probability of occlusion for every region. The importance of feature vectors in regions with high occlusion probability are weakened so that the robust face recognition with occlusion is achieved. Hotta [4] proposed local Gaussian summation kernel with SVM for face recognition with partial occlusion. A series of local kernels are constructed and the summation of them is used to replace the global kernel in traditional SVM so that the robustness to occlusion is improved. Jia and Martinez [5] proposed robust SVM to deal with the feature vectors with missing entries because of the image occlusion. Yi Ma and his group [17][20] proposed a series of sparse representation classifier (SRC) based face recognition methods. SRC treats the probe image as a linear combination of gallery images and the sparse constraints are imposed onto the solutions. Their method demonstrated good robustness to face recognition, especially with occlusions. Yi, Lei and Li [18] combined local features and SRC to realize robust NIR face recognition with eye glasses occlusions.

There is few work in the first category. Singh et al. [14] used 2D log polar Gabor transform and learned a dynamic neural network architecture to extract phase based textural features to deal with disguises problem in face recognition. Liu et al. [10] proposed a generalization of kernel discriminant analysis, where they extracted the face features by comparing the face images with a set of face images and grouping the similarity scores. Recently, Tzimiropoulos et al. [15] proposed a principle component analysis (PCA) representation of gradient orientation. They revealed that the gradient orientation differences of occlusion and non-

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occlusion areas usually obey uniform distribution. The combination of gradient orientation and cosine similarity measure provides a good representation for face occlusion image.

In this paper, we propose a Gabor phase based occlusion robust face representation method. First, we analyze the Gabor phase (GP) difference of occlusion and non-occlusion areas and find that GP difference is more stable than gradient orientation in the case of occlusion and it is expected to be more robust than gradient orientation to image occlusion. Second, we combine the multi-scale and multi-orientation Gabor responses to utilize more sufficient information useful for face recognition. Third, a discriminant analysis method is adopted to find the most discriminant subspace to obtain the discriminant and compact occlusion robust face representation. Experiments on various databases show that the proposed method achieves better performance than some state-of-the-art methods.

The rest of this paper is organized as follows. Section 2 introduces the Gabor phase feature and analyzes the robustness of Gabor phase feature for face image occlusion. Section 3 details the spectral regression based discriminant analysis method. Experimental results and analysis are demonstrated in Section 4 and in Section 5, we conclude the paper.

## 2. Occlusion Robust Gabor Phase Information

### 2.1. Gabor filters

Gabor filter has been widely and successfully used in face recognition [7, 9, 16]. The Gabor kernels are defined as follows:

$$\psi_{(\mu,\nu)} = \frac{k_{(\mu,\nu)}^2}{\sigma^2} \exp(-\frac{k_{\mu,\nu}^2 z^2}{2\sigma^2})[\exp(ik_{\mu,\nu}z) - \exp(-\frac{\sigma^2}{2})] \tag{1}$$

in which $\mu$ and $\nu$ define the orientation and scale of the Gabor kernels, $z = (x, y)$, and the wave vector $k_{\mu,\nu}$ is defined as follows:

$$k_{\mu,\nu} = k_v e^{i\phi_\mu} \tag{2}$$

where $k_v = k_{max}/f^v$, $k_{max} = \pi/2, f = \sqrt{2}$, $\phi_\mu = \pi\mu/8$. The Gabor kernels in Eq. 1 are all self-similar since they can be generated from the same filter, the mother wavelet, by scaling and rotating via the wave vector $k_{\mu,\nu}$. Each kernel is a product of a Gaussian envelope and a complex plane wave, and can be separated into real and imaginary parts. Hence, a band of Gabor filters is generated by a set of various scales and rotations.

### 2.2. Gabor phase vs. Gradient orientation

The recent work [15] shows that gradient orientation is robust to image occlusion. The principle of their observation is that the gradient orientation difference of two randomly selected nature images follows a uniform distribution and the metric by summing the cosine value of gradient orientation differences equals zero. Based on this characteristic, they claim that the gradient orientation difference is robust to image occlusion because the occlusion areas are automatically ignored when computing the similarity metric between two images. However, in our experiment, we find that given an image pair, one of which is occluded, the gradient orientation difference does not always (approximately) follows uniform distribution. Even it does, we argue that simply ignoring the occlusion area is not a good way for robust face recognition. For example, suppose $a$ and $b$ are images from the same person and $c$ is an image belonging to another person. In the normal case, the similarity metric of $a$ and $b$ is larger than that of $a$ and $c$ (or $b$ and $c$). However, when $b$ is occluded, since the occluded area is ignored like in gradient orientation, the similarity metric between $a$ and $b$ may be smaller than that of $a$ and $c$, resulting in the misclassification. In this paper, we argue that a good occlusion robust face representation should make the similarity of the occluded images as close as that of the normal ones, rather than simply ignores the occluded areas.

We carry out the following experiment to compare Gabor phase and gradient orientation in the occlusion case. We pick out 5000 pairs of faces from the FERET [13] database. Suppose $P_i$ and $P_j$ are one pair of them, $\phi_i$ and $\phi_j$ are gradient orientation (or Gabor phase) of $P_i$ and $P_j$ and $\Delta\phi_{ij}$ is the difference between $\phi_i$ and $\phi_j$, we define the dissimilarity between the two faces using the cosine kernel as follows [15]:

$$s(\phi_i, \phi_j) = \sum_{p \epsilon K} cos(\Delta\phi_{ij}(p)) \tag{3}$$

where $K = \{1, \ldots, k\}$ is the set of pixel indices.

Then, we pollute one of the two images by setting the pixels of the half bottom face to zero to simulate the occlusion case, as shown in Fig. 1. Denoting the correlation between the two original faces as $s_1$, and the correlation between the two faces in the occlusion case as $s_2$, the effect of the occlusion on the similarity between the two faces can be measured as:

$$E = \frac{1}{N} \sum_{n=1}^{N} \frac{|s_{1n} - s_{2n}|}{|s_{1n}|} \tag{4}$$

where $N = 5000$ is the number of image pairs we used in the experiment. The larger of $E$ means the stronger effect of occlusion on the similarity between two face images. Table 1 shows the comparison of value $E$ between gradient orientation and Gabor phase. For the Gabor phase, one scale with eight orientations are listed. From the result, one can see that that in some orientations (e.g., orientation 1, 2 &

Figure 1. The first two images are the original face pair and the last two images are the face pair where the second picture is partially occluded.
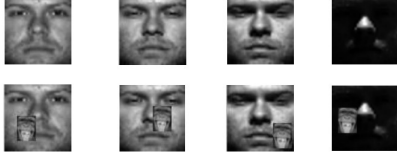


Figure 2. The first row are the original faces without occlusion and the second row are the original faces under occlusion.
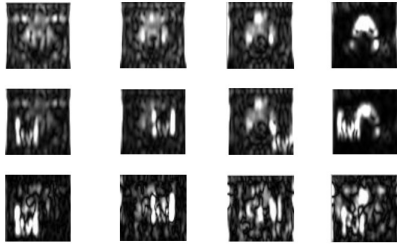


Figure 3. The first row are the faces without occlusion represented by Gabor magnitude and the second row are the faces under occlusion represented by Gabor magnitude, while the third row are the reconstructions of the faces under occlusion represented by Gabor magnitude.
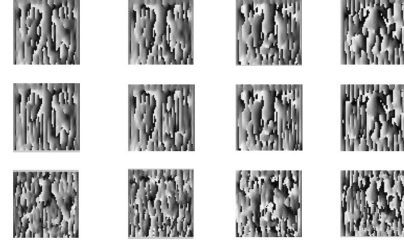


Figure 4. The first row are the faces without occlusion represented by Gabor phase and the second row are the faces under occlusion represented by Gabor phase, while the third row are the reconstructions of the faces under occlusion represented by Gabor phase.

eight principle components are used to reconstruct the face image. Fig. 2 shows the original faces with/without occlusion. Fig. 3 shows the Gabor magnitude faces and its reconstructed ones. Fig. 4 shows the Gabor phase faces and its reconstructed ones. We can see that the occlusion part in Gabor magnitude face is more obvious than that in Gabor phase face, indicating that Gabor phase representation is more robust to image occlusion and is suitable for occlusion robust face recognition.

## 3. Spectral Regression based Discriminant Analysis

As in [15], we measure the dissimilarity between two images using the cosine kernel as

$$s(\phi_i, \phi_j) = \sum_{p \epsilon K} cos(\Delta\phi_{ij}(p)) \qquad (5)$$

where $\phi_i$, $\phi_j$ are Gabor phase (or Gradient orientation) representations of face images, $\Delta\phi_{ij}$ is the difference between them and $K = \{1, \ldots, k\}$ is the set of pixel indices. With the mapping $z_i(\phi_i) = e^{j\phi_i}$, we can further apply discriminant analysis method to the transformed data $z_i$ to derive the most separable subspace to be classified.

In this paper, we utilize spectral regression (SR) to derive the discriminant subspace efficiently. Spectral regression (SR) [1] is an efficient alternative framework for traditional discriminant analysis method. SR models the discriminant analysis as a regression problem. The computational expensive process of eigenvalue decomposition is avoided and hence it greatly reduces the computational cost. Unlike traditional discriminant analysis, SR solves the solution with two steps. First, the discriminant low dimension embeddings are derived. Second, the relationship between the low dimension embeddings and the original data is learned. As stated in [2], for LDA, the discriminant low dimension embeddings can be constructed in a straightforward way as:

8), the effect measure value of Gabor phase is significantly smaller than that of gradient orientation, meaning that Gabor phase in these orientations is more robust to occlusion than gradient orientation. In the following, we integrate the robust Gabor phase information to obtain face occlusion robust representation.

### 2.3. Gabor phase vs. Gabor magnitude

Traditional face recognition prefers Gabor magnitude feature due to its robustness to illumination and misalignment. However, in the occlusion case, we find that Gabor phase response is more stable and robust than Gabor magnitude one.

We use 50 aligned face images from Yale B face database [3]. The images are from the same subject but captured under different lighting conditions. The first ten pictures are occluded by a $24 \times 18$ Pongo face placed at random locations. Gabor magnitude and phase features are extracted from these images respectively (here we use scale 2 and orientation 1 as an example). After that, PCA is applied on Gabor magnitude or phase images and the first

Table 1. The comparison of value $E$ between Gradient orientation and Gabor phase. GO and GP denotes gradient orientation and Gabor phase respectively.

| Method | GO | GP ori. 1 | GP ori. 2 | GP ori. 3 | GP ori. 4 | GP ori. 5 | GP ori. 6 | GP ori. 7 | GP ori. 8 |
|--------|------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| E | 0.47 | 0.27 | 0.20 | 0.35 | 0.36 | 0.56 | 0.33 | 0.48 | 0.19 |

$$y_k = [\,\underbrace{0,\ldots,0}_{\sum_{i=1}^{k-1} m_i},\underbrace{1,\ldots,1}_{m_k},\ \underbrace{0,\ldots,0}_{\sum_{i=k+1}^{c} m_i}\,]^T, k = 1,\ldots,c \quad (6)$$

where $c$ is the class number and $m_i$ is the sample number in $i$-th class. Under linear assumption, the second step can be formulated as a least square regression problem to learn the projective matrix from the original data to the low dimension subspace as described in [1] :

$$a = \arg\min_a \sum_{i=1}^{m}(a^T x_i - y_i)^2 \quad (7)$$

where $m$ is the total sample number.

## 4. Experiments

In this section we conduct comprehensive experiments to verify the effectiveness of the proposed algorithm. Both simulated and real occlusion cases are tested. In simulated experiment, we consider the occlusion by deliberately adding facial wearings like glasses, masks and hats etc. Moreover, we compare various methods in the case of occlusion caused by eyeglasses on NIR face recognition problem, where the high light reflectance always makes the situation worse.

In the following experiments, two face features (gradient orientation and Gabor phase) with four subspace learning methods (PCA, FLDA, RLDA and SRLDA) are combined. There are totally eight combinations: GPCA (gradient orientation+ PCA), GFLD (gradient orientation+ FLDA), GRLDA (gradient orientation+ regularized LDA), GSRLDA (gradient orientation+ spectral regression LDA), GPPCA (Gabor phase+ PCA), GPFLD (Gabor phase + FLDA), GPRLDA (Gabor phase + regularized LDA), GP-SRLDA (Gabor phase + spectrum regression LDA).

### 4.1. Way to choose the scales and orientations for Gabor phase feature

Multi-scale and multi-orientation Gabor phase features are utilized. In order to improve the efficiency of the algorithm, we try to select the optimal scales and orientations for Gabor phase representation. Five scales and eight orientations of Gabor filters are compared. We combine the Gabor phase features with SRLDA and compare the recognition accuracy on FERET face database. Fig. 5 shows the recognition accuracy for 40 Gabor filters. Overall, scales

2, 3 and orientations 1, 2, 8 get better performance. In the following experiments, we utilize the Gabor phase features with scales 2, 3 and orientations 1, 2, 8 to represent faces.
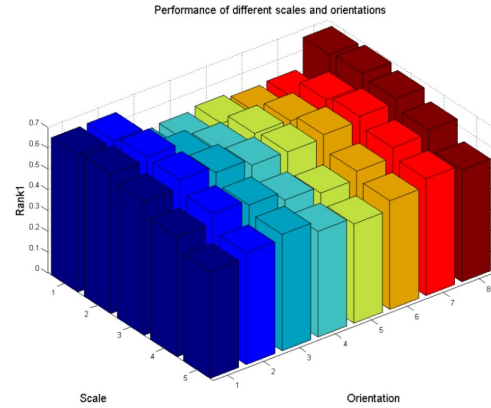


Figure 5. Rank-1 face recognition rate with different scales and orientations for Gabor phase feature on FERET database.

### 4.2. Artificial occlusion experiment

In this experiment, we use FERET [13] database to evaluate the proposed algorithm by adding artificial occlusion to the original images. Several occlusion masks are designed and placed at random locations within the face images (Fig. 4.2).



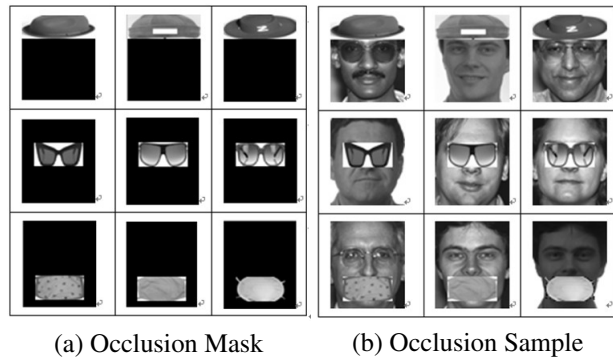(a) Occlusion Mask          (b) Occlusion Sample

Figure 6. Examples of occlusion mask and occlusion sample used in our experiment.

We collect 1204 subjects from FERET database, and there are totally 3988 samples, most of which are frontal faces. The images are divided into three sets, named training set, target set and query set. We randomly select half

of subjects to form the training set. For each person not included in the training set, one image is selected as the target one and the left images make up the query set. We design two experimental settings to examine the robustness of different methods to occlusion. In the first setting, there is no occlusion in training and target sets and all images in query set are artificially occluded. In the second setting, there is no occlusion in target set. Partial images in training set and query set are artificially occluded. The second setting is used to evaluate the robustness of different methods when there is occlusion in training set. The images in query set are compared with the images in target set and the Rank-1 recognition accuracy is reported.

Table 2 lists the recognition results of various methods on FERET database. Gabor phase based methods always outperform gradient orientation based ones, validating that Gabor phase feature is an occlusion robust face representation. The combination of Gabor phase information and spectral regression achieves the best recognition result.

Table 2. Rank-1 recognition rates of different methods on FERET database with artificial occlusion.

| Setting 1 | | | | |
|---|---|---|---|---|
| Method | PCA | LDA | LDA | SRLDA |
| Gradient orientation | 0.53 | 0.28 | 0.58 | 0.60 |
| Gabor phase | 0.65 | 0.61 | 0.61 | 0.67 |
| Setting 2 | | | | |
| Method | PCA | LDA | RLDA | SRLDA |
| Gradient orientation | 0.62 | 0.21 | 0.67 | 0.67 |
| Gabor phase | 0.72 | 0.71 | 0.68 | 0.72 |

### 4.3. Real occlusion experiment

In this part, we compare the performance of different methods on AR [11] face database with real occlusions. The AR database consists of more than 4,000 images of 126 subjects, including 70 males and 56 females. The images were taken in two sessions separated by two weeks, considering expression (neutral, smile, anger and scream),illumination and occlusion (sunglass and scarf) variations. Fig. 7 shows some examples from AR face database. In this experiment, we select 64 male and 52 female subjects from the database, each of which contains 26 images taken in two sessions. Half of the subjects (32 males and 26 females) are selected to make up the training set and the left ones make up the testing set. As in the first experiment, we adopt two experimental settings to examine the robustness of different methods. In the first setting, there is no occlusion in training set. We utilize $1 \sim 7$ and $14 \sim 20$ images from each person for training. In testing phase, the first sample of each person is treated as the target one and the images with number $8 \sim 13$ and $21 \sim 26$ make up the query set. In the second setting, all the images in training set are used for training. In testing phase, the first image of each person is utilized as the target

one and the left images are used as the query ones. The images in query set are compared with the image in target set and the Rank-1 recognition accuracy is reported.
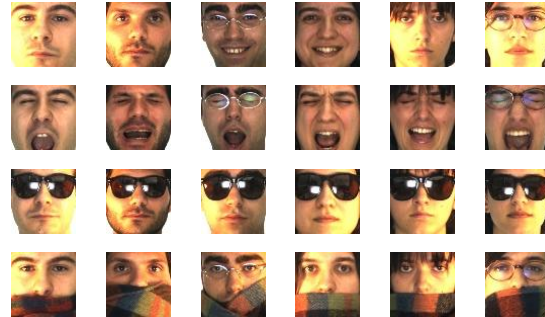


Figure 7. Examples of face images from AR database with different expressions, illuminations and occlusions.

The experimental results are shown in Table 3. It can be seen that Gabor phase feature achieves better recognition performance than gradient orientation representation in the occlusion case, validating the robustness of Gabor phase representation. The combination of Gabor phase and spectral regression achieves the highest recognition rate.

Table 3. Rank-1 recognition rates of different methods on AR database.

| Setting 1 | | | | |
|---|---|---|---|---|
| Method | PCA | LDA | RLDA | SRLDA |
| Gradient orientation | 0.75 | 0.44 | 0.67 | 0.70 |
| Gabor phase | 0.85 | 0.73 | 0.78 | 0.86 |
| Setting 2 | | | | |
| Method | PCA | LDA | RLDA | SRLDA |
| Gradient orientation | 0.70 | 0.25 | 0.63 | 0.68 |
| Gabor phase | 0.83 | 0.71 | 0.73 | 0.84 |

### 4.4. Data occluded by eyeglasses



Figure 8. NIR face sample, the left face is the face with eyeglasses and the right face is the face without eyeglasses

Now we turn to evaluate the performance of the proposed method in near infrared (NIR) face recognition problem.

Although NIR based face recognition achieves very high accuracy [8], one of the main problems is that the face images are easily contaminated by high light reflectance, especially when there are eyeglasses. Fig. 8 illustrates two examples where the appearances of images with/without eyeglasses changes dramatically, especially in eye region. In this part, we check the performance of the proposed method (GP-SRLDA) in eyeglasses occluded NIR face images and compare it with PCA of gradient orientation [15] and multi-scale block local binary pattern (MBLBP) + SRLDA [8], which is one of the state-of-the-art methods in NIR face recognition.

There are 239 subjects in NIR database, each of which contains images with or without eyeglasses. In training phase, 3794 images without eyeglasses from 120 subjects are used. In testing phase, one sample without eyeglasses for each person from the other 119 subjects are selected to form the target set and the rest 2218 images with eyeglasses are used as the query set. The images from the query set are compared with those in target set and the rank-1 recognition rate is reported to compare different methods.

Table 4 lists the recognition rate results of different methods. It can be seen that the proposed method (Gabor Phase + SRLDA) achieves highest recognition rate compared to GPCA and MBLBP+SRLDA in the eyeglasses occlusion case. It validates that the Gabor phase information is robust to eyeglasses occlusion in NIR images and is effective to improve the state-of-the-art performance of NIR face recognition.

Table 4. Recognition rate of different methods on NIR face database with eyeglasses occlusion.

| Method | GPCA | MBLBP+SRLDA | GPSRLDA |
|---|---|---|---|
| Recognition Rate | 0.70 | 0.82 | 0.89 |

## 5. Conclusion

In this paper, we propose a Gabor phase representation with spectral regression discriminant analysis method for robust face recognition with occlusions. Instead of the Gabor magnitude features widely used in face recognition or the gradient orientation proposed in [15], we show that Gabor phase features are more robust to face occlusion and thus more efficient for face representation in the occlusion case. Moreover, the spectral regression in complex domain is adopted to find the discriminant occlusion robust subspace for face recognition. Extensive experimental results demonstrate that the proposed method is robust to image occlusion in face recognition and outperforms the existing ones.

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