Compare Gabor fisher classifier and phase-based Gabor fisher classifier for face recognition

Nouar Larbi[1] , Dine Mohamed[2]

[1]Department of Electronique, University of Sidi Bel Abbes 22000, Algeria
[2]College of Engineering, Djillali Liabes University, Sidi-Bel-Abbes 22000, Algeria

Email address:

nouar220@yahoo.fr(N. Larbi)

Abstract: The paper compares two feature extraction techniques for face recognition with Gabor Filters. Firstly Gabor Filters based methods which mainly use only Gabor magnitude features like Gabor Fisher Classifier (GFC), and secondly the proposed method called the Phase-based Gabor Fisher Classifier (PBGFC) by turk[3]. The PBGFC method constructs an augmented feature vector which encompasses Gabor-phase information derived from a novel representation of face images - the oriented Gabor phase congruency image (OGPCI) - and then applies linear discriminant analysis to the augmented feature vector to reduce its dimensionality. In ours experiments we use the ORL data base, the feasibility of the proposed methods was assessed in a series of face verification experiments. The experimental results show that the PBGFC method performs better than other popular feature extraction techniques such as (LDA), while it ensures nearly similar verification performance as the established Gabor Fisher Classifier (GFC).

Keywords: Face Recognition, Gabor Filter, Gabor Phase Congruency

1. Introduction

Face recognition has been one of the most active research area in biometrics for several decades. The development of these systems can be found in the countless application possibilities in various areas such as human computer interaction, access control, homeland security and entertainment[1].

Researchers have explored various techniques on feature extraction and matching algorithms ,The key element of each face recognition system is the employed feature extraction technique which must be able to extract stable and discriminative features from a face image regardless of the external conditions[2].

Liu and Wechsler[4] used the Gabor wavelet. Their method, the Gabor Fisher Classifier (GFC), used a set of forty Gabor filters (with five scales and eight orientations) to derive an augmented feature vector of Gabor magnitude features and then applied the Enhanced Fisher linear discriminant model (EFM) to the augmented vector to reduce its' dimensionality.

Several modifications of the described technique were also presented in the literature, including[1],[5].

The feature extraction technique, i.e., the Phase-based Gabor Fisher Classifier (PBGFC), presented the feature extraction technique the Phase- based Gabor Fisher Classifier (PBGFC), presented in this paper motivated by the work of Vitomir Struc[3] however, different from other Gabor wavelet based methods; the proposed approach exploits Gabor-phase information rather than Gabor magnitude information. It first constructs an augmented feature vector that contains Gabor-phase information derived from a novel representation of face images - the oriented Gabor phase congruency image (OGPCI) - and then applies linear discriminant analysis to the resulting vector to enhance its discriminatory power,. As will be shown in Section V, features extracted with the proposed approach ensure a high face verification accuracy even in the presence of severe illumination changes.

The rest of the paper is organized as follows. In Section 2 the theory of the Gabor Fisher Classifier is briefly described and the Phase-based Gabor Fisher Classifier is introduced. Sections 3 and 4 present the matching procedure and the database employed in the verification experiments. The experimental results are given in Section 5. We conclude the paper with conclusion and future work in Sections 6.

2. The Phase-Based Gabor Fisher Classifier

This section introduces the novel Phase-based Gabor Fisher Classifier (PBGFC).

Gabor filters (sometimes also called Gabor wavelets or kernels) are a powerful tool for facial feature extraction. Their use in automated face recognition systems is motivated mainly by two major factors: their biological relevance and their computational properties. They exhibit desirable characteristics of spatial locality and orientational selectivity and are optimally localized in the space and frequency domains[1],[4-9].

2.1. 2D Gabor Filter

Gabor filter can be defined as follows:

$$\Psi_{\mu,\nu}\left(y,x\right)=\frac{f_{\mu}^{2}}{\pi\gamma\eta}e^{-\left(\frac{f^{2}}{\gamma^{2}}x'^{2}+\frac{f^{2}}{\eta^{2}}y'^{2}\right)}e^{j2\pi f_{\mu}x'} \tag{1}$$

Where:

$$x'=x\cos\theta_{\nu}+y\sin\theta_{\nu}, y'=-x\sin\theta_{\nu}+y\cos\theta_{\nu}$$

$f_{\mu}=f_{max}/2^{(\mu/2)}$ And $\theta_{\nu}=\nu\pi/8$. Each filter represents a Gaussian kernel function modulated by a complex plane wave whose center frequency and orientation are defined by f_{μ} and θ_{ν}, respectively. The parameters γ and η determine the ratio between the center frequency and the size of the Gaussian envelope and when set to a fixed value they ensure that Gabor filters of different scales and a given orientation behave as scaled versions of each other1. Commonly the values of γ and η are set to $\gamma=\eta=\sqrt{2}$. The last parameter f_{max} denotes the maximum frequency of the filters and is usually set to $f_{max}=0.25$. When employed for facial feature extraction, researchers typically use Gabor filters with five scales and eight orientations, i.e., $\mu=0$, 1, ..., p−1 and $\nu=0$, 1, ..., r−1, where p = 5 and r = 8, resulting in a filter bank of 40 Gabor filters[1],[4],[5].

It should be noted that Gabor filters represent complex filters which combine an even (cosine-type) and odd (sine-type) part[6]. An example of both filter parts is shown in Fig. 1.
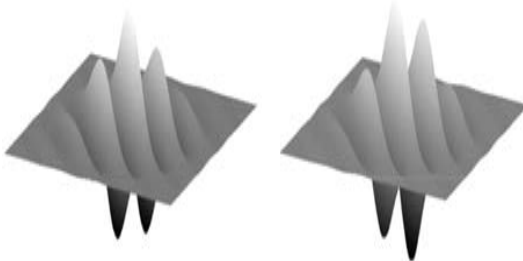

Fig. 1. *Example of a Gabor filter: (left) the real (cosine-type) part, (right) the imaginary (sine-type) part.*

2.2. Feature extraction with Gabor Filters

Let I(x, y) $\in$ Ra×b, where a and b stand for the image dimensions (in pixels), denote a grey-scale face image and let $\Psi_{\mu,\nu}\left(y,x\right)$ represent a Gabor filter at the center frequency f_{μ} and orientation θ_{ν}. The filtering operation can then be written with fixed values of the parameters γ and η the scale of the Gabor filter is defined by its center frequency f_{μ} as a convolution of the image $I\left(y,x\right)$ with the Gabor filter $\Psi_{\mu,\nu}\left(y,x\right)$, i.e.,

$$G_{\mu,\nu}\left(y,x\right)=I\left(y,x\right)*\Psi_{\mu,\nu}\left(y,x\right) \tag{2}$$

Here $G_{\mu,\nu}\left(y,x\right)$ denotes the complex convolution result which can be decomposed into its real (or even) and imaginary (or odd) parts:

$$E_{\mu,\nu}(y,x)=\text{Re}[G_{\mu,\nu}\left(y,x\right)]$$

$$O_{\mu,\nu}(y,x)=\text{IM}[G_{\mu,\nu}\left(y,x\right)] \tag{3}$$

Based on these results we can compute both the phase ($\Phi_{\mu,\nu}(y,x)$) as well as the magnitude ($A_{\mu,\nu}(y,x)$) responses of the filter, i.e.

$$A_{\mu,\nu}(y,x)=\sqrt{E^{2}_{\mu,\nu}(y,x)+O^{2}_{\mu,\nu}(y,x)} \tag{4}$$

$$\Phi_{\mu,\nu}(y,x)=\arctan\left(E_{\mu,\nu}(y,x)/O_{\mu,\nu}(y,x)\right)$$

Researchers commonly discard the phase information contained in the convolution result and use only the magnitude information to construct the facial feature vector.

2.3. The Gabor Fisher Classifier

The Gabor Fisher Classifier uses only magnitude information derived from the convolution results of (2) to construct the facial feature vector.

Specifically, the GFC method derives an augmented feature vector x by concatenating the magnitude responses $A_{\mu,\nu}(y,x)$ of all filters from the filter bank, i.e., for u = 0, 1... 5 and v = 0, 1... 7.

Prior to the concatenation, each of these responses is first downsampled with the help of a rectangular sampling grid and then normalized to zero mean and unit variance.

The described procedure results in a feature vector of Gabor magnitude features which, however, still resides in a very high-dimensional space[4]. To reduce the vectors dimensionality and to further enhance its discriminatory power the GFC method employs a linear discriminant analysis (LDA) which will be presented in the last part of this section.

2.4. The OGPCI Face Representation and the PBGFC Method

Gabor magnitude is known to vary slowly with the spatial position unlike the (Gabor) phase can take very different values even if it is sampled at image locations only a few pixels apart. This fact makes it difficult to extract reliable and discriminative features from the phase responses of (2) and is the primary reason that most of the existing methods use only the (Gabor) magnitude to construct the Gabor feature vector[10]. To overcome this problem Vitomir Struc propose to employ a modification of the phase congruency model introduced by Kovesi[11],[12].

Rather than combining phase congruency information computed over several orientations and using the result for construction of the facial feature vector, we therefore propose to compute an oriented Gabor phase congruency image (OGPCI) for each of the employed filter orientations and to construct an augmented (Gabor) phase feature vector based on the results. he use conventional Gabor filters as defined by (1) instead of log-Gabor filters. Considering Kovesi's phase congruency model. we can define an oriented version of phase congruency which, when presented in image form, we call the oriented Gabor phase congruency image (OGPCI):

$$OPGCI_v(y,x) = \frac{\sum_{\mu}^{p-1} A_{\mu,v}(y,x)\Delta\Phi_{\mu,v}(y,x)}{\sum_{\mu}^{p-1}\left(A_{\mu,v}(y,x)+\varepsilon\right)} \qquad (5)$$

where _ denotes a small constant which prevents division by zero and $\Delta\Phi_{\mu,v}(y,x)$ stands for the following phase deviation measure:

$$\Delta\Phi_{\mu,v}(Z) = \cos\left(\phi_{\mu,v}(z) - \bar{\phi}_v(z)\right) - \left|\sin(\phi_{\mu,v}(z) - \bar{\phi}_v(z))\right| \quad (6)$$

Here $\phi_{\mu,v}(z)$ denotes the phase angle of the Gabor filter (with a frequency f_μ and orientation θ_v) at the spatial location z =(y, x), while $\bar{\phi}_v(z)$ represents the mean phase angle at the vth orientation.

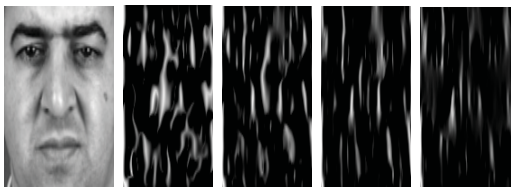Several examples of the OGPCIs for a sample image are shown in Fig 2[3].

Fig. 2. Examples of OGPCIs (from left to right): the original image, the OGPCI for θ_v = 0° and p = 2, the OGPCI for θ_v 0° and p = 3, the OGPCI for θ_v = 0° and p = 4, the OGPCI for θ_v = 0° and p = 5.

Kovesi showed that expression (5) can be computed directly from the filter outputs defined by (3), however, for details on computing the OGPCIs the reader should refer to[11].

The OGPCIs as defined by Eq. (5) represent illumination invariant because they do not depend on the overall magnitude of the filter responses. This property makes the OGPCPs a very useful image representation for face recognition[3].

The presented OGPCIs form the foundation for the PBGFC method which computes an augmented (phase-based) feature vector from a given face image by taking the following steps[3]:

(I) for the given face image it computes all r OGPCIs for a chosen number of filter scales p,

(II) it downsamples the resulting OGPCIs by a factor ρ, and (III) forms the final feature vector x by concatenating the rows (or columns) of the vectors D_v^T constructed from the downsampled and OGPCIs, i.e.,

$$x = (\ D_1^T\ D_2^T \cdots D_{r-1}^T\ )^T, \qquad (7)$$

Where T denotes the transform operator and D_v stands for the vector derived from the OGPCI at the v-th orientation. Note that in the experiments presented in Section V a downsampling factor of ρ = 16 was used for the PBGFC method as opposed to the GFC method where a factor of ρ = 64 was employed. This setup led to similar lengths of the constructed (Gabor) feature vectors of both methods and thus enabled a fair comparison of their verification performances.

2.5. Linear Discriminant Analysis

The augmented feature vectors constructed in the first step of the GFC and PBGFC methods reside in a very high dimensional space. Therefore a linear discriminant analysis (LDA)[13] is employed in the second step to project the augmented feature vectors into a low dimensional space.

3. Matching and Decision

Matching is a process that the extracted features are compared against the stored templates to generate match scores.

In general, a face recognition system can operate in one of two modes, either in verification or in identification mode[14]. In the verification mode, the system validates the individual's identity by comparing the captured biometric data with her own biometric template(s) stored in the system database. The system operates a one-to-one comparison to determine whether the claim identity is either rejected or accepted.

In the identification mode, the system recognizes an individual by searching the templates of all the users in the database for a match. The system performs a one-to-many comparison to establish an individual's identity without the subject having to claim an identity. If the subject is not

enrolled in the system database, the system will not be able to identify the subject's identity. It should be noted that, in the experiments presented in the remainder of this paper, the user-templates are constructed as the mean vectors of the feature vectors extracted from the enrollment images of the users.in our experiments the mhalanobis cosine was used.

4. Database and Experimental Setup

The two methods was tested in ORL database (formerly 'The ORL Database of Faces') There are ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement) The size of each image is 92x112 pixels, with 256 grey levels per pixel[15].

Prior to the employment of the PBGFC method a photometric normalization procedure that normalized face images from the database to zero mean and unit variance was used. We Partition data into training, evaluation and test sets. In our case, the first 3 images of each ORL subject will serve as the training/gallery/target set, the next three images will' serve as the evaluation set and the remaining images will serve as test image set. During the verification experiments each of the feature vectors extracted from an image of the client group was matched against the corresponding client template, while each of the feature vectors extracted from an impostor image was matched against all client templates in database In both the evaluation as well as the test stage two error rates were computed to assess the verification accuracy of the proposed PBGFC method:

(I)   The false acceptance rate (FAR) which measures the frequency of falsely accepted impostors.

(II)   The false rejection rate (FRR) which measures the frequency of falsely rejected clients.

5. Experiments and Results

For the GFC method we followed the work of Liu and Wechsler[4] where filters at five scales and eight orientations were used for image filtering and linear discriminant analysis was applied to the filtered images to reduce their dimensionality.

And for PBGFC we followed the work Vitomir sturk[3] he find that the best verification performance was achieved when Gabor filters at eight orientations and only two scales. Employing filters at more than two scales resulted in less performance.

While the values of verification rate at FRR=10^{-3}, for the threshold that ensures equal error rates are presented in Table 1.

Table 1. *Verification rate at FRR=10^{-3}, for the threshold that ensures equal error rates at different scales for PBGFC method.*

Number of scales(p)	P =5	P=4	P=3	P=2
Verification rate	80.83	80.83	80	87,50

The error rates obtained with the feature sets of both methods discussed in section 2 were higher than LDA method but GFC have small advantage the result is shown in Fig 3, 4, 5. There are at least two important differences in the way these feature sets are extracted. First, the GFC method requires 40 Gabor filters, i.e., filters with five scales and eight orientations, to achieve the presented performance, while the PBGFC employs only 16 Gabor filters, i.e., filters with 2 scales and eight orientations, to achieve nearly the same verification performance. This fact makes the PBGFC method significantly faster than the GFC method because the resulting feature vector for PBGFC method is very compact (response of only 16 Gabor filters) than GFC method use 40 Gabor filters this is significant for the time need for extracting the feature vectors. Second, the PBGFC method operates on a much narrower frequency band than the GFC method.

The verification rate of three methods at at FRR=10^{-3}, for the threshold that ensures equal error rates are presented in Table 2.

Table 2. *The verification rate of three methods PBGFC+LDA, GFC+LDA and LDA at FRR=10^{-3}, for the threshold that ensures equal error rates.*

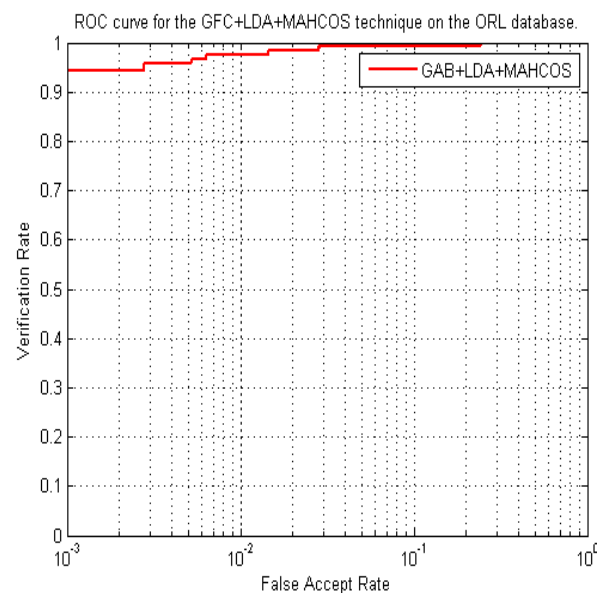| Methods	PBGFC + LDA	GFC+LDA	LDA
Verification rate	87.5	94.17	72.14

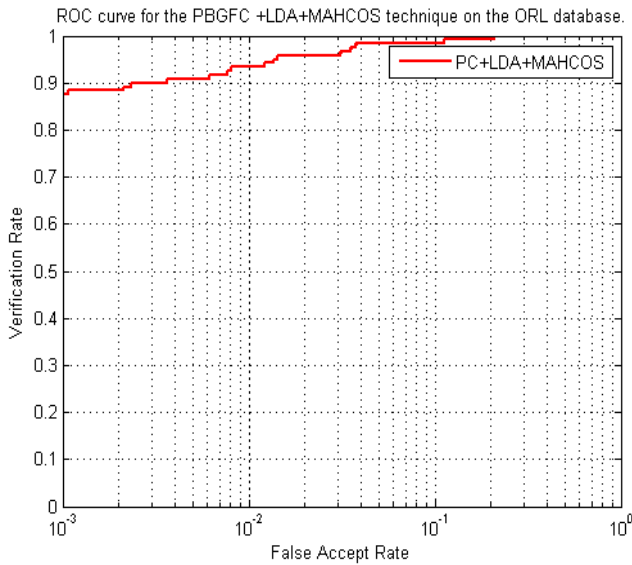**Fig. 3.** *The ROC curves for GFC+LDA method*

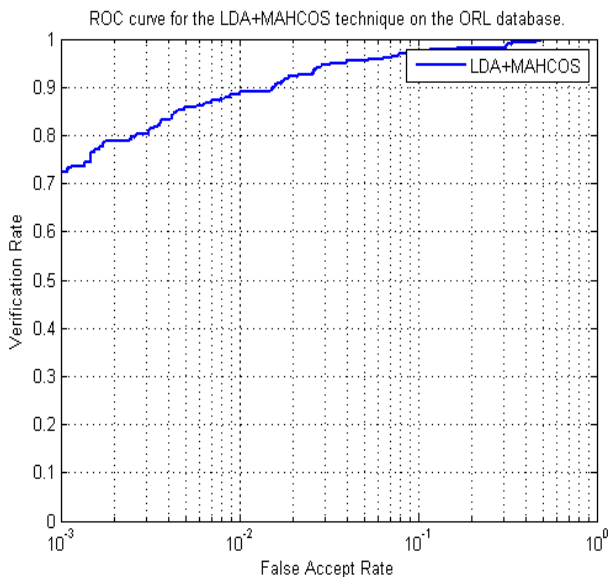**Fig. 4.** *The ROC curves for PBGFC+LDA method*

Fig. 5. *The ROC curves for LDA method*

6. Conclusion and Future Work

In this paper we have shown that the proposed PBGFC method ensures nearly similar verification performance as the established Gabor Fisher Classifier (GFC), while it significantly reduces the computational burden required for extraction of the facial features. We try test PBGFC method in large database with sever illumination to test her robustness and how faster is it and try to combine PBGFC techniques with preprocessing methods which would ensure an even better face verification performance.

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