The Phase-Based Gabor Fisher Classifier and its Application to Face Recognition Under Varying Illumination Conditions

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***Abstract*—The paper introduces a feature extraction technique for face recognition called the Phase-based Gabor Fisher Classifier (PBGFC). 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. The feasibility of the proposed method was assessed in a series of face verification experiments performed on the XM2VTS database. The experimental results show that the PBGFC method performs better than other popular feature extraction techniques such as principal component analysis (PCA), the Fisherface method or the DCT-mod2 approach, while it ensures similar verification performance as the established Gabor Fisher Classifier (GFC). The results also show that the proposed Phase-based Gabor Fisher Classifier performs the best among the tested methods when severe illumination changes are introduced to the face images.**

I. Introduction

Amongst the numerous biometric systems presented in the literature, face recognition systems have received a great deal of attention in recent years. The main driving force in 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].

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 present during the image acquisition process. It was pointed out by Short et al. [2] that the appearance of the same face can vary tremendously from image to image due to changes of the external conditions, especially illumination. Many feature extraction techniques, among them the appearance based methods in particular, have difficulties extracting stable features from images captured under varying illumination conditions. Researchers have therefore proposed a number of alternatives that should compensate for the illumination changes and thus ensure a stable face recognition performance.

Sanderson and Paliwal [3], for example, proposed a feature extraction technique called DCT-mod2 which first applied the Discrete Cosine Transform (DCT) to sub-regions (or blocks) of the given face image to extract several feature sets of DCT coefficients and then replaced the coefficients most affected by the illumination changes with their corresponding vertical and horizontal deltas. The method was tested on images rendered with an artificial illumination model as well as on images actually captured under varying illumination conditions. In both cases promising results were achieved.

Liu and Wechsler [4] used the Gabor wavelet representation of face image to achieve robustness to illumination changes. 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 in this paper is partially motivated by the work of Liu and Wechsler [4], 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 II the theory of the Gabor Fisher Classifier is briefly described and the Phase-based Gabor Fisher Classifier is introduced. Sections III and IV present the matching procedure and the database employed in the verification experiments. The experimental results are given in Section V. We conclude the paper with some final comments and directions for future work in Sections VI and VII, respectively.

II. The Phase-Based Gabor Fisher Classifier

This section introduces the novel Phase-based Gabor Fisher Classifier (PBGFC). First the basic principles of Gabor filter construction and Gabor filter based feature extraction are reviewed, then the concept of the Gabor Fisher Classifier is described and finally the PBGFC method is presented.

A. Gabor filter construction

Gabor filters (sometimes also called Gabor wavelets or kernels) have proven to be 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],[5],[6].

A 2D Gabor filter can be defined as follows :

$$\psi_{u,v}(y,x) = \frac{f_u^2}{\pi\gamma\eta} e^{-(\frac{f_u^2}{\gamma^2}x'^2 + \frac{f_u^2}{\eta^2}y'^2)} e^{j2\pi f_u x'}, \quad (1)$$

where $x' = x\cos\theta_v + y\sin\theta_v$, $y' = -x\sin\theta_v + ycos\theta_v$, $f_u = f_{max}/2^{(u/2)}$ and $\theta_v = v\pi/8$. Each filter represents a Gaussian kernel function modulated by a complex plane wave whose center frequency and orientation are defined by f_u and θ_v, 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 other[1]. 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., $u = 0, 1, ..., p-1$ and $v = 0, 1, ..., r-1$, 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.

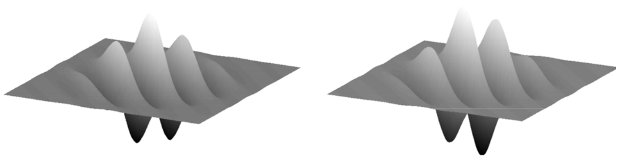

Fig. 1. Example of a Gabor filter: (left) the real (cosine-type) part, (right) the imaginary (sine-type) part

B. Feature extraction with Gabor filters

Let $I(x,y) \in \mathbb{R}^{a\times b}$, where a and b stand for the image dimensions (in pixels), denote a grey-scale face image and let $\psi_{u,v}(y,x)$ represent a Gabor filter at the center frequency f_u and orientation θ_v. The filtering operation can then be written as a convolution of the image $I(x,y)$ with the Gabor filter $\psi_{u,v}(y,x)$, i.e.,

$$G_{u,v}(y,x) = I(y,x) * \psi_{u,v}(y,x). \quad (2)$$

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

$$\begin{aligned} E_{u,v}(y,x) &= Re[G_{u,v}(y,x)] \\ O_{u,v}(y,x) &= Im[G_{u,v}(y,x)]. \end{aligned} \quad (3)$$

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

$$\begin{aligned} A_{u,v}(y,x) &= \sqrt{E_{u,v}^2(y,x) + O_{u,v}^2(y,x)} \\ \phi_{u,v}(y,x) &= \arctan\left(O_{u,v}(y,x)/E_{u,v}(y,x)\right). \end{aligned} \quad (4)$$

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

C. The Gabor Fisher Classifier

Similar to other feature extraction techniques which employ Gabor filters for feature extraction, the Gabor Fisher Classifier also 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 $A_{u,v}(y,x)$ 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]. For example, for a face image of size 128×128 pixels (which is a commonly used size for face images) and a sampling grid with 16 horizontal and 16 vertical grid lines, the dimension of the augmented feature vector is still 10240. To reduce the vectors dimensionality and to further enhance its discriminatory power the GFC method employs a variant of the linear discriminant analysis (LDA) which will be presented in the last part of this section.

D. The OGPCI face representation and the PBGFC method

Unlike the (Gabor) magnitude which is known to vary slowly with the spatial position, 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 [7].

To overcome this problem we propose to employ a modification of the phase congruency model introduced by Kovesi [8]. The model was originally intended to provide the means for robust detection of edges and corners in digital images,

[1]Note that with fixed values of the parameters γ and η the scale of the Gabor filter is defined by its center frequency f_u

however, as we will show, it can (though with a few modifications) also be used to encode phase information of the Gabor filter responses.

Kovesi's original phase congruency model searches for points in an image where the log-Gabor filter responses over several scales and orientations are maximally in phase [9],[8]. Thus, a point in an image is of significance only if the phase responses of the log-Gabor filters over a range of scales (i.e., frequencies) display some kind of order. In Kovesi's approach phase congruency is first computed for each of the employed filter orientations, then the results are combined to form the final phase congruency image (PCI).

While the presented approach is suitable for robust (in terms of noise, illumination variations and image contrast) edge and corner detection, its usefulness for facial feature extraction is questionable. As it was emphasized by Liu in [1], a desirable characteristic of a feature extraction procedure is orientational selectivity. Rather then 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. Note that we 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):

$$OGPCI_v(y,x) = \frac{\sum_u^{p-1} A_{u,v}(y,x)\Delta\Phi_{u,v}(y,x)}{\sum_u^{p-1}(A_{u,v}(y,x)+\epsilon)}, \quad (5)$$

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

$$\begin{aligned}&\Delta\Phi_{u,v}(z) = \\ &= \cos(\phi_{u,v}(z) - \bar{\phi}_v(z)) - |\sin(\phi_{u,v}(z) - \bar{\phi}_v(z))|.\end{aligned} \quad (6)$$

Here $\phi_{u,v}(z)$ denotes the phase angle of the Gabor filter (with a frequency f_u and orientation θ_v) at the spatial location $z = (y,x)$, while $\bar{\phi}_v(z)$ represents the mean phase angle at the v-th orientation. Several examples of the OGPCIs for a sample image are shown in Fig 2.

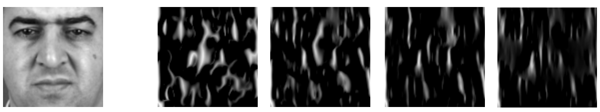

Fig. 2. Examples of OGPCIs (from left to right): the original image, the OGPCI for $\theta_v = 0°$ and $p = 2$, the OGPCI for $\theta_v = 0°$ and $p = 3$, the OGPCI for $\theta_v = 0°$ and $p = 4$, the OGPCI for $\theta_v = 0°$ and $p = 5$

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 [8].

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: *(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, *(III)* it normalizes the results to zero mean and unit variance and *(IV)* forms the final feature vector $\mathbf{x}$ by concatenating the rows (or columns) of the vectors $\mathbf{D}_v^T$ constructed from the downsampled and normalized OGPCIs, i.e.,

$$\mathbf{x} = (\mathbf{D}_1^T \mathbf{D}_2^T \cdots \mathbf{D}_{r-1}^T)^T, \quad (7)$$

where T denotes the transform operator and $\mathbf{D}_v$ 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 $\rho = 16$ was used for the PBGFC method as opposed to the GFC method where a factor of $\rho = 64$ 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.

E. 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 variant of the linear discriminant analysis (LDA) [10] is employed in the second step to project the augmented feature vectors into a low dimensional space where the matching procedure (see Section III for details) is ultimately applied.

The employed projection technique (i.e, LDA) identifies a subspace (i.e., a subspace projection matrix $\mathbf{W}_{LDA}$) by maximizing a class separability criterion in the form of the ratio of the between-class Σ_B to the within-class Σ_W scatter matrix [9], i.e., $\mathbf{W}_{LDA} = \arg\max_{\mathbf{W}} |\mathbf{W}\Sigma_B\mathbf{W}^T|/|\mathbf{W}\Sigma_W\mathbf{W}^T|$. Once computed, the LDA transformation matrix $\mathbf{W}_{LDA}$ is used to project an arbitrary d-dimensional augmented feature vector $\mathbf{x}$ into the low dimensional subspace, i.e.,

$$\mathbf{y} = \mathbf{W}_{LDA}^T(\mathbf{x} - \boldsymbol{\mu}), \quad (8)$$

where $\mathbf{y}$ denotes the d'-dimensional projection of the centered feature vector $\mathbf{x}$. Note that the maximal value of d' is determined by the number of classes N (i.e., different subjects) contained in the training set that is used for computation of the LDA transformation matrix ($d'_{max} = N - 1$).

III. MATCHING AND DECISION

In a face verification system, where the goal is to determine wether the feature vector $\mathbf{y}$ extracted from a face image of the user currently presented to the system (also referred to as the "live" feature vector) corresponds to the claimed identity C_i or not, the matching procedure plays a crucial role.

At this stage the "live" feature vector is compared to the feature vector associated with the claimed identity C_i (in our case the mean feature vector of the i-th subjects training images). If the "live" feature vector $\mathbf{y}$ and the claimed person's feature vector $\bar{\mathbf{y}}_i$ display a degree of similarity that is higher than a predefined decision threshold t, the claim of identity is accepted, otherwise the claim is rejected [11].

The comparison performed during the matching procedure is based on a similarity measure δ which determines the similarity between the vectors $\mathbf{y}$ and $\bar{\mathbf{y}}_i$. In our experiments the cosine similarity measure was used. The measure is defined as follows:

$$\delta_{cos}(\mathbf{y}, \bar{\mathbf{y}}_i) = \mathbf{y}^T \bar{\mathbf{y}}_i / (\|\mathbf{y}\| \|\bar{\mathbf{y}}_i\|), \tag{9}$$

where $\| \cdot \|$ denotes the norm operator.

IV. Database and experimental setup

The effectiveness of the presented PBGFC method was assessed on the standard face image subsets, i.e., subsets CDS001 and CDS006, of the multimodal XM2VTS database. The subsets comprise of 2360 frontal face images that correspond to 295 subjects. They were recorded in controlled conditions during four photo sessions that were distributed over a period o five months. At each session two recordings were made resulting in a total of eight color face images (at a resolution 720×576 pixels) per subject [12].

Prior to the employment of the PBGFC method, a preprocessing procedure was applied to the images from the database. Specifically, the following steps were taken to preprocess the face images: *(I)* a conversion of the (color) face images to 8-bit grey-scale images, *(II)* a geometric normalization procedure which rotated and scaled the images in such a way that the centers of the eyes were located at predefined positions (here, the eye positions were marked manually), *(III)* a cropping procedure that cropped the face region of the image to a standard size of 128×128 pixels (i.e., $a = 128$, $b = 128$), *(IV)* a photometric normalization procedure that normalized the cropped face region to zero mean and unit variance.

Following the first configuration of the established experimental protocol, i.e., the Lausanne protocol - LP [12], associated with the XM2VTS database, the subjects from the database were divided into two groups - the group of clients (200 subjects) and the group of impostors (95 subjects). Images of subjects from the two groups were then assigned to image subsets which were used for training, evaluation and testing. The training subset was comprised of 600 images (i.e., each of the 200 subjects assigned to the client group was represented with 3 training images) and was used to compute the LDA transformation matrix and to create the client database. The evaluation subset contained 600 images from the client group (3 images per client) and 200 images from the impostor group (all 8 face images of the 25 subjects defined by the LP as evaluation impostors). This subset was employed in the evaluation stage to compute the decision threshold t and to optimize the parameters (i.e., the number of scales to be used with the proposed technique) of the PBGFC method. Finally, the test set comprised of 400 client images (2 images per client) and 560 impostor images (all 8 face images of the 25 subjects defined by the LP as test impostors) and was used solely for the final performance assessment.

However, as the XM2VTS subsets CDS001 and CDS006 contain only images captured in a controlled environment and the goal of our experiments was to assess the performance of the PBGFC method on images captured under varying illumination conditions, an artificial illumination change was introduced to the pre-processed images from the test subset. To this end, we used the model previously employed by Sanderson and Paliwal in [3] which simulates different illumination conditions during the image acquisition process by modifying the pre-processed input face images $I(y, x)$, i.e.,

$$\widetilde{I}(y, x) = I(y, x) + mx + \tau, \tag{10}$$

where $y = 0, 1, ..., a-1$; $x = 0, 1, ..., b-1$; $m = -2\tau/(b-1)$ and τ denotes the parameter that controls the "strength" of the introduced artificial illumination. As pointed out by Sanderson and Paliwal this model does not cover all the illumination effects possible in real life situations, but it is useful for providing suggestive results [3]. Four examples of the modified face images $\widetilde{I}(y, x)$ obtained with the presented model for different values of τ are shown in Fig. 3.

Fig. 3. Examples of modified face images (from left to right): the original image, the modified image for $\tau = 40$, the modified image for $\tau = 80$, the modified image for $\tau = 120$, the modified image for $\tau = 160$

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. The described setup led to the following verification experiments: 600 client verification attempts in the evaluation stage, 40000 impostor verification attempts in the evaluation stage, 400 client verification attempts in the test stage and 112000 impostor verification attempts in the test stage

In both the evaluation as well as the test stage three 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 and *(III) the half total error rate* (HTER) defined as HTER $=$ (FAR $+$ FRR)$/2$. Unfortunately the error rates FAR and FRR both depend on the value of the employed decision threshold t (choosing a threshold that reduces the FAR usually leads to an increase of the FRR and vice versa), thus a threshold that ensures certain predefined values of FAR and FRR has to be chosen for the final performance assessment. In accordance with the LP we used the decision threshold t that ensured equal error rates (FAR=FRR) in the verification experiments on the evaluation subset.

V. Experiments and results

A. Parameter tuning

The first set of our verification experiments assessed the performance[2] of the PBGFC method for different numbers

[2]Note that at this stage only images from the evaluation subset were used in the experiments.

of scales p of the employed Gabor filters. While the number of scales was varied from $p = 2$ to $p = 5$, the number of orientations r of the filters was fixed and set to $r = 8$ (the value of $r = 8$ was chosen based on other Gabor filter based methods presented in the literature - see for example [4],[5]). In all of the performed experiments the length of the PBGFC feature vectors was set to its maximal value, i.e., $d' = 199$. The ROC curves (which display the dependency of the FAR and FRR at various decision thresholds) generated during our experiments are shown in Fig. 4 , while the values of the three error rates, i.e., FAR, FRR and HTER, for the threshold that ensures equal error rates are presented in Table I.

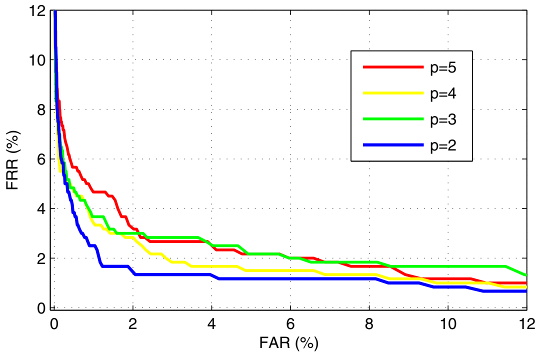

Fig. 4. The ROC curves generated during the verification experiments

TABLE I
THE ERROR RATES AT THE EQUAL ERROR OPERATING POINT FOR VARYING NUMBERS OF GABOR FILTER SCALES

$Number of scales (p)$	$p = 5$	$p = 4$	$p = 3$	$p = 2$
FRR(%)	2.67	2.33	2.83	1.67
FAR(%)	2.61	2.33	2.71	1.63
HTER(%)	2.64	2.33	2.77	**1.65**

From the presented results we can find that the best verification performance was achieved when Gabor filters at eight orientations and only two scales were used for calculation of the PBGFC features. Employing filters at more than two scales resulted in higher error rates. It should also be noted that computing features with Gabor filters at just two scales significantly reduced the computational burden of the PBGFC method when compared to the PBGFC implementations with more filter scales. The experimental results suggest that Gabor filters at two scales and eight orientations should be used for the implementation of the PBGFC method in the final performance assessment.

B. Performance assessment

The goal of our second series of experiments was threefold: *(I)* to assess the verification accuracy of the PBGFC method using a fixed threshold t (determined in the first series of verification experiments) and images acquired in controlled conditions (i.e., the image subsets CDS001 and CDS006), *(II)* to test the robustness of the proposed method in respect to varying illumination conditions and *(III)* to compare the verification accuracy as well as the robustness of the PBGFC method to those of some popular feature extraction techniques. To this end the following techniques were implemented in addition to the PBGFC method: the principal component analysis (PCA)[13], the Fisherface (FF) method [10], the DCT-mod2 technique [3] and the Gabor-Fisher Classifier (GFC) [4].

The PCA method was implemented using 300 principal components which ensured the best verification results on the evaluation subset (among the tested numbers of principal components). In a similar manner the Fisherface method was found to perform best when feature vectors with 199 components were employed in the experiments. 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. In our case this approach resulted in 199 dimensional feature vectors. Finally, the DCT-mod2 technique was implemented according to [3]. Thus the technique was applied on blocks (8×8 pixels) of the face images which overlapped with horizontally and vertically adjacent blocks by 50%. From each block a feature vector comprising of 18 DCT-mod2 features was extracted resulting in a set of several feature vectors for each of the images used in our experiments. At the matching stage the cosine similarity measure was employed for matching score calculation for all methods except the DCT-mod2 technique which (in accordance with [3]) used a Gaussian mixture model (GMM) based classifier with 64 Gaussian mixtures.

The results of the experiments are presented in Fig 5 and Table II. Fig 5 shows the half total error rates of the tested methods for varying illumination conditions, i.e., for different values of the parameter τ. Here the value of $\tau = 0$ indicates that no change was made to the face images from the database and thus the HTER at $\tau = 0$ represents the final verification accuracy of the PBGFC method on the XM2VTS database. Table II presents the values of the error rates FAR, FRR and HTER for the tested methods for different τ.

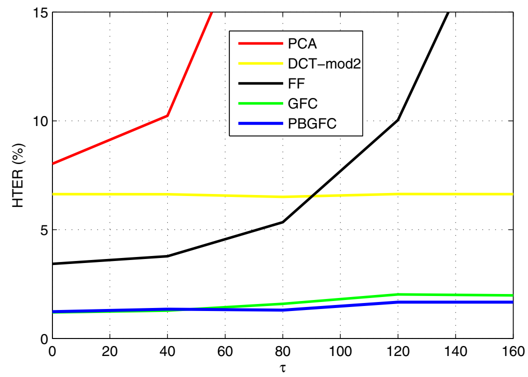

Fig. 5. Robustness of the PCA, DCT-mod2, FF, GFC and PBGFC methods to varying illumination conditions

We can see that when original (unaltered, $\tau = 0$) images from the XM2VTS database were used in the verification experiments the GFC performed slightly better than the proposed PBGFC method, followed in order by the Fisherface,

TABLE II

THE VALUES OF FAR, FRR AND HTER (ON THE TEST SET) FOR THE PCA, FF, DCT-MOD2, GFC AND PBGFC METHODS WITH RESPECT TO VARYING VALUES OF THE PARAMETER τ. THE ERROR RATES WERE OBTAINED WITH THE DECISION THRESHOLD THAT ENSURED EQUAL ERROR RATES ON UNALTERED IMAGES FROM THE EVALUATION SET.

Method	PCA			FF			DCT-mod2			GFC			PBGFC		
Error (%)	FRR	FAR	HTER	FRR	FAR	HTER	FRR	FAR	HTER	FRR	FAR	HTER	FRR	FAR	HTER
$\tau = 0$	6.75	9.30	8.03	3.00	3.86	3.43	6.50	6.77	6.64	0.75	1.65	**1.20**	1.00	1.46	1.23
$\tau = 40$	12.50	7.97	10.24	4.25	3.31	3.78	6.50	6.76	6.63	1.00	1.56	**1.28**	1.25	1.44	1.35
$\tau = 80$	38.25	6.97	22.61	8.25	2.44	5.35	6.25	6.77	6.51	1.75	1.44	1.60	1.25	1.36	**1.31**
$\tau = 120$	59.25	6.52	32.89	18.25	1.83	10.04	6.50	6.78	6.64	2.75	1.30	2.03	2.00	1.34	**1.67**
$\tau = 160$	67.50	6.08	36.79	41.25	1.49	21.37	6.50	6.77	6.64	2.75	1.21	1.98	2.00	1.34	**1.67**

DCT-mod2 and PCA methods. However, when the value of τ was varied only the GFC, PBGFC and DCT-mod2 methods ensured fairly stable verification errors, the Fisherface and PCA methods, on the other hand, exhibited a drop in their performance as shown in Fig 5. Among the stable methods the PBGFC method achieved the lowest error rates across all tested values of τ followed by the GFC and DCT-mod2 methods.

VI. DISCUSSION ON THE GFC AND PBGFC METHODS

From the experimental results presented in the previous section we found that amongst the tested feature extraction techniques the GFC and PBGFC methods ensured by far the lowest verification errors on both images captured in controlled conditions as well as images altered with the artificial illumination model defined by (10). While the error rates obtained with the feature sets of both methods were quite similar, 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 the same (or even better) verification performance. This fact makes the PBGFC method significantly faster than the GFC method.

Second, the PBGFC method operates on a much narrower frequency band than the GFC method. Based on the experimental results presented in Section V-A we can in fact conclude that most of the discriminatory Gabor-phase information is contained in the OGPCIs obtained with Gabor filters of high frequencies ($u = 0, 1$). In addition to the high frequency filters the GFC method effectively uses also the low frequency Gabor filters. This finding suggests that the PBGFC and GFC methods extract feature sets with complementary information and could therefore be combined into a unified feature extraction technique which uses Gabor magnitude as well as Gabor phase information for face verification.

VII. CONCLUSION AND FUTURE WORK

In this paper we have presented the Phase-Based Gabor Fisher Classifier (PBGF) - a novel feature extraction technique for face verification. Using the XM2VTS database we have shown that the proposed PBGFC method ensures similar verification performance as the established Gabor Fisher Classifier (GFC), while it significantly reduces the computational burden required for extraction of the facial features. Furthermore, we have demonstrated that the PBGFC-based features maintain (within reasonable bounds) their verification performance even in the presence of severe illumination changes. Our next goal in respect to the PBGFC method is to find a way to combine the GFC and PBGFC techniques into a unified feature extraction approach which would ensure an even better face verification performance.

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