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FACE RECOGNITION AGAINST VARYING LIGHTING CONDITIONS USING ORIENTED PHASE CONGRUENCY IMAGE FEATURES

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ABSTRACT

Although face recognition has become a topic of active research in recent decades, an accurate face recognition is still a tough job and still struggle with its performance especially if it is unconstrained lighting variations. The external conditions present during the facial image acquisition stage deeply influence the appearance of a face in the acquired image and hence affect the performance of the recognition system. This paper presents an efficient method for robust face recognition against varying lighting condition by using Oriented Phase Congruency features. The extracted features, derived from the Gabor Phase Congruency response are concatenated to construct a feature vector to be used for classification by Subspace LDA. We demonstrate the effectiveness and superiority of our proposed method by conducting some experiments on Yale B face databases and our proposed method shows robust face recognition performance in the presence of severe lighting changes.

Keywords: *Face Representation, Varying Lighting Conditions, Oriented Gabor Phase Congruency Features, Gabor Phase High Energized Point, Subspace LDA.*

1. INTRODUCTION

Among the different biometric technologies presented in the literature, face recognition has captured a great deal of both public and private institutions attention over the last few years. Due to its non-intrusive nature, automatic face recognition is becoming a very active research topic [1]. There are many different industrial applications interested in face recognition, mostly related to security and safety, In the last two decades, various approaches have been proposed for face image recognition and substantial progress has been made. Nevertheless, further research is still needed to make face recognition systems more robust under uncontrolled circumstances particularly those imposed on varying illumination.

Numerous approaches to achieve illumination invariant face recognition have been proposed in the literature. As identified in a number of surveys [2] [3] [4].

In this paper, we propose a method of face recognition under varying lighting conditions by using phase congruency features, that first introduced by Kovesi 1999 [5] from the Gabor phase congruency model. The phase congruency feature vectors are extracted from points with high information content of the face image. The proposed phase congruency feature extraction algorithm has two main steps, i.e. feature point localization and, feature vector computation.

The remainder of this paper is organized as follows: Section 2 describes the related work. Section 3 presents the proposed framework, i.e. Gabor phase congruency feature extraction and selection. The experimental results and discussions are given in Section 4. Finally, the conclusion is described in Section 5.

2. RELATED WORK

Lighting variations problem that occur in an uncontrolled environment is one of the main problems in face recognition. Such variations in the face appearance can be much larger than the variation caused by personal identity [6]. Several research works have been published in literature for illumination robust face recognition.

Gao & Leung, 2002 [7] proposed a method that using edge maps representations map. The edge pixels are grouped into line segments, and a revised Hausdorff Distance is designed to measure the similarity between two line segments. Wei & Lai, 2004 in [8] proposed a gradient-based features, The relative image gradient G(x, y)

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is defined as, $\bar{G}(x, y) = \frac{|\nabla I(x,y)|}{\max_{(u,v)\in W(x,y)}|\nabla I(x,y)|+c}$, where *I(x,y)* is the image intensity, ∇ is the gradient operator, *W(x, y)* is a local window centered at *(x,y)*, and c is a constant value to avoid dividing by zero. Illumination insensitive face recognition by using a method based on Symmetric Shape from Shading was presented by Zhao and Chellappa [9]. The symmetry of every face and the shape similarity among all faces are utilized. Marcel et al., [10] introduces local binary patterns. Liu, 2006 [11], Štruc & Pavešic, 2009 [12] proposed Gabor wavelet based features which are less sensitive to the influence of illumination. Sanderson and Paliwal 2003[13], proposed a feature extraction technique called DCT-mod2, at which first applies the Discrete Cosine Transform (DCT) to sub-regions (or blocks) of facial images to extract several feature sets of DCT coefficients, and then compensates for illumination induced appearance changes by replacing the coefficients most affected by illumination variations with the corresponding vertical and horizontal delta coefficients. Basically illumination invariance can be achieved by finding features or face representations that are stable under different illumination conditions.

3. PROPOSED FRAMEWORK

The components of our proposed face recognition system is described in this section in detail, i.e. Oriented Gabor Phase Congruency features, high-energized Gabor phase congruency points selections, Subspace LDA dimensionality reduction and nearest neighbor recognition. The stages of processing are illustrated in Fig. 1.

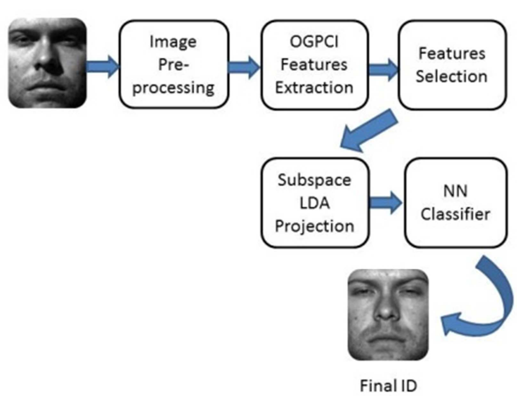

Figure 1: The Block Diagram of face recognition system

Note that prior to the experiments, all images are subjected to a pre-processing procedure such as undergoing geometric and photometric normalization and cropped to 128x128 pixels.

3.1. Gabor Filter Construction

The Gabor filters, have been considered as a very useful tool in computer vision and image analysis due to its optimal localization properties in both spatial analysis and frequency domain [14][15][16][17]. In the spatial domain, the family of 2D Gabor filters can be defined as follows [11] [12][14] [18],

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

$$x' = x\cos\theta_v + y\sin\theta_v, \quad y' = -x\sin\theta_v + y\cos\theta_v, f_u = f_{max}/2^{(u/2)}, \theta_v = v\pi/8.$$

Where u and v define the scale and orientation of the Gabor kernels. The parameters κ and η determine the ratio between the centre frequency and the size of the Gaussian envelope. Commonly the values of the parameters κ and η are set to $\kappa = \eta = \sqrt{2}$. f_{max} denotes the maximum frequency of the filters and generally is set to $f_{max} = 0.25$. Many face recognition studies use five different scales, $u \in \{0,1,2,3,4\}$ and eight orientations, $v \in \{0,1,\ldots,7\}$. which results in a filter bank of 40 Gabor filters [11][12][18].

3.2. Gabor Features Representation

The Gabor features are the result of convolving the image *I(x, y)* with a bank of Gabor filters of different scales and orientations $\psi_{u,v}(x, y)$. Computationally, the feature extraction procedure can be written as,

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

Where * denotes the convolution operator and $O_{u,v}(x, y)$ represents the complex convolution output which can be decomposed into its real $E_{u,v}(x, y)$ and imaginary parts $F_{u,v}(x, y)$ as follows:

$$E_{u,v}(x, y) = Re[G_{u,v}(x, y)] \quad \text{and}$$
$$F_{u,v}(x, y) = Im[G_{u,v}(x, y)] \quad (3)$$

The magnitude and phase responses of the filter can be computed, i.e.:

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$$A_{u,v}(x,y) = \sqrt{E_{u,v}^2(x,y) + O_{u,v}^2(x,y)}$$
$$\phi_{u,v}(x,y) = \tan^{-1}\left(\frac{O_{u,v}(x,y)}{E_{u,v}(x,y)}\right) \quad (4)$$

Hence The Gabor features is essentially the concatenated selected pixels of the 40 modulus-of-convolution images obtained by convolving the input image with those 40 Gabor kernels. The selected pixels can be found from downsampling procedure or from high-energized points/pixels.

Most of the face recognition techniques found in the literature get rid of the phase information of the filtering output and retain only the magnitude information for the Gabor face representation. According to Opeinheim and Lim [19], phase component is more important than the magnitude component in the reconstruction process of an image from its Fourier domain. There is also physiological evidence, showing that human visual system responds strongly to the points in an image where the phase information is highly ordered.

3.3. The Oriented Gabor Phase Congruency Representation

Kovesi [5] developed The original 2D phase congruency model with the goal of robust edge and corner detection in digital images. Phase congruency provides a measure that is independent of the overall magnitude of the signal making it invariant to variations in image illumination as well as contrast independent. Oriented Gabor phase congruency patterns (OGPCPs) are proposed by Štruc et al., [12] with a few modifications of Kovesi's original phase congruency model and the OGPCPs for the v-th orientation can be computed as follow,

$$\boldsymbol{OGPCP_v(x,y)} = \frac{\sum_{u=1}^{p-1} A_{u,v}(x,y)\Delta\phi_{u,v}(x,y)}{\sum_{u}^{p-1}(A_{u,v}(x,y)+\epsilon)} \quad (5)$$

$$\Delta\phi_{u,v}(x,y) = \boldsymbol{cos}\left(\phi_{u,v}(x,y) - \bar{\phi}_v(x,y)\right) - \left|\boldsymbol{sin}\left(\phi_{u,v}(x,y) - \bar{\phi}_v(x,y)\right)\right| \quad (6)$$

Note that ϵ denotes a small constant that prevents division by zero, $\Delta\phi_{u,v}(x,y)$ is the phase deviation measure as shown by equation (6). $\phi_{u,v}(x,y)$denotes the phase angle of the Gabor filter (with a centre frequency f_u and orientation θ_v) at the spatial location (x,y), while $\bar{\phi}_v(x,y)$ represents the mean phase angle at the v-th orientation. Take into account that since the OGPCPs as defined by Eq. (5) and (6) do not depend on the magnitude of the filter responses hence they represent illumination invariant (and contrast independent). This speciallity makes the OGPCPs a very suitable image representation for face recognition. The examples of the OGPCPs for a sample face image are shown in Fig. 2.

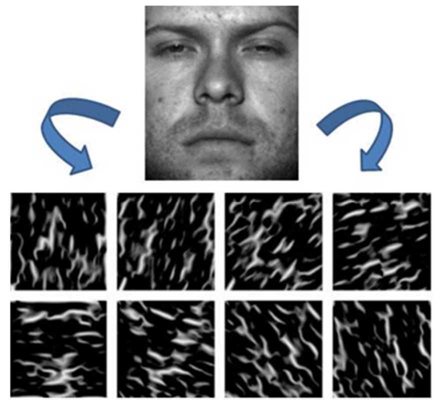

Figure 2: An example of The OGPCPs: the original image (upper), the OGPCPs (for 8 orientations)

3.4. The Gabor Phase Congruency Feature Vectors

The Gabor phase congruency feature vector for a given face image can be computed by using equations (5) and (6) for v orientations and u scales. To alleviate the high dimensional problem, the points in OGPCPs are selected to be feature points based on the high information content of the face image or high-energized points in a W x W window. Points with high-energized are found by searching the pixels in a sliding window [20][21]. The Window size (W x W) must be small enough to capture the important features and large enough to avoid redundancy information. A W = 7 i.e. 7×7 window is used to search feature points on Gabor filter responses.

3.5. Subspace LDA

The Oriented Gabor Phase Congruency Feature Vector sets are high-dimensional, and simply concatenating them would tend to worsen any 'curse of dimensionality' problems. To prevent this we use Subspace LDA as a dimensionality reduction techniques. Basically Subspace LDA is an approach to improve LDA that often encounters the so-called small sample size (SSS) problem. LDA defines a projection that makes the within-class scatter small and the between class scatter large. This projection has shown to be able to improve classification performance over PCA. However, it requires a large training sample set for

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good generalization, which is usually not available for face recognition applications. To address such Small Sample Size (SSS) problems, Zhao et al (1998) perform PCA to reduce feature dimension before LDA projection.

PCA aims to find a set of projection vectors that map the original D-dimensional image space into a D_{PCA} - dimensional feature space, in which $D_{PCA} << D$. In PCA, the N images of the training set are converted to N column vectors $\mathbf{x}_i$ of length D equal to the number of pixels in the images. If their mean is $\bar{\boldsymbol{x}}$ then the total scatter is given by the D x D matrix, i.e.

$$\boldsymbol{S}_T = \sum_{i=1}^{N}(\boldsymbol{x}_i - \bar{\boldsymbol{x}})\,(\boldsymbol{x}_i - \bar{\boldsymbol{x}})^T \qquad (7)$$

PCA attempts to find a set of orthonormal eigenvectors, $\{\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_{D_{PCA}}\}$ of $\boldsymbol{S}_T$, to form the projection matrix $\boldsymbol{W}_{PCA} = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_{D_{PCA}}]$ corresponding to the $\boldsymbol{D}_{PCA}$ largest eigenvalues. The new feature vector $\boldsymbol{y}_n \in \mathbb{R}^{D_{PCA}}$ can be obtained by,

$$\boldsymbol{y}_n = \boldsymbol{W}_{PCA}^t \boldsymbol{x}_n,\ n = 1,2,\ldots,N \qquad (8)$$

LDA aims to find the optimal set of discriminant vectors that maps the original D-dimensional image space into a D_{LDA}-dimensional feature space ($D_{LDA} \ll D$) such that images from different classes are more separated and images of the same class are more compact. LDA then aims to find a projection matrix $\boldsymbol{W}$ which maximizes the quotient of the determinants of $\boldsymbol{S}_b$ and $\boldsymbol{S}_w$ [19][20],

$$\boldsymbol{W} = \arg max \frac{|w^T S_b W|}{|W^T S_w w|} \qquad (9)$$

where $\boldsymbol{S}_b$ and $\boldsymbol{S}_w$ are the between-class scatter and within-class scatter respectively. Consider a C class problem and let N_c be the number of samples in class c , a set of M training patterns from the C class can be defined as $\{x_{ck}, c = 1,2,\ldots,C; k = 1,2,\ldots,N\}, M = \sum_{c=1}^{C} N_c$. The $\boldsymbol{S}_b$ and $\boldsymbol{S}_w$ of a training set can be computed as :

$$\boldsymbol{S}_w = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{N_c}\sum_{k=1}^{N_c}(x_{ck} - \mu_c)(x_{ck} - \mu_c)^T \qquad (10)$$

$$\boldsymbol{S}_b = \frac{1}{C}\sum_{c=1}^{C}(\mu_c - \mu)(\mu_c - \mu)^T \qquad (11)$$

where $\boldsymbol{\mu}$ is the mean of the whole training set, and $\boldsymbol{\mu}_c$ is the mean for the class c. It was shown in [14] that the projection matrix $\boldsymbol{W}$ can be computed from the eigenvectors of $\boldsymbol{S}_w^{-1}\boldsymbol{S}_b$. The major drawback of applying LDA for the face recognition task is that it may encounter the so-called small sample size (SSS) problem. It is because the high dimensionality of the feature vector, $\boldsymbol{S}_w$ is usually does not have inverse ($\boldsymbol{S}_w$ is singular). To overcome this problem, a two-phase framework PCA plus LDA [15]. The original feature vectors are first projected to a lower dimensional space by PCA as defined in equ. (8), and secondly it applies the LDA-based algorithm in the reduced subspace to get the optimal projection matrix. Let $\boldsymbol{W}_{PCA}$ be the projection matrix from the original image space to the PCA subspace, the LDA projection matrix $\boldsymbol{W}_{LDA}$ is thus composed of the eigenvectors of $(\boldsymbol{W}_{PCA}^T \boldsymbol{S}_w \boldsymbol{W}_{PCA})^{-1}(\boldsymbol{W}_{PCA}^T \boldsymbol{S}_b \boldsymbol{W}_{PCA})$. The final projection matrix $\boldsymbol{W}$ subspace LDA can thus be obtained by :

$$\boldsymbol{W}_{subspaceLDA} = \boldsymbol{W}_{PCA} \times \boldsymbol{W}_{LDA} \qquad (12)$$

Note that the rank of $\boldsymbol{S}_b \leq C - 1$, while the rank of $\boldsymbol{S}_w \leq M\text{-}C$. As a result, it is suggested that the dimension of the PCA subspace should be M-C [15]. Therefore a reduced face feature vector $\boldsymbol{y}_n \in \mathbb{R}^{D_{LDA}}$ are given as follows,

$$\boldsymbol{y}_n = \boldsymbol{W}_{subspaceLDA}^t \boldsymbol{x}_n,\ n = 1,2,\ldots,N \qquad (13)$$

4. EXPERIMENTS, RESULTS AND DISCUSSION

To illustrate the effectiveness of the proposed method, we used publicly available databases containing large illumination variations i.e Yale-B database. We first briefly introduce the Yale-B database employed in the assessment and then the actual experiments.

4.1. Yale-B Database

The Yale B database consists of 5760 frontal face images with single light source of 10 individuals. It exhibits large variations in illumination. The size of each image is 192 x 168. Each distinct subject is seen under 576 views conditions: 9 different pose and 64 different illumination conditions. The Yale-B is divided into 5 (five) distinct subsets and according to the angle the light source direction with the camera axis(12°, 25°, 50°, 77° and above 78°). The subsets 1, 2, 3, 4 and 5 contain 120, 130, 130, 130, and 130 images per pose, respectively [16]. Since this paper mainly deals with the impact of the illumination variations, we only choose 64 frontal images captured under 64 different lighting conditions for each of 10 subjects, i.e., a subset of 640 facial

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images. Some examples of the images are shown in figure 3.

Figure 3: Sample images from the YaleB database

4.2. Experimental Settings

Preprocessing procedure is very important step prior to the experiments, all images were subjected to geometric and photometric normalization to counter the effects of pose and to normalize intensity, as well as local shadowing. First all images were converted to 8 bit gray-scale, aligned and then cropped to a standard size of 128 × 128 pixels in accordance with the given eye coordinates supplied with the original datasets. This is to ensure that all images have uniform size and shape.

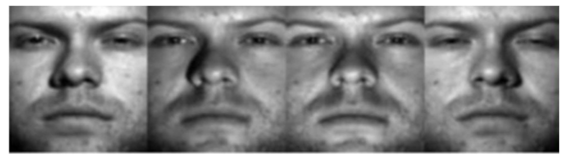
After the cropping procedures, all the 640 images were processed with histogram equalization and were distributed into five subsets depending on the extremity in illumination. The first image subset, denoted as S1 (with the most controlled-like conditions) was used for training and enrollment, while the remaining subsets (S2, S3, S4 and S5) were employed for testing. Note that the conditions got more extreme for the image subsets two (S2) to five (S5). Figure 4 shows some examples of the preprocessed five subsets facial images S1 to S5. Also all the images then were further normalized to zero-means and unit variance.

The tests are performed using Subspace LDA (i.e. PCA+LDA) with various number of eigenvectors used. The number of training images per individual are 12 but we used only 7 and 5. In [22] it has been argued that the Subspace LDA method performs best with the angle or cosine distance, therefore classification was performed using a nearest neighbor classifier and a cosine - based distance measure, which is defined as,

$$d_{cos}(\boldsymbol{x}, \boldsymbol{y}) = \frac{\boldsymbol{x}^T \boldsymbol{y}}{\sqrt{\boldsymbol{x}^T \boldsymbol{x} \boldsymbol{y}^T \boldsymbol{y}}} \qquad (14)$$

To construct The Oriented Gabor Phase Congruency Feature, we use five filter scales (u =5) and eight filter orientations (v = 8). These number of scales and orientations, i.e. u = 5 and v = 8, was

(a) subset 1 (used for training)



(b) subset 2

(c) subset 3

(d) subset 4

(e) subset 5

Figure 4 : Examples of the preprocessed images from the five subsets of the YaleB database

chosen based on other Gabor filter based methods presented in the literature. [12][15][16]

4.3. Experimental Results

We tested the performance of our proposed method on the Yale-B databases. The Cosine distance and the nearest neighbor classifier is adopted. The rank-one recognition rate is calculated as the ratio of the number of tested images that were correctly identified and the total number of test images. We tested under 2-different

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number of images per individual (class) i.e, 7 and 5 images per individual in training sets (S1). We also evaluated the impact of the number of filter scales *u* in the Gabor filter bank on the performance of the subspace LDA technique applied to the phase

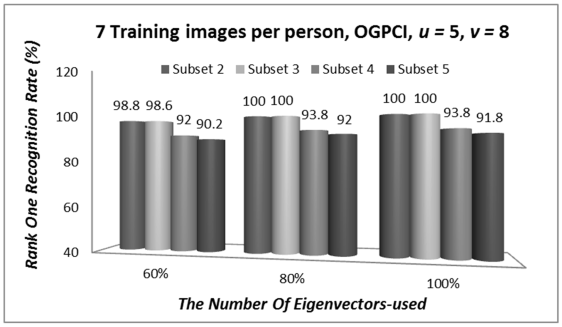

Figure 5 : Rank one recognition rates (%) on the Yale-B database for 7 training images, u = 5 and v = 8

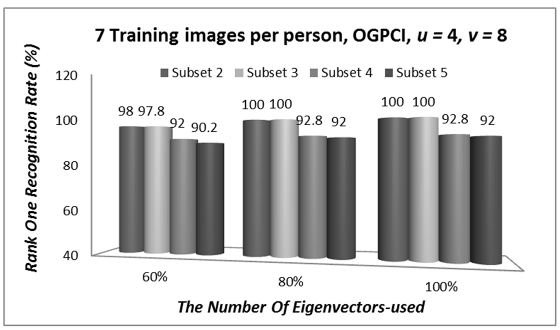

Figure 6 : Rank one recognition rates (%) on the Yale-B database for 7 training images, u = 4 and v = 8

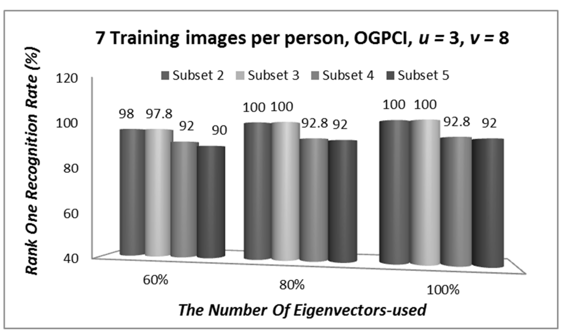

Figure 7 : Rank one recognition rates (%) on the Yale-B database for 7 training images, u = 3 and v = 8

congruency feature vectors. We fixed the orientation of the filter bank to v = 8 and vary the value of the filter scales from u = 3 to u = 5.

Table 1 and Figures 5 to 10 present the results of the experiments in the form of rank one recognition rates for the Yale-B database.

4.4. Discussion

From the series of experimental results presented in previous section, we found that the Subspace LDA combined with the Gabor phase congruency features that we proposed, ensured the

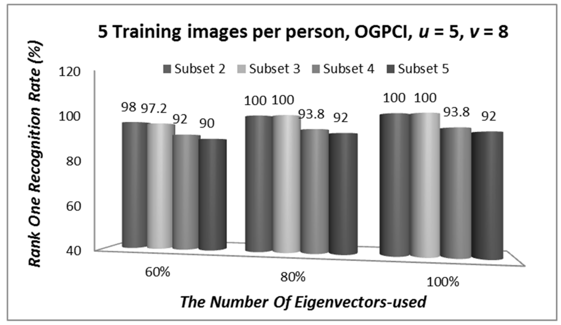

Figure 8 : Rank one recognition rates (%) on the Yale-B database for 5 training images, u = 5 and v = 8

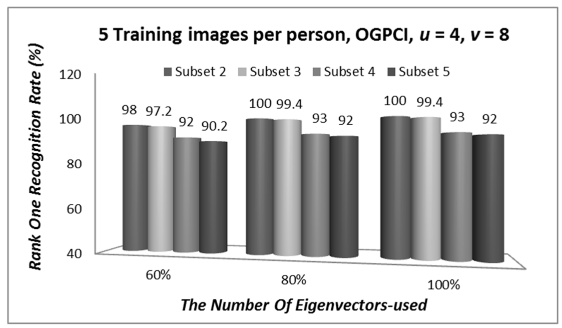

Figure 9 : Rank one recognition rates (%) on the Yale-B database for 5 training images, u = 4 and v = 8

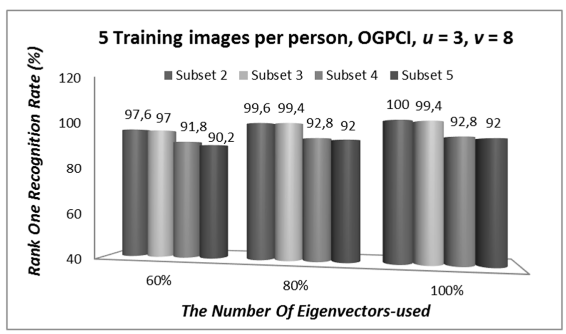

Figure10: Rank one recognition rates (%) on the Yale-B database for 5 training images, u = 3 and v = 8

best recognition performance on Yale-B database. This is because the OGPCPs as defined by equ. (5) represent illumination invariant, since they do not depend on the overall magnitude of the filter responses. As can be seen from the experiment results that the number of training images per

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person i.e., 7 and 5 images respectively does not much influence the recognition rate.

A number of studies from the literature [12][15][16], that utilized the Gabor magnitude based for face recognition require 40 Gabor filters, i.e., filters with five scales and eight orientations, to achieve their optimal performance. We investigated the impact of reducing the number filter scale on the performance of our proposed method and we found that there is no significant different in employing 5 or 4 as well as 3 filter scales. This fact makes our proposed methods outstandingly faster than the Gabor magnitude based methods.

Table 1: Rank one recognition rates (%) on the Yale-B database for different numbers of filter OGPC scales

u	NOE	7 Training images per person				5 Training images per person			
		S2	S3	S4	S5	S2	S3	S4	S5
5	60%	98.8	98.6	92,4	90.2	98	97.2	92	90
	80%	100	100	93.8	92	100	100	93.8	92
	100%	100	100	93.8	91.8	100	100	93.8	92
4	60%	98	97.8	92	90.2	98	97.2	92	90.2
	80%	100	100	92.8	92	100	99.4	93	92
	100%	100	100	92.8	92	100	99.4	93	92
3	60%	98	97.8	92	90	97.6	97	91.8	90.2
	80%	100	100	92.8	92	99.6	99.4	92.8	92
	100%	100	100	92.8	92	100	99.4	92.8	92

5. CONCLUSION

In this paper an efficient approach for face recognition is presented. OGPCPs is used for finding feature points, then the peak selection algorithm is applied on these feature points, to form the feature vectors. These vectors are then classified using Subspace LDA. To achieve optimal face recognition performance, the Gabor phase congruency features based methods presented in this paper, require only 24 Gabor filter banks (three scales and eight orientations). The feasibility of the proposed face recognition approach was assessed on publicly available database, i.e. Yale B database, and from the experiment results, our proposed method shows a promising face recognition performance, especially to ensure a robust recognition performance in the presence of extreme lighting changes. We can achieve outstanding recognition accuracy which are, 100%, 100%, 92.8%, 92% for subset 2, 3, 4 and 5 respectively.

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