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Gabor-based Face Recognition with Illumination Variation using Subspace-Linear Discriminant Analysis

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Abstrak

Teknik pengenalan wajah telah menjadi topik riset yang aktif dalam beberapa dekade terakhir karena potensi aplikasinya. Pengenalan wajah yang akurat masih merupakan pekerjaan yang sulit, terutama jika iluminasinya tak terbatas. Makalah ini menyajikan suatu metoda yang efisien untuk pengenalan wajah dengan iluminasi yang berbeda-beda menggunakan fitur Gabor, yang diekstraksi dari tapis log-Gabor dengan enam orientasi dan empat skala. Fitur-fitur wajah ini diekstraksi pada daerah-daerah blok pada citra wajah menggunakan algoritma jendela geser. Fitur-fitur hasil ekstraksi kemudian diproses oleh analisis komponen utama (PCA) dan analisis diskriminan linier (LDA). Untuk pengembangan dan pengujian digunakan citra-citra wajah yang berasal dari basis data Yale-B. Metoda yang diusulkan ini menghasilkan laju pengenalan rank 1 sebesar 86–100 %.

Kata kunci: *iluminasi, fitur Gabor, LDA, PCA, pengenalan wajah*

Abstract

Face recognition has been an active research topic in the past few decades due to its potential applications. Accurate face recognition is still a difficult task, especially in the case that illumination is unconstrained. This paper presents an efficient method for the recognition of faces with different illumination by using Gabor features, which are extracted by using log-Gabor filters of six orientations and four scales. By Using sliding window algorithm, these features are extracted at image block-regions. Extracted features are passed to the principal component analysis (PCA) and then to linear discriminant analysis (LDA). For development and testing we used facial images from the Yale-B databases. The proposed method achieved 86–100 % rank 1 recognition rate.

Keywords: *illumination, face recognition, Gabor feature, LDA, PCA*

1. Introduction

Face Recognition is an active research topic in computer vision and image processing. This trend is driven by some applications like surveillance, security monitoring, and so on. Even though human beings can detect and identify faces with no effort, building an automated system that accomplishes such objectives is very challenging. The challenges are even more profound when there are large variations due to illumination conditions. Robust face recognition under various illumination environments turns out to be difficult to achieve [1].

It is now well known that variation of illumination conditions can change face appearance dramatically so that the variations between the images of the same face due to illumination can be larger than image variations due to change in face identity [2]. Of all image analysis of human face, facial feature extraction is very important. Especially on finding features that are insensitive to changes in illumination. To obtain good features robust to such variations, many methods applied Gabor-wavelet transform which can capture the properties of orientation selectivity and spatial frequency selectivity [3].

A number of research works have been published in literature for Gabor based image recognition. Wiskott et. Al [4] proposed a method that extracting Gabor-wavelet features fiducial points and developed a Gabor wavelet-based elastic bunch graph matching (EBGM) method to label and recognize facial images. Liu and Wechsler in [5] proposed a Gabor feature based classification protocol using the Fisher linear discriminant model for dimension reduction. Holistic kernel methods have been also applied in combination with Gabor wavelets. For example, Liu proposed fractional power polynomial kernels $k(x,y) = (x \cdot y)^d$ for his version of

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Gabor Kernel PCA. [6]. Shen and Bai proposed LDA-based kernel methods called Gabor Kernel Direct Discriminant Analysis [7], whose authors claimed to outperform Gabor KPCA using a Gaussian kernel.

Two-dimensional versions of PCA have the advantage of keeping structural information. Wang et al. used 2DPCA and $(2D)^2$PCA of the Gabor extracted features, with very good results in a face recognition problem [8]. Mutelo et. Al [9] proposed A new technique called two-dimensional Gabor Fisher discriminant (2DGFD) which is derived and implemented for facial image representation and recognition.

The Gabor wavelets, whose kernels are similar to the two-dimensional (2-D) receptive field profiles of the mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity. The biological relevance and computational properties of Gabor wavelets for image analysis have been described in [10], [11], [12], and [13]. The Gabor wavelet representation facilitates recognition without correspondence because it captures the local structure corresponding to spatial frequency (scale), spatial localization, and orientation selectivity [14]. As a result, the Gabor wavelet representation of face images should be robust to variations due to illumination changes.

Usually, 40 Gabor kernels (5 different scales and 8 orientations) are used. As a result, the dimension of the filtered vectors is up to 40 x d, where d equals the product of the width w and the height h of the image (i.e. $d = w \times h$). When the size of original image is 100 x 100*;* the dimension of the filtered vector can be as large as 400,000. Such a high dimensional vector will lead to expensive computation and storage cost. Usually a downsampling method is used for feature vectors dimension reduction, as suggested by Liu et al. [5].

In this paper, a novel combined face recognition method based on Log Gabor-wavelet and subspace linear discriminant analysis (LDA) is proposed. We used Log Gabor filter instead of Gabor filter since in log Gabor filter, its DC component is always zero, thus the filter bandwidth is not limited to 1 octave, as it is for Gabor filters, and thereby a lesser number of filters can be used (We used only 4 scales and 6 orientations). Also to alleviate the high dimensional problem, we do not use the downsampling method instead of Gabor-wavelet features were extracted on points with high-energized Gabor wavelet response, which contain high facial feature information. For further dimensionality reduction and good recognition performance, we adopt a subspace LDA i.e. two-phase framework PCA plus LDA for feature compression and selection in our face recognition system. The accuracy of the proposed combination scheme has been evaluated in Yale-B database.

2. Research Method

2.1. System Architecture

Figure 1 shows a block diagram demonstrating the use of Gabor features and subspace LDA analysis for face recognition. Initially a set of Log-Gabor wavelets are used to extract appropriate features, this process is detailed in the next section. The Gabor features extracted from a set of training images are then used to learn the LDA subspace, which is represented by the projection matrix **W**. To identify a person, Gabor features of the face image are extracted, concatenated into a vector, projected to the learned LDA subspace and finally compared with the projections of training (gallery) images in the database. After comparison using a distance measure (such as Euclidean distance or Cosine-based distance measure) the person is identified as the one whose image produces the smallest distance.

2.1. Gabor Feature extraction using log-Gabor filters and sliding window algorithm

To perform feature extraction from the normalized greyscale facial images, this research uses the log-Gabor filters that were proposed in [15] for coding of natural images. The log Gabor function is a modification to the basic Gabor function, in that the frequency response is a Gaussian on a log frequency axis, as defined in equation (1). The log Gabor function has the advantage of the symmetry on the log frequency axis. The log axis, as pointed out in [15], is the optimum method for representing spatial frequency response of visual cortical neurons. The Log-Gabor filters spread information equally across the channels as shown in Figure 2(b) [15]. On the contrary, ordinary-Gabor filters over-represent low frequencies. As a result, it introduces redundancy in the response of low frequencies [15] as shown in Figure 2(a).

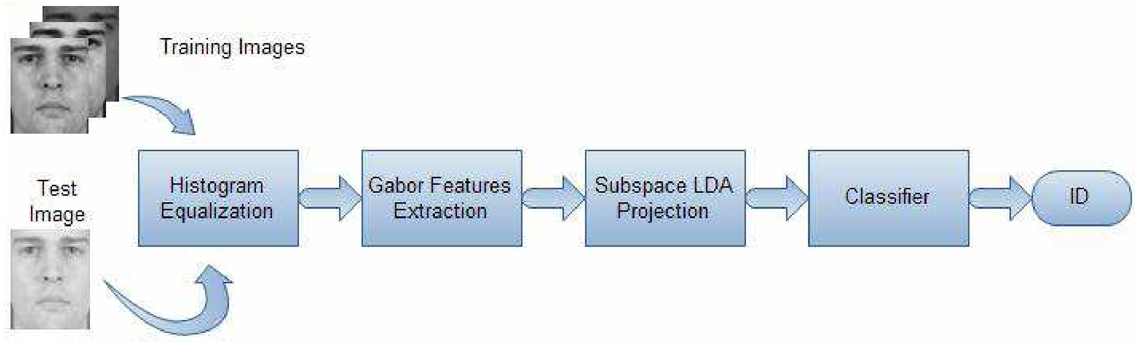
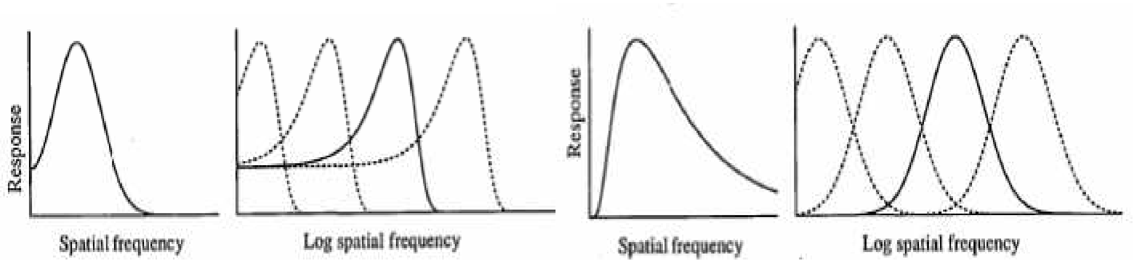


Figure 1. System Architecture



(a) Gabor function (b) Log Gabor function

Figure 2. Comparison of the Gabor and log Gabor function [15]

The experiments showed that these filters are more suitable for image coding than the traditional Gabor filters. The log-Gabor filter in the frequency domain and polar coordinates can be calculated using the following equation [16]:

$$G(f,\theta) = \exp\left(-\frac{ln^2(\frac{f}{f_0})}{2.ln^2(\frac{k}{f_0})}\right).\exp\left(-\frac{(\theta-\theta_0)}{2.\sigma_\theta^2}\right) \quad (1)$$

Here, f_0 : the centre frequency of the filter,
k : the bandwidth of the filter,
θ_0 : the orientation angle of the filter,
$\sigma_\theta = \Delta\theta / s_\theta$
where
s_θ : scaling factor,
$\Delta\theta$: orientation spacing between filters.

For this research, we generated multiple log-Gabor filters $G_{no,ns}$ of different orientations n_o and scales n_s using the following relationships: [17]

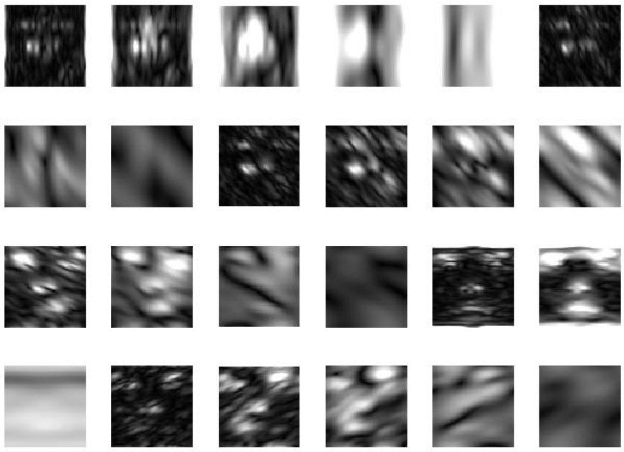
$$f_0 = {}^1/_\lambda\,, \qquad \lambda = \lambda_0 . s_\lambda^{(n_s-1)}\,, \qquad \frac{k}{f_0} = \sigma_f\,, \qquad \sigma_f(\beta) = \exp\left(-0.25\beta\sqrt{2.\ln(2)}\right)$$

$$n_s = 1,\dots,N_s\,, \qquad \theta_0 = \frac{\pi(n_0-1)}{N_0}, \qquad \Delta\theta = {}^\pi/_{N_0}, \qquad n_0 = 1,\dots,N_0$$

Here, λ_0 : the wavelength of the smallest scale filter,
s_λ : the scaling factor between successive filter scales,
β : the bandwidth of the filter in octaves,
N_s : the number of scales, i.e. 4,
N_o : the number of orientations, i.e 6.

After image filtering with multiple log-Gabor filters (N_s scales and N_o orientations) we get a very large number of log-Gabor features (magnitude values in all $N_s \cdot N_o$ magnitude images as it is shown in Figure 3). The size of each magnitude image M is the same as the size of facial image I. In order to reduce the number of features we use sliding window algorithm that is illustrated in Figure 4. Rectangular window of a chosen size is slided over the magnitude image $M_{no,1}$ (scale n_s = 1) using a chosen sliding steps. In each window we find one maximal magnitude value and remember the location (coordinates in image $M_{no,1}$) of this value. Features at all other scales $n_s = 2, ..., N_s$ of the same orientation n_o are extracted at the same locations without using sliding window as it is shown in Figure 4. The same feature's finding procedure is repeated for all N_o orientations. The log-Gabor features (found using sliding window) for each image from the database of faces are calculated only once and stored. Then all extracted log-Gabor features (magnitude values) are stored in a one-dimensional vector ***X*** and passed to the subspace LDA-based recognition method.

(a)



(b)

Figure 3. (a) Original Image, (b) Log-gabor magnitude images of N_s = 4 scales and N_o = 6 orientations (dark regions mean high magnitudes).

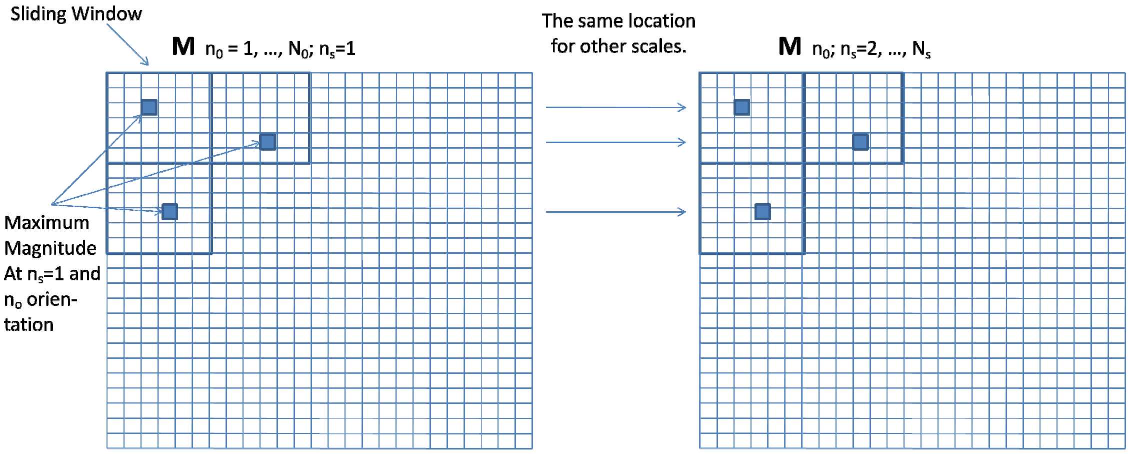


Figure 4. Feature-vectors Localization

2.2. Subspace LDA Method

The method implemented in this paper is the Subspace LDA method. Basically This method consists of two steps i.e. PCA step and LDA step. The face image is projected into the eigenface space which is constructed by PCA, and then the eigenface space projected vectors are projected into the LDA classification space to construct a linear classifier. The choice of the number of eigenfaces used for the PCA step is critical since the choice enables the system to generate class separable features via LDA from the eigenface space representation**.**

The aim of PCA is to identify a subspace spanned by the training images $\{x_1, x_2, \dots, x_M\}$, which could decorrelate the variance of pixel values. This can be achieved by eigen analysis of the covariance matrix, $= \frac{1}{M-1}\sum_{i=1}^{M}(x_i - \bar{x})\,(x_i - \bar{x})^T$:

$$\boldsymbol{\Sigma E} = \boldsymbol{\Lambda E} \tag{2}$$

where $\boldsymbol{E}$, $\boldsymbol{\Lambda}$ are the resultant eigenvectors, also referred to as eigenfaces, and eigenvalues respectively. The representation of a face image in the PCA subspace is then obtained by projecting it to the coordinate system defined by the eigenfaces [18].

While the projection of face images into PCA subspace achieves decorrelation and dimensionality reduction, LDA aims to find a projection matrix W which maximizes the quotient of the determinants of $\boldsymbol{S}_b$ and $\boldsymbol{S}_w$ [19][20],

$$\boldsymbol{W} = \arg max \frac{|\boldsymbol{w}^T \boldsymbol{s}_b \boldsymbol{W}|}{|\boldsymbol{W}^T \boldsymbol{s}_w \boldsymbol{w}|} \tag{3}$$

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 $\{x_{ck}, c = 1, 2, \dots, C; k = 1, 2, \dots, N\}, M = \sum_{c=1}^{C} N_c$. The $\boldsymbol{S}_b$ and $\boldsymbol{S}_w$ of a training set can be computed as :

$$\boldsymbol{S}_w = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{N_c}\sum_{k=1}^{N_c}(x_{ck} - \mu_c)(x_{ck} - \mu_c)^T \tag{4}$$

$$\boldsymbol{S}_b = \frac{1}{C}\sum_{c=1}^{C}(\mu_c - \mu)(\mu_c - \mu)^T \tag{5}$$

where μ is the mean of the whole training set, and μ_c is the mean for the class c. It was shown in [20] that the projection matrix $\boldsymbol{W}$ can be computed from the eigenvectors of $\boldsymbol{S}_w^{-1}\boldsymbol{S}_b$. However, due to the high dimensionality of the feature vector, especially in face recognition applications, $\boldsymbol{S}_w$ is usually singular, i.e. the inverse of $\boldsymbol{S}_w$ does not exist. As a result, a two-stage dimensionality reduction technique, named the Most Discriminant Features (MFD) or subspace LDA, was proposed by [21][22]. The original face vectors are first projected to a lower dimensional space by PCA, which is then subjected to LDA analysis. Let $\boldsymbol{W}_{pca}$ be the projection matrix from the original image space to the PCA subspace, the LDA projection matrix W_{lda} is thus composed of the eigenvectors of $\left(\boldsymbol{W}_{pca}^T \boldsymbol{S}_w \boldsymbol{W}_{pca}\right)^{-1}\left(\boldsymbol{W}_{pca}^T \boldsymbol{S}_b \boldsymbol{W}_{pca}\right)$. The final projection matrix $\boldsymbol{W}_{mfd}$ or $\boldsymbol{W}$ subspace LDA can thus be obtained by :

$$\boldsymbol{W}_{mfd} = \boldsymbol{W}_{pca} \times \boldsymbol{W}_{lda} \tag{6}$$

Note that the rank of $\boldsymbol{S}_b \le C-1$, while the rank of $\boldsymbol{S}_w \le M\text{-}C$. As a result, it is suggested that the dimension of the PCA subspace should be $M\text{-}C$ [21][22].

3. Results and Analysis

Before we describes the experiments performed to assess our proposed methods. First, the database employed in the assessment is briefly introduced and then the actual experiments with the corresponding results are presented.

3.1. Yale-B Database

The Yale B database contains 5,760 single light source images of 10 individuals. The size of each image is 192 x 168. Each individual is seen under 576 views conditions: 9 different pose and 64 different illumination conditions. The database is divided into five different subsets and according to the angle the light source direction forms with the camera axis (0° to 12°, 13° to 25°, 26° to 50°, 51° to 77° and above 78%). The subsets 1, 2, 3, 4, and 5 contain 70, 120, 120, 140, and 190 images per pose, respectively [23].

Since we are interested only in the impact of the illumination variations on the verification performance, we use only the subset of the facial images from the Yale-B database with frontal pose, i.e., a subset of 640 facial images. Some examples of the images from the employed frontal-pose-subset are shown in Figure 5.

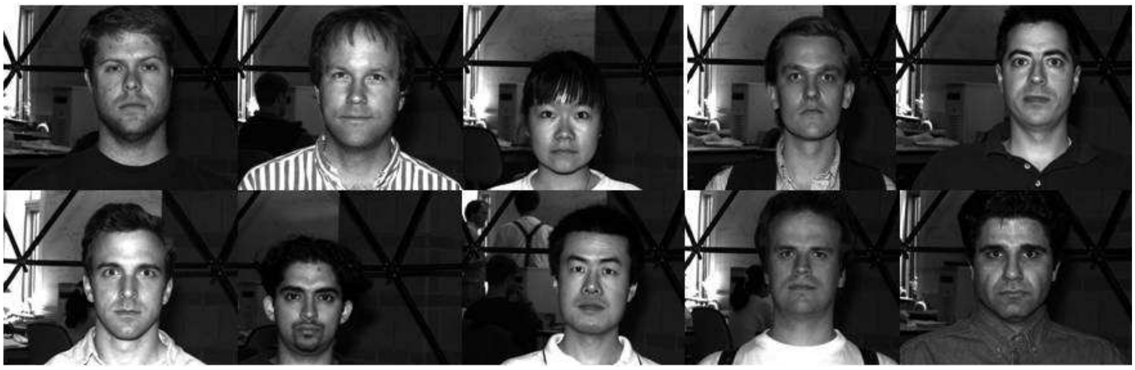


Figure 5. Sample images from the YaleB database

(a)

(b)

(c)

(d)

(e)

Figure 6. Examples of the preprocessed images from the five subsets of the YaleB database, (a) subset 1, (b) subset 2, (c) subset 3, (d) subset 4, and (e) subset 5.

3.2. Experimental Settings

Prior to the experiments, all face images (subset 1 to 5) were manually rotated, resized and then cropped to 128 × 128 pixels with 256 gray levels according to the coordinates of manually marked two eyes. They were cropped so that the only face regions are considered. This procedure to ensure that our results are comparable with other results presented in the literature. After the alignment and cropping procedures, all face images were processed with histogram equalization. By performing histogram equalization, the histogram of the pixel intensities in the resulting image is flat (Note that this is the standard procedure of preprocessing image). The first or second subset (assuming to be the most controlled-like conditions) were used for training and enrollment, while the remaining subsets were employed for testing. Figure 6 shows four examples of the preprocessed face images from the five subsets respectively. [24]

To obtain log-Gabor magnitude features by using sliding window algorithm, the rectangular window is set to 8 x 8 pixels and sliding step is 8 pixels. Log-Gabor filters were generated using the following parameters: λ_0 = 5, s_λ = 1.6, β = 1, $\sigma_f(\beta)$ = 0.745, N_s = 4, s_θ = 1.5, N_o = 6.

To investigate how the performance of the Subspace-LDA algorithm depends on the number of training images per class (individu), we performed 2 experiments with seven, five and four images per class (person) respectively. For the first experiment we used Subset 1 as training and other subsets were for testing then for second experiments, subset 2 were used as training while the remaining subsets were employed for testing. Classification was performed using a nearest neighbor classifier and a cosine-based distance measure.

3.3. Experimental Results

The results of these experiments in terms of the rank one recognition rate are presented in figure 7-12. Note that the rank one recognition rate is defined as the percentage of tested images that were correctly identified.

Figure 7 demonstrate that Gabor Subspace-LDA can achieve the best performance. A 96% and 100 % recognition rate can be obtained from subset 2 and 3 respectively. This is because Gabor wavelets can effectively generalize local and discriminating features, which are less sensitive to illumination variations so the face can be distinguished and easily recognized. Whereas the images of subset 4 where the illumination appears to come from the side, the recognition result is 92%. The images of subset 5 for each of the subject have an illumination in which the lighting is uneven or complex. The images are distorted, thus there is a fall in recognition rate of subset 5 with 86 % recognition rate. For all subsets, best results were obtained by using 80% eigenvectors from subspace-LDA algorithm. However using the other number of eigenvectors does not significantly reduced the recognition rates.

Figure 8-12 show the other performance of Gabor Subspace-LDA when the number of training images were varied and the training subset was changed from subset 1 to be subset 2. As can be seen from those figures, the recognition rate does not vary as much and the average rank one recognition rate is about 96% for subset 1 or 2 and subset 3, while for subset 4 and 5 is about 86%.

In order to compare our method with other existing methods, Table 1 shows the comparison of the proposed method with the some referenced subspace methods and other Gabor methods using the Yale-B databases. The results show that the proposed method outperforms other methods.

Table 1. Performance comparisons on Yale B database (multiple sample images per person)

Methods	Average Recognition Rate
Eigenface (PCA)	75%
Fisherface (LDA)	79%
Downsampling Gabor-based PCA	81%
Downsampling Gabor-based LDA	84%
Gabor-based 2DPCA[9]	91.8%
Gabor-based 2DLDA[9]	91.6%
Our Method	94%

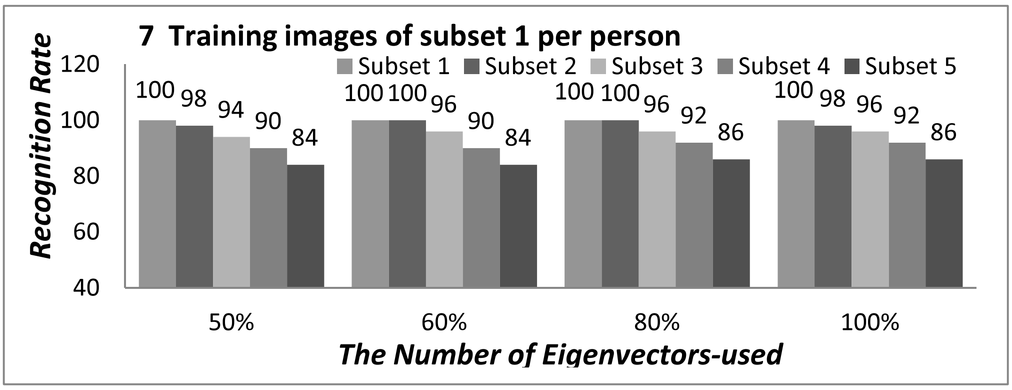


Figure 7. Rank one recognition rates (%) when using 7 images of subset 1 as training set for the five subsets of the Yale-B database.

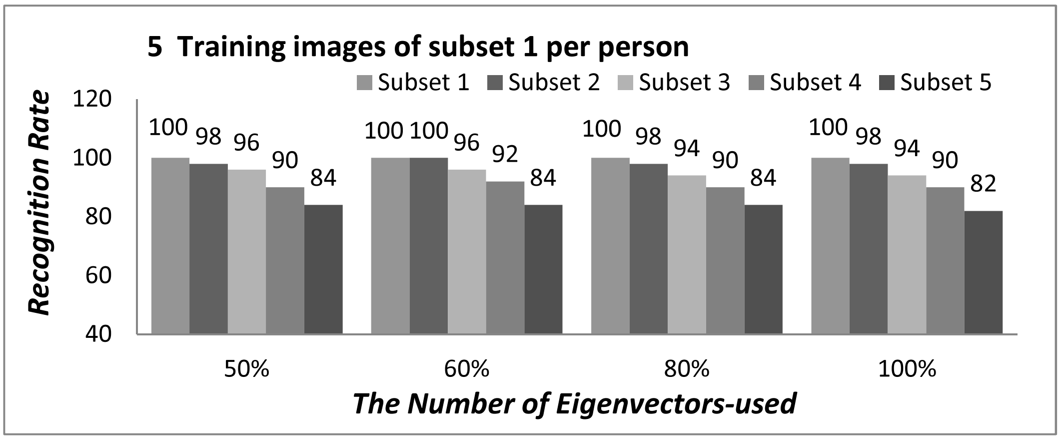


Figure 8. Rank one recognition rates (%) when using 5 images of subset 1 as training set for the five subsets of the Yale-B database

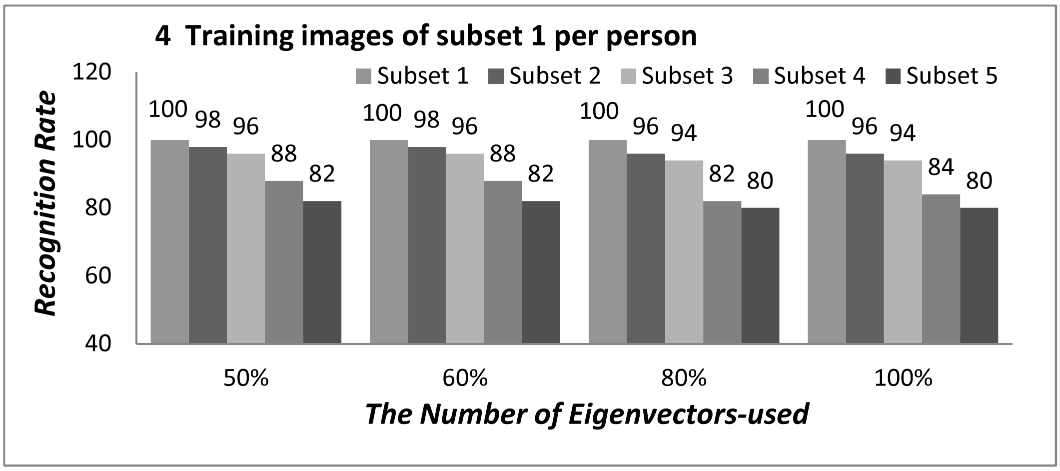


Figure 9. Rank one recognition rates (%) when using 4 images of subset 1 as training set for the five subsets of the Yale-B database

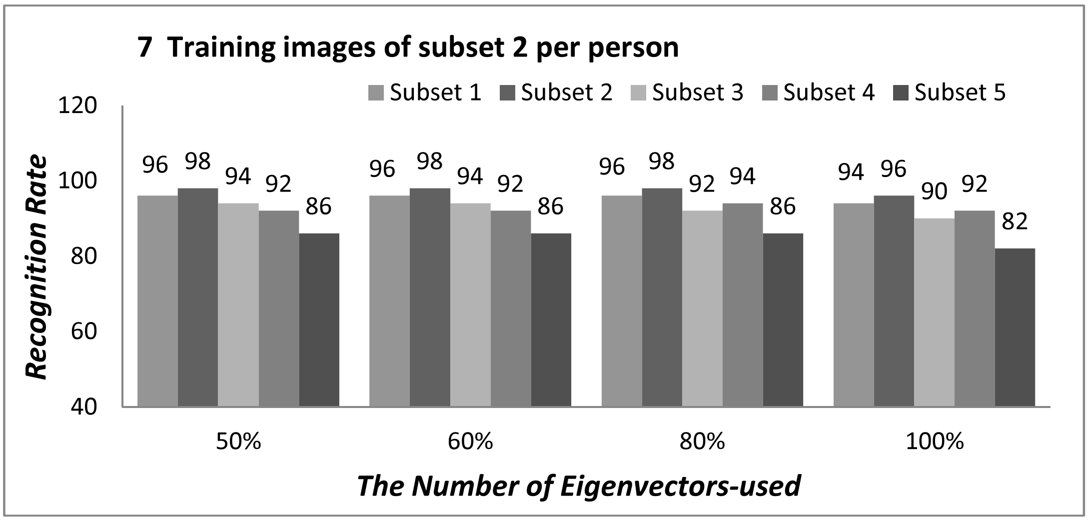


Figure 10. Rank one recognition rates (%) when using 7 images of subset 2 as training set for the five subsets of the Yale-B database

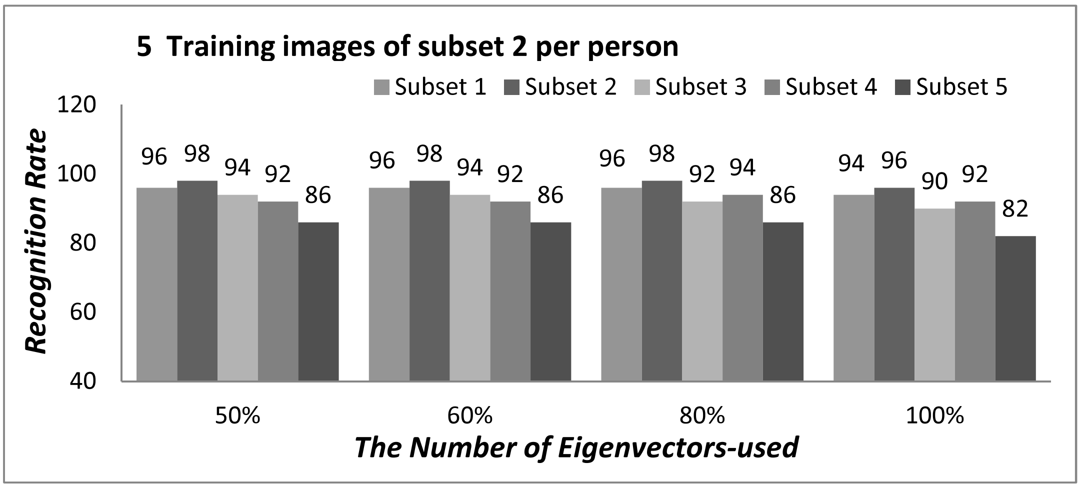


Figure 11. Rank one recognition rates (%) when using 5 images of subset 2 as training set for the five subsets of the Yale-B database

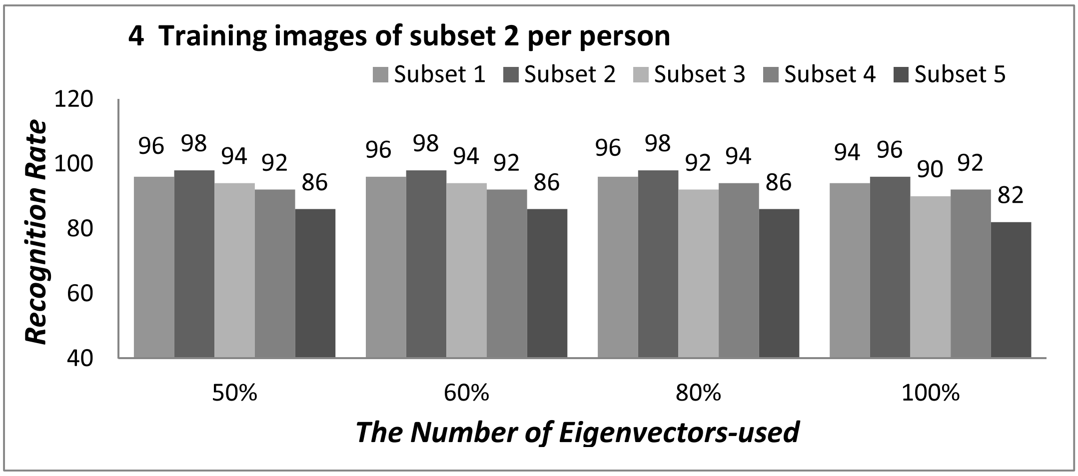


Figure 12. Rank one recognition rates (%) when using 4 images of subset 2 as training set for the five subsets of the Yale-B database

4. Conclusion

In this paper we present a face recognition method based on log-Gabor features and subspace linear discriminant analysis under varying illumination condition. The method uses log-Gabor wavelet transform for both finding feature points and extracting feature vectors. By using log-Gabor wavelet, the dimension of Gabor feature vectors is lower than by using Gabor wavelet. We used 4 scales and 6 orientations rather than 5 scales and 8 orientations as usual. The experiments with the Yale-B databases showed that using the proposed method, i.e. using log-Gabor features, sliding window-based feature selection method, subspace-linear discriminant analysis, and a cosine-based distance measure (nearest-neighbour classifier), we can achieve very high recognition accuracy which are, 100%, 96%, 92% and 86 % for subset 2, subset 3, subset 4 and subset 5 respectively.

Acknowledgement

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References

[1] Li SZ, Jain AK. *Handbook of Face Recognition*. Springer. 2005.

[2] Adini Y, Moses Y, Ullman S. Face Recognition: The problem of compensating for changes in illumination direction, *IEEE Trans. on Pattern Analysis and Machine Intelligence.* 1997; 19(7): 721-732.

[3] Bolme, David S. Elastic Bunch Graph Matching. Master Thesis. Colorado State University. 2003.

[4] Wiskott L, Fellous JM, Kruger N, Malsburg CV. Face recognition by elastic bunch graph matching. *IEEE Transaction On Pattern Analysis Machine Intelligence*. 1997; 19(7): 775–779.

[5] Liu C, Wechsler K. Gabor feature based classification using the enhanced Fisher linear discriminant model for face recognition. *IEEE Transactions On Image Processing.* 2002; 11(4): 467–476.

[6] Liu C. Gabor-based kernel PCA with fractional power polynomial models for face recognition. *IEEE Transaction On Pattern Analysis Machine Intelligence.* 2004; 26(5): 572–581.

[7] Shen L, Bai L. *Gabor wavelets and kernel direct discriminant analysis for face recognition*. Proceding IAPR ICPR. 2004; 1: 284–287.

[8] Wang L, Li Y, Wang C, Zhang H. *Face recognition using Gaborface-based 2DPCA and $(2D)^2$PCA classification with ensemble and multichannel model*. IEEE Symposium Computational Intelligence in Security and Defense Application. 2007; 1–6.

[9] Mutelo RM, Woo WL, Dlay SS. Discriminant analysis of the two-dimensional Gabor features for face recognition. *IET Computer Vision*. 2008; 2(2): 37-49.

[10] Daugman JG. Two-dimensional spectral analysis of cortical receptive field profiles. *Vis. Res.* 1980; 20: 847–856.

[11] Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional cortical filters. *J. Opt. Soc. Amer.* 1985; 2(7): 1160–1169.

[12] Jones J, Palmer L. An evaluation of the two-dimensional Gabor filter model of simple receptive fields in cat striate cortex. *J. Neurophys.* 1987; 1233–1258.

[13] Marcelja S. Mathematical description of the responses of simple cortical cells. *J. Opt. Soc. Amer.* 1980; 70 : 1297–1300.

[14] Schiele B, Crowley J L. Recognition without correspondence using multidimensional receptive field histograms. *Int. J. Comput. Vis.* 2003; 36(1) : 31–52.

[15] Field DJ. Relations between the statistics of natural images and the response properties of cortical cells. *Journal of Optical Society of America.* 1987; A4(12) : 2379–2394.

[16] Gosselin B, Thillou. C. M., Character Segmentation-by-Recognition Using Log-Gabor Filters, ICPR 2006

[17] Boukerroui D, Noble JA, Brady JM. On the choice of band-pass quadrature filters, *Journal of Mathematical Imaging and Vision (JMIV).* 2004; 21(1): 53–80.

[18] Turk M, Pentland A. Eigenfaces for Recognition. *Journal of Cognitive Neuroscience.* 1991; 3: 71-86.

[19] Zhao W, Krishnaswamy A, Chellapa R, Swets DL, Weng JJ. Discriminant Analysis of Principal Components for Face Recognition. In H.Wechsler, P. J. Phillips, V. Bruce, F. F. Soulie, & Y. P. Huang. *Editors.* Face Recognition: From Theory to Applications. CAR-TR-914 ed. Springer-Verlag; 1998 : 73-85.

[20] Jian L, Shaohua Z, Shekhar C. A Comparison of Subspace Analysis For Face Recognition. *IEEE International Conference on Acoustics & Speech Signal Processing*. Hong Kong. 2003; 3: 121-4.

[21] Swets DL, Weng JJ. Using discriminant eigenfeatures for image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 1996; 18 : 831-836.

[22] Muntasa A, Indah AS, Mauridhi HP. Appearance global and local structure fusion for face image recognition. TELKOMNIKA. 2011; 9(1): 125-132.

[23] Belhumeur PN, Georghiades AS, Jacobs DW. From few to many: illumination cone models for face recognition under variable lighting and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 2001; 23: 643–660.

[24] Shan D, Rabab K. Ward Adaptive Region-Based Image Enhancement Method for Robust Face Recognition Under Variable Illumination Conditions. *IEEE Transactions On Circuits And Systems For Video Technology.* 2010; 20(9): 1165-1175.