Face Recognition using Principal Component Analysis and Log-Gabor Filters

Vytautas Perlibakas

Image Processing and Analysis Laboratory, Computational Technologies Centre,
Kaunas University of Technology, Studentu st. 56-305, LT-51424 Kaunas,
Lithuania

Abstract

In this article we propose a novel face recognition method based on Principal Component Analysis (PCA) and Log-Gabor filters. The main advantages of the proposed method are its simple implementation, training, and very high recognition accuracy. For recognition experiments we used 5151 face images of 1311 persons from different sets of the FERET and AR databases that allow to analyze how recognition accuracy is affected by the change of facial expressions, illumination, and aging. Recognition experiments with the FERET database (containing photographs of 1196 persons) showed that our method can achieve maximal 97-98% first one recognition rate and 0.3-0.4% Equal Error Rate. The experiments also showed that the accuracy of our method is less affected by eye location errors and used image normalization method than of traditional PCA-based recognition method.

Key words: Face recognition, Principal Component Analysis, Log-Gabor filters, FERET database

1 Introduction

Principal Component Analysis (PCA) or Karhunen Loeve Transform (KLT) -based face recognition method was proposed in [Turk and Pentland, 1991] and became very popular because of its relatively simple implementation and high recognition accuracy. During past fifteen years face recognition was a field of active research, and many other statistical methods (related to PCA) were investigated and proposed for face recognition: Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) [Bartlett et al.]

Email address: vperlib@mmlab.ktu.lt (Vytautas Perlibakas).
Because KLT is data dependent and is not very fast, other transforms were also used for face recognition: Discrete Cosine Transform (DCT) [Hafed and Levine, 2001], Fast Fourier Transform (FFT) [Spies and Ricketts, 2000], Discrete Wavelet Transform (DWT) [Feng et al., 2000], Wavelet Packet Decomposition (WPD) [Garcia et al., 2000]. Wiskott et al. [1997] proposed Elastic Bunch Graph Matching (EBGM) and Gabor wavelets-based face recognition method that achieved very high recognition accuracy. Escobar and Solar [2002] used EBGM-based recognition of faces in Log-Polar coordinates. Comprehensive overview of various face recognition methods could be found in [Zhao et al., 2000]. As it was shown by numerous experiments, face recognition accuracy can be increased by combining several methods, for example, DCT+PCA [Ramasubramanian and Venkatesh, 2001], DWT+PCA [Feng et al., 2000], WPD+PCA [Perlibakas, 2004], PCA+LDA [Zhao et al., 1998], or by using various image pre-processing methods. Recent results also showed that using Gabor or Log-Gabor features instead of traditional greyscale features and by combining these features with well known recognition methods like PCA, ICA, LDA or SVM it is possible to achieve very high recognition accuracy. Now we will overview various combined face recognition methods that use Gabor or Log-Gabor features and that are related with a method that we propose in this publication. Although many researchers used the same Gabor filters and well known feature compression and classification methods, all proposed methods differ from each other by feature selection techniques, parameters of filters, used classification method and its parameters, distance measure, and image normalization method. After filtering face image with Gabor filters of multiple scales (usually 4-5) and orientations (usually 6-8) we get very large number of features (24-40 images of the same dimensions as initial image). Perhaps one of the most important questions is how to reduce the number of these features for further processing. The most popular method is to extract Gabor features at a small number (usually less than 100) of face points around face features (like eyes, lips, nose) that were detected using EBGM [Wiskott et al., 1997] or similar method. At each detected point are extracted Gabor features from all scales and orientations. Lyons et al. [2000] combined EBGM Gabor features and LDA-based recognition method. Smeraldi and Bigun [2002] detected face features using saccadic search with a set of Log-Gabor filters that were arranged to concentric circles (retinas). At detected points were extracted Log-Gabor features and passed to the SVM-based classifier. EBGM-based feature selection was also used by Wang and Tang [2003] for Bayesian PCA-based recognition. Because EBGM-based methods require training with manually labelled faces, other researchers use feature extraction methods that do not require such training. One possible approach is to combine Gabor magnitude images from all scales and orientations to a single feature vector (image) and use this vector for recognition. Such method was used by Zhang et al. [2004] for Gabor+AdaBoost face recognition. Because such combined feature vectors may be too large for further processing, we can reduce the number of features by
using smaller initial images. Liu and Wechsler (2002) decided to downsample feature images of each scale and resolution and then combine these features to a single vector for Gabor+Enhanced LDA (Liu and Wechsler, 2002) and Gabor+ICA (Liu and Wechsler, 2003) -based recognition using $L_1$, Euclidean, and cosine -based distance measures. In order to reduce the number of Gabor features, Kepenekci et al. (2002) used sliding window based search at all scales and orientations. In each window were extracted features with maximal magnitudes, stored their locations, and then both magnitudes and locations were used for comparison. For recognition was used very similar distance measure that was used by (Wiskott et al., 1997) with additional constraints to feature locations.

In this article we propose to find the locations of Log-Gabor (Field, 1987) features with maximal magnitudes at single scale and multiple orientations using sliding window -based search and then use the same feature locations for all other scales. For further feature compression we used Principal Component Analysis (PCA) because its simple implementation, fast training and because using PCA with ”whitened” angle -based distance measure it is possible to achieve similar recognition accuracy like using EBGM and LDA -based recognition methods (CSU, 2003). We tested our method using 5151 face images of 1311 persons from the FERET and AR databases and the results showed that the proposed recognition method can achieve higher recognition accuracy than many other existing methods. The results of experiments also showed that PCA using Log-Gabor features is less sensitive to face detection errors and used image normalization method than PCA using greyscale features.

2 Feature extraction using Log-Gabor filters

The Log-Gabor filters were proposed by Field (1987) for coding of natural images. The experiments showed, that these filters are consistent with the measurements of the mammalian visual system and are more suitable for coding of natural images than Gabor (1946) filters. The Log-Gabor filter in frequency domain can be constructed in terms of two components, namely the radial filter component $G(f)$ and the angular filter component $G(\theta)$. In polar coordinates the filter transfer function could be written in the following form (Field, 1987), (Bigun and du Buf, 1994), (Kovesi, 1996):

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

here $f_0$ is the centre frequency of the filter, $k$ determines the bandwidth of the filter, $\theta_0$ is the orientation angle of the filter, and $\sigma_\theta = \frac{\Delta \theta}{s_{\theta}}$ where $s_{\theta}$ -
scaling factor, $\Delta \theta$ - orientation spacing between filters. For face recognition we generated multiple Log-Gabor filters of different scales and orientations using the following parameters:

$$f_0 = 1/\lambda, \lambda = \lambda_0 \cdot s^\lambda(n_s-1), k/f_0 = \sigma_f, n_s = 1, ..., N_s;$$

$$\theta_o = \pi(n_o - 1)/N_o, \Delta \theta = \pi/N_o, n_o = 1, ..., N_o;$$

$$\lambda_0 = 5, s_\lambda = 1.6, \sigma_f = 0.75, N_s = 4, s_\theta = 1.5, N_o = 6,$$

where $\lambda_0$ is the wavelength of the smallest scale filter, $s_\lambda$ is the scaling factor between successive filter scales, $N_s$ is the number of scales, $N_o$ is the number of orientations. Most of these parameters were chosen following the recommendations of (Kovesi, 2003).

Using Eq. 1 we calculate two-dimensional Log-Gabor filter $G_{n_o,n_s}$ in Fourier space of a chosen filter scale and orientation. The size of the filter array $G_{n_o,n_s}$ is the same as the size of the two-dimensional image $I$ that we wish to filter. Then we perform filtering (convolution in Fourier space), magnitude calculation and masking using the following equation:

$$V_{n_o,n_s} = \text{abs}(\text{IFFT}2(G_{n_o,n_s} \cdot \text{FFT}2(I))) \cdot \text{mask},$$

(2)

where $\cdot$ - array (not matrix) multiplication, $I$ - normalized (cropped, masked) face image, $G_{n_o,n_s}$ - Log-Gabor filter of desired orientation and scale in Fourier space, $\text{FFT}2$ - two-dimensional Fast Fourier Transform, $\text{IFFT}2$ - inverse $\text{FFT}2$, $\text{mask}$ - binary mask for masking magnitude image (the same as is used for masking greyscale face image $I$ in order to leave only the internal part of the face), $V_{n_o,n_s}$ - masked Log-Gabor magnitude image.

After image filtering with multiple Log-Gabor filters ($N_s$ scales and $N_o$ orientations) we get very large number of Log-Gabor features (magnitude values in all $N_s \cdot N_o$ magnitude images). In order to reduce the number of features and achieve partial face recognition invariance with respect to different facial expressions and minor face detection errors, we use sliding window algorithm that is illustrated in Fig. 1. Rectangular window of a chosen size (e.g., 8x8 pixels) is slid over the magnitude image $V_{n_o,1}$ using some sliding step (e.g., 6 pixels, overlapping of windows is 8-6=2 pixels). In each window we find one maximal magnitude value and remember the location (coordinates in image $V_{n_o,1}$) of this value. If several equal values are found, we use the one that is closer to the centre of the window. If magnitude image is masked, we perform search only in an unmasked image part.

We apply sliding window algorithm only for the first scale ($n_s = 1$) (obtained using filter with the smallest chosen wavelength) of each orientation and find the locations of highest magnitudes. Then these locations are used for extracting magnitudes from other scales, corresponding to the analysed orientation, as it is illustrated in Fig. 1. In this figure feature locations are marked with black points. Using scales $n_s = 1$ we decide at what locations (coordinates) we will extract the features and then use the same coordinates for all magnitude images, corresponding to the same processed orientation $n_o$ (the same orientations $n_o$ - the same locations, different orientations - different loca-
All extracted Log-Gabor features (magnitude values) are stored in a one-dimensional vector $X$ and used as input for Principal Component Analysis-based face recognition method.

Example Log-Gabor magnitude images are presented in Fig. 2 (images are inverted, dark points mean high magnitude values). In this example we used filters of $N_o = 6$ orientations and $N_s = 4$ scales ($N_o \cdot N_s = 24$ filters), and filtered a normalized (derotated, masked) facial image with these filters. Calculated Log-Gabor magnitude images were also masked. Left-most binary images in Fig. 2 show the locations (black points) of Log-Gabor features that were found using sliding window algorithm. It must be noted, that for the selected image size the Log-Gabor filters (of different sizes and orientations) can be calculated only once and stored. When we perform face recognition, the Log-Gabor features (found using sliding window) for each image from the database of faces are also calculated only once and stored.

3 Face recognition using Principal Component Analysis of Log-Gabor features

In this section we will describe Karhunen-Loeve transform (KLT)-based face recognition method, that is often called Principal Component Analysis (PCA).
We will present only the main formulas of this method, which details could be found in (Groß, 1994).

Let $X_j$ be $N$-element one-dimensional image-column (vector) and suppose that we have $r$ such images ($j = 1, ..., r$). In traditional PCA-based face recognition method, these images contain grey values of the two-dimensional facial photographs. In our case these one-dimensional images $X_j$ (data vectors) contain Log-Gabor features. We calculate the mean vector, centred data vectors and covariance matrix:

$$m = \frac{1}{r} \sum_{j=1}^{r} X_j, \quad d_j = X_j - m, \quad C = \frac{1}{r} \sum_{j=1}^{r} d_j d_j^T,$$

here $X = (x_1, x_2, ..., x_N)^T$, $m = (m_1, m_2, ..., m_N)^T$, $d = (d_1, d_2, ..., d_N)^T$.

In order to perform KLT, it is necessary to find eigenvectors $u_k$ and eigenvalues $\lambda_k$ of the covariance matrix $C$ ($Cu_k = \lambda_k u_k$). Because the dimensionality ($N^2$) of the matrix $C$ is usually large even for small images, and computation of the eigenvectors using traditional methods is complicated, dimensionality of matrix $C$ is reduced using the decomposition described in (Kirby and Sirovich, 1990) (if the number of training images is smaller than the length of the vector
Found eigenvectors \( u = (u_1, u_2, ..., u_N)^T \) are normed and sorted in decreasing order according to the corresponding eigenvalues. Then these vectors are transposed and arranged to form the row-vectors of the transformation matrix \( T \). Now any data \( X \) can be projected into the eigenspace and "whitened" (Bishop, 1995) using the following formula:

\[
Y = \Lambda^{-1/2}T(X - m),
\]

(3)

here \( X = (x_1, x_2, ..., x_N)^T, \ Y = (y_1, y_2, ..., y_r, 0, ..., 0)^T, \)

\( \Lambda^{-1/2} = diag(\sqrt{1/\lambda_1}, \sqrt{1/\lambda_2}, ..., \sqrt{1/\lambda_r}). \)

For projection we can use not all found eigenvectors, but only a few of them, corresponding to the largest eigenvalues. We can manually select the desired number of eigenvectors or use the method described in (Swets et al., 1998).

For each facial image (that we wish to use for recognition) we find Log-Gabor features, projected these features into the eigenspace and calculate eigenfeature vector \( Z = (z_1, z_2, ..., z_n)^T = (y_1, y_2, ..., y_n)^T \), here \( n \) is the number of features. Recognition of unknown face is performed by calculating its feature vector \( Z_{\text{new}} \) and comparing it with the feature vectors of known faces. For comparison we calculate the distances \( \varepsilon_i(Z_{\text{new}}, Z_i) \) between unknown face and each known face and say that the face with feature vector \( Z_{\text{new}} \) belongs to a person \( s = \arg \min_i [\varepsilon_i] \). For rejection of unknown faces a threshold \( \tau \) is chosen and it is said that the face with projection \( Z_{\text{new}} \) is unknown if \( \varepsilon_s \geq \tau \). For recognition we used cosine-based distance measure \( \varepsilon_i(Z_{\text{new}}, Z_i) = -\cos(Z_{\text{new}}, Z_i) \), because using this distance measure we can achieve higher recognition accuracy (Perlibakas, 2004) than using the Euclidean or Manhattan distance measures.

4 Normalization of face images

For recognition experiments we used two image normalization methods. One method uses manually selected centres of eyes and the tip of chin (3-point normalization method), and another method for normalization uses only the centres of eyes (2-point normalization method). Image normalization procedure of 3-point method is presented in Fig. 3. The last image (Fig. 3 (e)) also presents the result of 2-point normalization. For illustration we used an image from our personal archive.

Now we will describe our implementation of 3-point normalization method. Initial images were denoised (using Gaussian filter with \( \sigma = 0.5 \) and window size 5x5), derotated (in order to make the line connecting eye centres hori-
For initial comparison of PCA and Log-Gabor PCA methods we used 3-point normalization method in order to perform experiments with faces that are not overcropped and also contain no scene’s background information. Because the tip of chin may be hard to locate, most recognition methods for normalization use only the centres of eyes. So we used 3-point normalization only for initial comparison of PCA and Log-Gabor PCA methods, and for the rest of experiments we used 2-point normalization method (for normalization are used only the centres of eyes). Because there is no agreement how images should be normalized for face recognition experiments, we implemented 2-point normalization that is very similar to the (CSU, 2003) normalization method. Similar method was also used by some participants of the FERET (NIST, 2001) tests. At first images are derotated in order to make the line connecting eye centres horizontal. Then images are resized in order to make the distance between eyes equal to 70 pixels and cropped to the size of 130x150 pixels. During cropping the centres of eyes are vertically positioned on y=45 line (the centre of coordinates (0,0) is in the left top corner). Then the image is masked using an ellipse with its central point (65.5,50.5), horizontal axis of 128 pixels, and vertical axis of 236 pixels. After masking are left 17237 unmasked pixels. For an unmasked image part is performed histogram equalization. The main differences between our 2-point normalization and (CSU, 2003) normalization are as follows: initial images we filtered using Gaussian filter (CSU used no
filtering), for image rotation and resizing we used bicubic interpolation (CSU used bilinear interpolation), cropped 130x150 images we resized to 128x128 pixels and then masked with resized (to 128x128) binary mask. After such masking were left 14454 unmasked pixels. Then for an unmasked image part we performed histogram equalization. The result of this normalization is presented in Fig. 3 (e).

When we performed face recognition using Log-Gabor PCA method, masked face images were filtered with Log-Gabor filters (24 filters of 6 orientations and 4 scales) and calculated magnitude images. We masked these Log-Gabor magnitude images using the same masks that were used for image normalization and performed sliding window search of Log-Gabor features. Search window size is 8x8 pixels, sliding step is 6 pixels (the same in horizontal and vertical directions), and window overlap is 8-6=2 pixels. After using sliding window algorithm with masked magnitude images, we select 9240 magnitude values (Log-Gabor features) for 3-point normalization method and 10008 magnitude values for 2-point normalization method, that are located in the unmasked parts of magnitude images. This is the total number of values in all 6 orientations and 4 scales. Also we can use an unmasked magnitude images (initial greyscale images are always masked), perform sliding window search in a whole magnitude image and select in total 10584 features for both 3-point and 2-point methods (the size of images is the same). In all the experiments we used the same normalized image patterns and the same implementation of PCA. The distances between ”whitened” feature vectors were measured using cosine-based distance measure.

5 Used recognition performance measures

For comparison of face recognition methods we used Cumulative Match Characteristic (CMC) and Receiver Operating Characteristic (ROC) - based measures described in [Brombal, 2003]: the area above Cumulative Match Characteristic (CMCA) (smaller CMCA means better overall recognition accuracy); how many images (in percents) must be extracted from the database in order to achieve some cumulative recognition rate (e.g., not smaller than 95-100%) (smaller values mean that we need to extract fewer images in order to achieve some cumulative recognition rate); Equal Error Rate (EER) and the area below Receiver Operating Characteristic (ROCA) (smaller values mean better results); first one recognition rate (First 1) that is achieved if only the first one (most similar) image from the database is extracted (larger values mean better result). Percent (rank) of images that we need to extract from the database in order to achieve 100% cumulative recognition rate in the future we will denote as Cum100. Graphical representation of the used characteristics is shown in Fig. 4 - 5.
6 Experiments and results

For recognition experiments we used the FERET database [Phillips et al., a, 1998] containing greyscale photographs of 1196 persons. This database was collected in 1993-1996 at George Mason University during the FERET (Face REcognition Technology) program. As far as we know, this is one of the largest databases of face photographs (of different persons) in the world that is publicly available for face recognition research purposes (Groß, 2005). This database is widely used for evaluating identification (Phillips et al., a, 1998) and verification (Rizvi et al., 1998) performance of face recognition methods.

For recognition experiments we used 3541 facial images from this database. The size of each image is 256x384 pixels, for each image this database contains manually selected eye coordinates. For training we used 1196 greyscale images from the fa set of this database. The same 1196 fa images were used as a gallery (known persons), and images from other sets (1195 fb images, 722 dup1 images, 234 dup2 images, 194 fc images) were used as probes (unknown persons that we wish to recognize). fb set contain face images with different facial expressions, dup1 and dup2 sets contain images that were taken after some time interval (up to 1.5 years) from fa images, and fc set contains images with different image input conditions (camera position and illumination).

At first we performed recognition experiments with fa and fb sets using different number (100-1000) of PCA features (different number of used eigenvectors, corresponding to the largest eigenvalues) and compared the proposed masked Log-Gabor PCA with traditional PCA (using cosine -based distance
measure between "whitened" feature vectors). Images were normalized using 3-point normalization method. The results are presented in Table 1. The results showed, that first one recognition rate of masked Log-Gabor PCA (89.29-98.41%) is always higher than of traditional PCA (80.42-88.03%), and EER values of masked Log-Gabor PCA (0.33-1.59 %) are always lower than EER values of traditional PCA (1.92-4.26 %). Other characteristics (CMCA, ROCA, cumulative recognition) of masked Log-Gabor PCA are also better than of traditional PCA. The results showed, that masked Log-Gabor PCA achieves larger first one recognition accuracy when we use larger number of features (e.g., 100 PCA features - 89.29% recognition accuracy, 1000 PCA features - 98.41% recognition accuracy). It must be noted, that masked Log-Gabor PCA uses shorter vectors (9240 Log-Gabor features) than traditional PCA (12646 greyscale features) for PCA training. Also we investigated another version of Log-Gabor PCA when Log-Gabor magnitude images are not masked (only magnitudes, initial images are always masked). In this case the sliding window search selects 10584 Log-Gabor features. The results showed, that in some cases unmasked Log-Gabor PCA can achieve higher first one recognition accuracy, but because these differences are not very large (<0.2% with >200 features) we prefer to use masked version of Log-Gabor PCA.

Also we compared our face recognition results with the results of other researchers. For comparison we used the best results of the FERET program participants that took official FERET 1996-1997 tests [Phillips et al., 2000], [NIST, 2001]. Also we present the best results of some other researchers who tested their recognition methods using all images (not subsets) from the FERET fa (images of 1196 persons) and fb (images of 1195 persons) sets that contain faces with different facial expressions. Most part of the compared methods for face normalization used manually located coordinates of eye centres. These coordinates were marked by the creators of the FERET database and are distributed with this database. The results are summarized in Table 2. Fully automatical methods are denoted by "auto", our different normalization methods are denoted by "3 pt." (3-point normalization) and "2 pt." (2-point normalization). In Figures 6 - 7 we also present CMC and ROC characteristics of our Log-Gabor PCA method (900 PCA features, 2-point normalization).

Now we will briefly describe face recognition methods of other researchers and will compare achieved results. MIT 1996 (Massachusetts Institute of Technology, MIT Media Laboratory) method was developed by [Moghaddam et al., 1996]. For recognition they used dual (intrapersonal and extrapersonal) PCA and Bayesian MAP (maximum a posteriori) similarity measure. For learning were used image pairs of the same and different persons. UMD 1996, UMD 1997 (University of Maryland) face recognition methods are based on PCA and LDA (Linear Discriminant Analysis) and were developed by [Etemad and Chellapa, 1997; Zhao et al., 1998]. For training were used several images per person, for
Table 1
Comparison of 3 face recognition methods: 1) Masked Log-Gabor PCA (MskLG),
2) UnMasked Log-Gabor PCA (UnMskLG), and 3) Traditional PCA (Trad).

| Method  | Feat. num. | Rank (%) in order to achieve desired cumulative recognition accuracy | CMCA | First 1 rec., % | EER, % | ROCA |
|---------|------------|-------------------------------------------------------------------|------|----------------|--------|------|
|         |            | 95  | 96  | 97  | 98  | 99  | 100 |               |          |       |      |
| MskLG   | 100        | 0.33| 0.42| 0.50| 0.84| 2.34| 18.14| 17.67| 89.29 | 1.59 | 9.49 |
| UnMskLG | 100        | 0.42| 0.50| 0.75| 1.17| 2.17| 11.87| 17.20| 89.87 | 1.42 | 9.03 |
| Trad    | 100        | 0.84| 1.17| 1.59| 2.93| 6.44| 36.87| 37.27| 83.85 | 2.26 | 28.77|
| MskLG   | 200        | 0.17| 0.25| 0.33| 0.42| 0.84| 6.69 | 11.34| 93.56 | 0.75 | 2.48 |
| UnMskLG | 200        | 0.17| 0.17| 0.25| 0.42| 0.75| 6.94 | 11.44| 93.56 | 0.75 | 2.61 |
| Trad    | 200        | 0.59| 0.84| 1.17| 2.34| 7.19| 84.20| 40.21| 86.44 | 2.01 | 31.59|
| MskLG   | 300        | 0.08| 0.17| 0.17| 0.25| 0.42| 7.27 | 10.36| 95.31 | 0.59 | 1.65 |
| UnMskLG | 300        | 0.08| 0.17| 0.17| 0.25| 0.59| 8.61 | 10.41| 95.40 | 0.50 | 1.73 |
| Trad    | 300        | 0.59| 0.84| 1.34| 2.84| 5.52| 93.65| 39.36| 87.87 | 1.92 | 29.91|
| MskLG   | 400        | 0.08| 0.08| 0.17| 0.17| 0.33| 3.76 | 9.46 | 96.99 | 0.42 | 0.93 |
| UnMskLG | 400        | 0.08| 0.08| 0.08| 0.17| 0.33| 6.44 | 9.58 | 97.15 | 0.42 | 1.04 |
| Trad    | 400        | 0.59| 0.92| 1.67| 3.09| 12.12| 92.73| 52.94| 88.03 | 2.09 | 42.79|
| MskLG   | 500        | 0.08| 0.08| 0.08| 0.17| 0.33| 2.84 | 9.39 | 97.24 | 0.42 | 0.69 |
| UnMskLG | 500        | 0.08| 0.08| 0.17| 0.25| 0.33| 3.68 | 9.26 | 97.15 | 0.42 | 0.63 |
| Trad    | 500        | 0.92| 1.25| 2.01| 4.10| 16.64| 74.50| 58.73| 87.53 | 2.34 | 48.26|
| MskLG   | 600        | 0.08| 0.08| 0.08| 0.17| 0.25| 2.26 | 9.07 | 97.74 | 0.33 | 0.48 |
| UnMskLG | 600        | 0.08| 0.08| 0.17| 0.25| 1.42| 8.91 | 97.74 | 0.33 | 0.39 |
| Trad    | 600        | 1.34| 1.67| 2.59| 5.94| 13.55| 82.86| 67.05| 86.03 | 2.59 | 56.21|
| MskLG   | 700        | 0.08| 0.08| 0.08| 0.17| 0.17| 2.76 | 8.89 | 97.91 | 0.42 | 0.36 |
| UnMskLG | 700        | 0.08| 0.08| 0.08| 0.17| 0.25| 2.42 | 8.86 | 98.08 | 0.33 | 0.32 |
| Trad    | 700        | 1.42| 2.26| 4.35| 8.86| 22.41| 95.07| 88.53| 85.02 | 3.18 | 77.03|
| MskLG   | 800        | 0.08| 0.08| 0.08| 0.17| 0.17| 3.51 | 8.98 | 97.99 | 0.33 | 0.38 |
| UnMskLG | 800        | 0.08| 0.08| 0.08| 0.17| 0.17| 3.18 | 9.02 | 98.08 | 0.33 | 0.38 |
| Trad    | 800        | 2.09| 3.34| 5.35| 10.28| 28.51| 93.14| 109.44| 83.09 | 3.51 | 97.12|
| MskLG   | 900        | 0.08| 0.08| 0.08| 0.08| 0.25| 1.84 | 8.92 | 98.16 | 0.33 | 0.33 |
| UnMskLG | 900        | 0.08| 0.08| 0.08| 0.17| 0.17| 1.76 | 8.85 | 98.08 | 0.33 | 0.32 |
| Trad    | 900        | 2.76| 4.35| 7.02| 12.63| 38.13| 92.89| 123.40| 82.43 | 3.93 | 110.99|
| MskLG   | 1000       | 0.08| 0.08| 0.08| 0.08| 0.17| 6.35 | 9.44 | 98.41 | 0.33 | 0.63 |
| UnMskLG | 1000       | 0.08| 0.08| 0.08| 0.17| 2.51| 9.01 | 98.24 | 0.33 | 0.35 |
| Trad    | 1000       | 4.01| 5.52| 9.28| 16.22| 45.48| 90.80| 143.82| 80.42 | 4.26 | 130.80|
Table 2. Recognition of expression-variant faces from the FERET database (gallery contains 1196 $fa$ images, and probe contains 1195 $fb$ images).

| Method and its authors | Rank (%) in order to achieve desired cumulative recognition, (0, 100%) | CMCA, First 1 EER, ROCA, |
|------------------------|-------------------------------------------------------------------|--------------------------|
|                        | 95       | 96       | 97       | 98       | 99       | 100      | [0, 10$^4$] | [0, 100%] | [0, 10$^4$] |
| MIT 1996 (Moghaddam et al., 1996) | 0.17 0.25 0.33 1.09 23.33 99.83 | 84.14 | 94.81 | 4.77 203.25 |
| MIT 1996 auto (Phillips et al., b, 1998) | - - - - - - | - | - | - 88.00 7.00 - |
| UMD 1996 (Etemad and Chellapa, 1997) | - - - - - - | - | - | - 83.50 7.00 - |
| UMD 1997 (Zhao et al., 1998) | 0.08 0.08 0.17 0.33 0.84 75.92 | 18.91 | 96.23 1.09 14.37 |
| USC 1997 (Okada et al., 1998) | 0.17 0.17 0.25 0.33 3.09 50.67 | 27.94 | 94.98 2.51 57.52 |
| USC 1997 auto (Okada et al., 1998) | - - - - - - | - | - | - 9.60 - - |
| MSU 1996 (Swets and Weng, 1996) | - - - - - - | - | - | - 8.50 3.00 - |
| Bayesian MAP (Teixeira, 2003) | 1.92 2.51 4.18 6.52 13.8 70.15 | 67.11 | 81.92 - - |
| EBGM Standard (Bolme, 2003) | 0.59 0.92 1.34 2.42 9.2 37.54 | 34.26 | 88.37 - - |
| EBGM Optimised (Bolme, 2003) | - - - - - - | - | - | - 89.80 - - |
| PCA MahCosine (CSU, 2003) | 0.84 1.17 2.26 4.43 10.28 60.45 | 48.90 | 85.27 - - |
| Gabor features (Kepenekci et al., 2002) | - - - - - - | - | - | - 96.30 - - |
| Haar+AdaBoost (Jones and Viola, 2003) | - - - - - - | - | - | - 94.00 1.00 - |
| Gabor+AdaBoost (Yang et al., 2004) | - - - - - - | - | - | - 95.20 - - |
| SOM (Tan et al., 2005) | - - - - - - | - | - | - 91.00 - - |
| Our Log-Gabor PCA, 900 PCA feat., 3 pt. | 0.08 0.08 0.08 0.08 0.25 1.84 | 8.92 | 98.16 0.33 0.33 |
| Our Log-Gabor PCA, 900 PCA feat., 2 pt. | 0.08 0.08 0.08 0.17 0.33 68.81 | 24.02 | 97.99 0.33 15.78 |
| Our trad. PCA, 900 PCA feat., 3 pt. | 2.76 4.35 7.02 12.63 38.13 92.89 | 123.40 | 82.43 3.93 110.99 |
| Our trad. PCA, 900 PCA feat., 2 pt. | 6.94 8.61 13.21 16.64 31.44 99.58 | 149.75 | 76.90 5.27 136.24 |
| Our Log-Gabor PCA 4x4, 900 PCA feat., 3 pt. | 0.08 0.08 0.08 0.08 0.17 0.59 | 98.49 0.17 0.14 |
recognition were used 300 features. USC 1997 (University of Southern California) method was developed by (Wiskott et al., 1997; Okada et al., 1998). For recognition they used Gabor Jets and Elastic Bunch Graph Maching (EBGM). Faces were resized to 128x128 pixels and normalized using histogram equalization. For recognition were used about 1920 features that correspond to 40 Gabor filters (5 scales and 8 orientations) at 48 graph nodes. MSU 1996 (Michigan State University) method was developed by Swets and Weng (1996). For recognition they used PCA and LDA. CSU (2003) Bayesian MAP (Teixeira, 2003), EBGM Standard, and EBGM Optimised (Bolme, 2003) face recognition methods were developed by the researchers at Colorado State University. These methods are similar to the corresponding methods developed at MIT and USC. The CSU (2003) PCA MahCosine method is a traditional PCA with cosine-based distance measure between "whitened" feature vectors. CSU (2003) for recognition used 130x150 images, faces were masked using elliptical mask, unmasked image part was normalized using histogram equalization. CSU EBGM method for recognition extracts more than 6000 features (80 Gabor features x 80 graph points). Kepenekci et al. (2002) for recognition used magnitudes of Gabor filters and similar distance measures as were used by (Wiskott et al., 1997). For recognition were extracted 40 Gabor features (5 scales and 8 orientations) and 2 coordinates of these features at varying number of face points. Jones and Viola (2003) used Haar-like features and AdaBoost training. For recognition were used 45x36 images without masking. The use small images may be related with the fact that AdaBoost training requires huge computational resources. Yang et al. (2004) used Gabor features and AdaBoost training-based recognition method. Tan et. al. (2005) for face recognition used Self-Organizing Map (SOM) and soft k nearest neighbor (soft k-NN) ensemble method.

As we can see from the Table 2, the highest first one recognition accuracy was achieved by the following methods: our Log-Gabor PCA (98.16% using 2-point normalization and 98.49% using 3-point normalization), Gabor features (Kepenekci et al., 2002) -based method (96.30%), and UMD 1997 (Zhao et al., 1998) PCA+LDA-based method (96.23%). The best EER results were achieved by our Log-Gabor PCA (0.33%), Haar+AdaBoost (Jones and Viola, 2003) method (~1.00), and UMD 1997 (Zhao et al., 1998) PCA+LDA-based method (1.09%). It is interesting to note that our traditional PCA with 2-point normalization achieves lower recognition accuracy than traditional PCA of (CSU, 2003). But when we combine our traditional PCA with Log-Gabor features, our method achieves higher recognition accuracy than many other methods. Also we can note that PCA with grayscale features is much more sensitive to the chosen image normalization method (76.90% first one recognition using 2-point normalization and 82.43% using 3-point normalization) than our Log-Gabor PCA (98.16% using 2-point normalization and 98.49% using 3-point normalization). Using 3-point normalization faces are masked and cropped more accurately than using 2-point normalization, and recogni-
Fig. 6. CMC characteristic of Log-Gabor PCA method

Fig. 7. ROC characteristic of Log-Gabor PCA method

tion results using Log-Gabor PCA and 3-point normalization are also better. These differences are especially visible when we compare Cum100, CMCA and ROCA values of 2-point and 3-point methods. It is interesting to note, that EBGM-based methods perform positioning of graph nodes around the face also enough accurately and this may be one of the reasons why EBGM-based methods and Log-Gabor PCA method using 3-point normalization achieve better Cum100 results than other methods that use 2-point normalization.

Using our method with 3-point normalization in order to achieve 100% cumulative recognition rate we need to extract from the database only 1.84% of images (that is 1196*1.84/100 = 22 images), and using CSU EBGM method we need to extract 37.54% of images (that is 449 images). In the last line of the Table 2 we present the results of our method if we use 3-point normalization, 4x4 sliding window (without overlapping), masking, and 19704 Log-Gabor magnitude features (the number of PCA features remains 900). As we can see from these results, using larger number of Log-Gabor features (smaller sliding window) we can achieve even better cumulative recognition results than using 8x8 window with 2 pixels overlapping. That is in order to achieve 99% cumulative recognition rate we need to extract from the database only 2 images (0.17%), and in order to achieve 100% cumulative recognition rate we need to extract 7 images (0.59%).

Because in real life situations face recognition methods are usually used with automatically detected faces and facial features. So it is desirable to know how detection errors affect recognition accuracy, what recognition method is less sensitive to feature detection errors. Using this information we can decide how accurately faces and facial features should be detected in order to achieve desirable recognition accuracy. In the Table 2 we presented some re-
sults of other researchers that used automatical detection of faces and facial features (notation "auto"). USC 1997 automatic method [Okada et al. 1998] for location of face and facial features (eyes, nose, lips, face contour) used EBGM with small number of graph nodes (16 nodes). As it is stated by the authors, their method locates facial features very accurately, so the difference between recognition results using manually and automatically detected features is $\sim 1\%$. MIT 1996 [Moghaddam et al. 1996] automatical method for detection of eyes and lips used PCA-based detector and probabilistic verification of detected feature locations. Automatical method achieved $\sim 7\%$ lower recognition accuracy than the same method that used manual feature detection. The results showed that fully automatical USC 1997 method can achieve much higher recognition accuracy than MIT 1996 method. But because the authors used different methods for detecting faces and facial features and did not present any quantitative information about feature detection accuracy, we cannot say for sure what recognition method (that was tested without automatical detection) it is better to use with automatical feature detection method. It is possible that one recognition method is less sensitive to feature detection errors than another, but also it is possible that the main differences are only in feature detection methods and their feature detection accuracy.

In order to find out how sensitive is our face recognition method to feature detection errors and not to bind to concrete feature detection method we manually shifted the markers of eye centres using pre-defined shift directions and distances. For this experiment we used all facial images from the FERET $fa$ and $fb$ sets. We shifted only eye markers of $fb$ images using 4 shift directions $(0, \pi/2, \pi, 3\pi/2)$ and the following shift distances: $0\%, 2\%, 4\%, 6\%, 8\%, 10\%, 12\%$. Recognition accuracy using each shift distance was calculated as an average of 4 results that correspond to 4 directions. Shift distance is calculated as a percentage of the distance between manually selected eye centres. For example, if the distance between manually selected eyes is 100 pixels and we wish to use 4% shift, then these 4% will correspond to 4 pixels. The results that were achieved using 0% shift (it means that no shift is performed and we simply use manually selected eye coordinates) were used as a baseline for comparison with the results that were achieved using other shift distances. The results are presented in Table 3, where notations First1d and EERd mean absolute differences between achieved recognition result using some shift and the result without any shift (baseline). For experiments was used 2-point normalization method.

The results (Table 3) showed that our Log-Gabor PCA is less sensitive to feature detection errors than traditional PCA and can achieve 89-90% recognition accuracy even if one eye is shifted by 10%. In order to create fully automatical face recognition method and achieve similar recognition accuracy that was achieved by USC 1997 [Okada et al. 1998] fully automatical method we should combine our recognition method with automatical eye detection
Table 3
Face recognition accuracy using shifted markers of eye centres (simulated eye location errors).

| Shift size, % | Method          | Shifted left eye marker |             | Shifted right eye marker |             |
|--------------|-----------------|-------------------------|-------------|--------------------------|-------------|
|              |                 | First1 | First1d | EER  | EERd | First1 | First1d | EER  | EERd |
| 0%           | PCA             | 76.90  | -       | 5.27 | -    | 76.90  | -       | 5.27 | -    |
|              | Log-Gabor PCA   | 97.99  | -       | 0.33 | -    | 97.99  | -       | 0.33 | -    |
| 2%           | PCA             | 73.10  | 3.80    | 6.05 | 0.78 | 72.95  | 3.95    | 6.05 | 0.78 |
|              | Log-Gabor PCA   | 97.45  | 0.54    | 0.40 | 0.07 | 97.41  | 0.58    | 0.40 | 0.07 |
| 4%           | PCA             | 62.45  | 14.45   | 8.39 | 3.12 | 61.86  | 15.04   | 8.56 | 3.29 |
|              | Log-Gabor PCA   | 96.76  | 1.23    | 0.44 | 0.11 | 96.88  | 1.11    | 0.50 | 0.17 |
| 6%           | PCA             | 47.78  | 29.12   | 12.32| 7.05 | 45.04  | 31.86   | 12.59| 7.32 |
|              | Log-Gabor PCA   | 95.65  | 2.34    | 0.65 | 0.32 | 95.31  | 2.68    | 0.63 | 0.30 |
| 8%           | PCA             | 31.17  | 45.73   | 16.38| 11.11| 31.30  | 45.60   | 17.22| 11.95|
|              | Log-Gabor PCA   | 93.41  | 4.58    | 0.96 | 0.63 | 92.95  | 5.04    | 0.96 | 0.63 |
| 10%          | PCA             | 19.21  | 57.69   | 21.51| 16.24| 19.29  | 57.61   | 22.53| 17.26|
|              | Log-Gabor PCA   | 90.02  | 7.97    | 1.46 | 1.13 | 89.02  | 8.97    | 1.55 | 1.22 |
| 12%          | PCA             | 11.40  | 65.50   | 26.46| 21.19| 11.92  | 64.98   | 27.13| 21.86|
|              | Log-Gabor PCA   | 84.29  | 13.70   | 2.24 | 1.91 | 83.24  | 14.75   | 2.36 | 2.03 |

method that detects the centres of eyes with smaller than 6% shifts (total shift for both images) when compared to manually selected eye centres. Those readers who are interested in automatical face and facial features detection methods can find an overview of such methods in (Yang et al., 2002) and (Perlibakas, 2003).

In real life situations the accuracy of face recognition is also affected by many other factors like aging and manual change of appearance (hairstyle, makeup), image input (camera position) and illumination conditions. It is natural that we cannot have the same looking faces and the same imaging conditions after a longer time period. In order to find out how recognition accuracy is affected by these factors we performed recognition experiments using the following probe sets of images from the FERET database: dup1 - 722 images of 243 persons, at least 2 images with different expressions per person, time interval from fa images is 0-34 months, photographs of 166 persons were taken after some period of time (not the same day than fa images); dup2 - 234 images of 75 persons, at least 2 images with different expressions per person, time interval from fa images is more than 18 months; and fc - 194 images of 194 persons that were acquired on the same day, but with different camera position and illumination.

The results (Table 4) showed that our Log-Gabor PCA method achieves
Table 4
The influence of aging and illumination to face recognition accuracy using 1196 fa
gallery images (FERET database) and the following probe sets: dup1, dup2, fc.

| Method and its authors                  | First one rec., [0,100%] | EER, [0,100%] |
|-----------------------------------------|--------------------------|--------------|
| MIT 1996 (NIST, 2001)                   | dup1  57.60  dup2  34.20  fc  32.00  dup1  17.70  dup2  21.20  fc  18.00 |
| MIT 1996 auto (Phillips et al., b, 1998)| ~50.00                            | -            |
| UMD 1996 (Phillips et al., b, 1998)    | ~32.00 ~9.00 ~30.00            | -            |
| UMD 1997 (NIST, 2001)                   | 47.20  20.90  58.80  12.60  13.40  10.00 |
| MSU 1996 (Phillips et al., b, 1998)    | ~33.00 ~17.00 ~32.00            | -            |
| USC 1997 (NIST, 2001)                   | 59.10  52.10  82.00  13.30  14.20  5.10  |
| USC 1997 (Okada et al., 1998)          | 62.00  52.00  82.00  -            |
| USC 1997 auto (Okada et al., 1998)     | 61.00  52.00  80.00  -            |
| Gabor feat. (Kepenekci et al., 2002)   | 58.30  47.40  69.60  -            |
| Our trad. PCA, 900 PCA feat., 2 pt.    | 44.74  35.04  62.89  13.99  19.03  9.79  |
| Our Log-Gabor PCA, 900 PCA feat., 2 pt.| 72.44  65.81  90.21  3.60  4.70  1.03  |

8-10% higher recognition accuracy and at least 4% lower EER than other compared methods. Our recognition results showed that even using single training image per person we can improve recognition accuracy of face images that were took after longer time period. But also it is obvious that different imaging conditions after longer time period significantly reduce face recognition accuracy of all compared methods and that for such difficult tasks we need better image normalization and feature extraction techniques.

We also performed several face recognition experiments using the AR database (Martinez [1998]). This database was created by A. Martinez and R. Benavente at Computer Vision Center, Purdue University in 1998. It contains facial photographs of 126 persons with strictly controlled facial expressions and lighting. The size of images is 768x576 pixels. Images of each person were captured in two sessions (s1, s2) that were separated by two weeks time. From this database we used 1610 images of 115 persons (14 images per person = 2 sessions x 7 images per session). We used the following images: neutral (ne), happy (ha), angry (an), and screaming (sc) expressions; neutral expression with left illumination source (lis) turned on, right illumination source (ris) turned on, and both illumination sources (bis) turned on. For training and as a gallery set we used 115 images with neutral expression from the first session (s1ne). For recognition we used the following probe sets that correspond to different type of transformation (neutral, expression, illumination) (Wang and Tang [2003]): s1expr (s1ha, s1an, s1sc images), s1illum (s1lis, s1ris, s1bis images), s2neutral (s2ne images), s2expr (s2ha, s2an, s2sc images), and s2illum (s2lis, s2ris, s2bis images). First one recognition results using these sets
are presented in Table 5. The last lines of this table also present EER results of our methods. For experiments was used 2-point normalization method.

Table 5

| Method and its authors                  | First one rec. results using different probe sets | s1expr | s1illum | s2neutral | s2expr | s2illum |
|----------------------------------------|-------------------------------------------------|--------|---------|-----------|--------|---------|
| PCA (Wang and Tang, 2003)              | -                                               | -      | 84.4    | 56.7      | 24.4   |
| EBGM Gabor features (Wang and Tang, 2003) | -                                               | -      | 86.7    | 66.7      | 52.2   |
| EBGM Gabor features + Bayes matching (Wang and Tang, 2003) | -                                               | -      | 93.3    | 86.0      | 86.7   |
| PCA (Martinez, 2003,a)                 | 72.00                                           | -      | -       | -         | -      |
| Correlation (Martinez, 2003,a)         | 74.33                                           | -      | -       | -         | -      |
| PCA + optical flow (Martinez, 2003,a)  | 83.00                                           | -      | -       | -         | -      |
| Motion estimation (Martinez, 2003,b)   | 84.67                                           | -      | -       | -         | -      |
| Our traditional PCA, 100 feat., 2 pt. | 70.43                                           | 62.90  | 92.17   | 58.52     | 46.67  |
| Our Log-Gabor PCA, 100 PCA feat., 2 pt.| 85.51                                           | 82.90  | 99.13   | 77.39     | 63.48  |

| EER results of our methods             |                                                |        |         |           |        |
|----------------------------------------|------------------------------------------------|--------|---------|-----------|--------|
| Our traditional PCA, 100 feat., 2 pt.  | 6.96                                           | 5.51   | 2.61    | 11.02     | 10.72  |
| Our Log-Gabor PCA, 100 PCA feat., 2 pt.| 3.48                                           | 3.19   | 0.87    | 6.67      | 6.67   |

The results (Table 5) showed that our method achieves slightly higher recognition accuracy than other compared methods that used single training image (with neutral expression) per person. It is important to note that the comparison of different methods in the Table 5 is not very exact, because for experiments different authors used different number of images: [Wang and Tang, 2003] used images of 90 persons, [Martinez, 2003,a], [Martinez, 2003,b] used images of 100 persons, and we used images of 115 persons. The results showed that EBGM Gabor features (features are extracted at graph nodes) and Bayes matching-based algorithm (Wang and Tang, 2003) can achieve much higher recognition accuracy than our method and all other methods (our method achieved better results only when recognizing faces with neutral expressions). But for training of this method we need multiple images per person, and this method was trained using 7 images per person from the first session with different expressions and illumination conditions. All other compared methods for training used single image per person (image with neutral expression from the first session). It is interesting to note PCA + optical flow (Martinez, 2003,a) and Motion estimation (Martinez, 2003,b) -based recognition methods were especially designed for recognizing expression-variant faces, and these methods use weighting of facial features in order to reduce the influence of changed expression to the accuracy of face recognition. Perhaps these weighting methods could improve recognition accuracy of our face recognition method, and in
the future we are going to investigate different feature weighting and masking methods in order to improve recognition accuracy of expression-variant faces.

7 Conclusions and future work

In this article we proposed a novel face recognition method based on Principal Component Analysis (PCA) and Log-Gabor filters. The experiments showed that using the proposed combination of Log-Gabor features and sliding window-based feature selection method, Principal Component Analysis, ”whitening”, and cosine-based distance measure we can achieve very high recognition accuracy (97-98%) and low error rates (0.3-0.4% Equal Error Rate) using the FERET database that contains photographs of more than 1000 persons. The results of our algorithm are among the best results that were ever achieved using this database. In the future we are going to investigate the possibilities of using decomposed Log-Gabor feature vectors and multiple PCA spaces in order to have the possibility of using this method with an unlimited number of training images. Because the results of all compared methods showed that the accuracy of face recognition is very affected by the lighting conditions, in the future we are going to investigate different lighting normalization methods and test them with the Log-Gabor PCA face recognition method.

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