Face Recognition Methods Based on Feedforward Neural Networks, Principal Component Analysis and Self-Organizing Map

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Abstract. *In this contribution, human face as biometric [1] is considered. Original method of feature extraction from image data is introduced using MLP (multilayer perceptron) and PCA (principal component analysis). This method is used in human face recognition system and results are compared to face recognition system using PCA directly, to a system with direct classification of input images by MLP and RBF (radial basis function) networks, and to a system using MLP as a feature extractor and MLP and RBF networks in the role of classifier. Also a two-stage method for face recognition is presented, in which Kohonen self-organizing map is used as a feature extractor. MLP and RBF network are used as classifiers. In order to obtain deeper insight into presented methods, also visualizations of internal representation of input data obtained by neural networks are presented.*

Keywords

Biometrics, face recognition, neural networks, PCA, multilayer perceptron, radial-basis function network, self-organizing map, visualization, LDA, kernels.

1. Introduction

1.1 Multilayer Perceptron

Basic multilayer perceptron (MLP) building unit is a model of artificial neuron. This unit computes the weighted sum of the inputs plus the threshold weight and passes this sum through the activation function (usually sigmoid) [2]:

$$v_j = \theta_j + \sum_{i=1}^{p} w_{ji} x_i = \sum_{i=0}^{p} w_{ji} x_i \tag{1}$$

$$y_j = \varphi_j(v_j) \tag{2}$$

where v_j is linear combination of inputs $x_1, x_2, \ldots, x_p$ of the neuron j, $w_{j0}=\theta_j$ is the threshold weight connected to the special input x_0=-1, y_j is the output of the neuron j and $\varphi_j(\ )$ is its activation function. Herein we use the well-known logistic function, which is the special form of sigmoidal (non-constant, bounded, and monotone-increasing) activation function

$$y_j = \frac{1}{1+\exp(-v_j)}. \tag{3}$$

In a multilayer perceptron, the outputs of the units in one layer form the inputs to the next layer. The weights of the network are usually computed by training the network using the backpropagation (BP) algorithm.

A multilayer perceptron represents nested sigmoidal scheme [2], its form for single output neuron is

$$F(\mathbf{x},\mathbf{w}) = \varphi\left(\sum_j w_{oj}\varphi\left(\sum_k w_{jk}\varphi\left(\ldots\varphi\left(\sum_i w_{li}x_i\right)\ldots\right)\right)\right) \tag{4}$$

where $\varphi(\ )$ is a sigmoidal activation function, w_{oj} is the synaptic weight from the neuron j in the last hidden layer to the single output neuron o, and so on for the other synaptic weights, x_i is the i-th element of the input vector $\mathbf{x}$. The weight vector $\mathbf{w}$ denotes the entire set of synaptic weights ordered by layer, then neurons in a layer, and then number in a neuron.

1.2 Radial Basis Function Network

Radial basis function (RBF) network [3], [4], [2] is based on a multivariable interpolation: Given a set of N distinct vectors $\{\mathbf{x}_i \in R^p \mid i = 1,\ldots, N\}$ and N real numbers $\{d_i \in R \mid i = 1,\ldots, N\}$, the aim is to find a function f: $R^p \rightarrow R$ satisfying the condition $f(\mathbf{x}_i)=d_i$, $\forall\, i$=1, …, N.

RBF approach works with N radial basis functions (RBF) Φ_i, where Φ_i: $R^p \rightarrow R$, i=1,…,N and $\Phi_i = (\|\mathbf{x}-\mathbf{c}_i\|)$, where Φ: $R^+ \rightarrow R$, $\mathbf{x} \in R^p$, $\|\ \|$ is a norm on R^p, $\mathbf{c}_i \in R^p$ are centers of RBFs. Centers are set to $\mathbf{c}_i = \mathbf{x}_i \in R^p$, i=1,…,N. A very often used form of RBF is the Gaussian function $\Phi(x)=\exp(-x^2/2\sigma^2)$, where σ is a width (parameter). Functions Φ_i, i=1,…,N form the basis of a linear space and the interpolation function f is their linear combination

$$f(\mathbf{x}) = \sum_{j=1}^{N} w_j \phi\left(\left\|\mathbf{x} - \mathbf{c}_j\right\|\right) \tag{5}$$

Interpolation problem is simple to solve, in contrast to approximation problem (there is N given points and n_0 functions Φ, where $n_0 < N$.), which is more complicated. Then it is a problem to set centers $\mathbf{c}_i$, i=1,…,n_0, also the parameter σ of each RBF can be not the same for all RBFs. One possible solution for RBF approximation problem is a neural network solution. RBF network is a feedforward network consisting of input, one hidden, and output layer. The input layer distributes input vectors into the network, the hidden layer represents RBFs Φ. Linear output neurons compute linear combinations of their inputs. RBF network learning consists of more different steps (a description of RBF network learning can be found in [3], [4]).

1.3 Self-Organizing Map

Self-organizing map [5] is a neural network, which we use here for the design of a codebook for vector quantization [6]. It usually consists of two-dimensional lattice of neurons with weight vectors $\mathbf{w}_i$. We denote input vectors as $\mathbf{x}$. The updating process (in discrete-time notation) is:

$$\mathbf{w}_i(n+1) = \mathbf{w}_i(n) + h_{ci}(n)\left[\mathbf{x}(n) - \mathbf{w}_i(n)\right] \tag{6}$$

$$h_{ci}(n) = h_0(n)\exp\left(-\left\|\mathbf{r}_i - \mathbf{r}_c\right\|^2 / \beta^2\right) \tag{7}$$

where the neurons' coordinates c and i are denoted by the vectors $\mathbf{r}_c$ and $\mathbf{r}_i$, $h_0 = h_0(n)$ and $\beta = \beta(n)$ are suitable decreasing functions of time. More details about self-organizing map training can be found in [5].

1.4 Principal Component Analysis

Principal component analysis PCA [2] is a standard statistical method used for feature extraction. It transforms the input data represented by a random vector $\mathbf{x}=[x_0,x_1,x_2,\ldots,x_{p-1}]^T$, $E[\mathbf{x}]=0$ with a correlation matrix $\mathbf{R}_x=E[\mathbf{x}\mathbf{x}^T]=\mathbf{R}_x^T$ to a set of coefficients (principal components)

$$a_j = \mathbf{u}_j^T \mathbf{x} = \mathbf{x}^T \mathbf{u}_j,\ j = 0,1,\ldots,p-1 \tag{8}$$

represented by the vector $\mathbf{a}=[a_0,a_1,a_2,\ldots a_{p-1}]^T$. Unit vectors $\mathbf{u}_j=[u_{j0},u_{j1},u_{j2},\ldots u_{jp-1}]^T$, ($\|\mathbf{u}\|=\sqrt{\mathbf{u}^T\mathbf{u}}$ = 1) form the matrix $\mathbf{U}=[\mathbf{u}_0,\mathbf{u}_1,\mathbf{u}_2,\ldots,\mathbf{u}_{p-1}]$ and they are eigenvectors of the correlation matrix $\mathbf{R}_\mathbf{x}$ associated with the eigenvalues $\lambda_0,\lambda_1,\ldots,\lambda_{p-1}$, where $\lambda_0>\lambda_1>\ldots>\lambda_{p-1}$ and $\lambda_0=\lambda_{MAX}$. The most important eigenvectors are those corresponding to the largest eigenvalues of $\mathbf{R}_\mathbf{x}$.

The representation of input data (analysis, forward transform) is defined by

$$\mathbf{a} = \mathbf{x}^T \mathbf{U} = \mathbf{U}^T \mathbf{x} \tag{9}$$

and synthesis (inverse transform) is represented by

$$\mathbf{x} = \mathbf{U}\mathbf{a} = \sum_{j=0}^{p-1} a_j \mathbf{u}_j\ . \tag{10}$$

Fig. 1. Subjects in the face database.

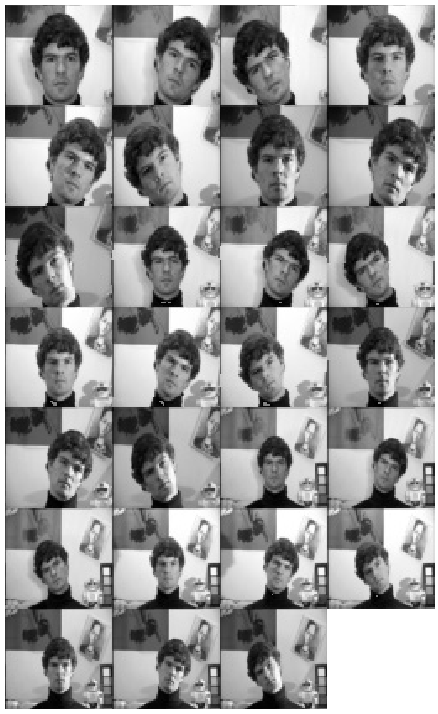


Fig. 2. Examples of one subject.

It is possible to represent the input data by a reduced number of principal components (dimensionality reduction). The transform uses the eigenvectors corresponding to the largest eigenvalues of $\mathbf{R}_\mathbf{x}$, and those corresponding to small eigenvalues are discarded

$$\mathbf{x}' = \sum_{j=0}^{m-1} a_j \mathbf{u}_j\ .\ m < p \tag{11}$$

Then the vector $\mathbf{x}'$ is an approximation of $\mathbf{x}$, while $\lambda_0>\lambda_1>\ldots\lambda_{m-1}>\lambda_m>\ldots>\lambda_{p-1}$.

2. Face Database

We use the face database from MIT (Massachusetts Institute of Technology) [7]. MIT face database, first time used in [8] belongs to the well known public domain face databases [9], such as Yale [10] and ORL databases [11]. It is mentioned and used in up-to-date works relating to facial biometric, e.g. [9], [12], [13], [14].

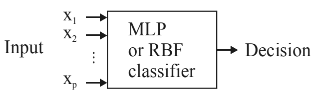
MIT database consists of face images of 16 people (shown in Fig. 1), 27 of each person under various conditions of illumination, scale, and head orientation. It means, the total number of face images is 432. Each image is 64 (width) by 60 (height) pixels, eight-bit grayscale. An example of different face images (patterns) belonging to the same class is shown in Fig. 2.

3. Face Recognition Methods

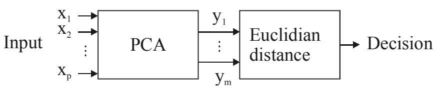
We use several different methods here; they are shown in Fig. 3, with the summary of results shown in Fig. 12. At first, we are concerned with one-stage recognition systems without feature extraction stage:

a. The direct classification of input face images by multilayer perceptron (MLP) and radial-basis function network (RBF) is shown in Fig. 3a). The configuration of MLP was 64x60-16 (i.e. 3840 input neurons and 16 output neurons). The input layer of this configuration agrees with number of pixels in an input image (64x60=3840). MLP was trained on the training face set containing 48 faces (those 16 shown in Fig. 1 plus other 32 images - two different scales of Fig. 1). MLP correctly classified 78.12 % of test faces, (300 successfully recognized faces from the total 384 test faces). Receptive fields of output neurons of such classifier are visualized in Fig. 4. We trained also MLPs containing one hidden layer with a different number of neurons (16, 32, 48, 96, 144, and 192). Recognition results were from 66.2 % to 78.24%.

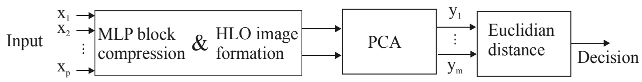
The configuration of RBF network was 64x60-48-16 (48 training faces for RBF network classifier, which gives the best results with 48 RBF neurons in the hidden layer). Receptive fields of hidden neurons of RBF classifier are shown in Fig. 5. RBF network behavior was comparable to MLP – the network correctly classified 78.12 % of test faces. These results are shown as methods No. 6 and 7 in Fig.12. We trained also RBF networks with a different number of hidden neurons (16, 32, 96, 144, and 192). Recognition results were from 47.45 % to 80.32 %.



a)

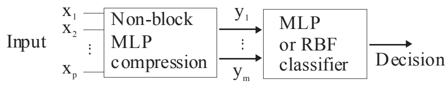


b)

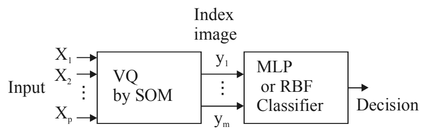


c)

d)



e)



f)

Fig. 3. Face recognition methods used in this paper.

The methods following from this point, in contrary to the method a) are based on two-stage systems, containing both feature extraction stage and classification stage:

b. Two-stage system, where PCA is applied directly to face images with Euclidian distance as a classification measure is shown in Fig. 3b). The correlation matrix was computed from 48 training faces (the same as method a)) and for classification first 48 eigenvectors of the correlation matrix are used (Fig. 6 shows the first 48 eigenfaces of the correlation matrix). 81.51 % of test faces was recognized successfully (313 from the total 384). This result corresponds to the method No. 3 in Fig. 12.

c. Our proposed method is shown in Fig. 3c). As the first stage, MLP block compression is used. 64x60 input face images are divided to 16x15 blocks. MLP configuration is 16x15-15-16x15 (i.e. 240 input and output neurons and 15 hidden neurons). Each face image is then represented by 240 hidden layer outputs. The compression perceptron was trained on the first twelve faces from Fig. 1, remaining four face images were used for testing purposes. Compression capability of MLP is illustrated in Fig. 7, where a low quality of reconstructions can be seen. After training, all input faces were represented by hidden layer outputs (HLO), which were used for HLO image formation, 240 HLO for each input image were used for formation of the 60x4 HLO image. 16 HLO images corresponding to faces in Fig. 1 are shown in Fig. 8. Then, PCA was applied on this representation of input data - correlation matrix 240x240 was computed from 48 HLO images corresponding to 48 training images (used also in the two previous methods). These 48 eigenvectors (or, better saying, 48 principal components obtained by projection of input data onto these eigenvectors) are used for classification, where classification criterion is Euclidian distance. This proposed system recognizes 83.07 % of the test faces successfully (319 of the total 384). See method No. 1 in Fig. 12.

d. For comparison purposes, we present the method based on c), where classifier is replaced by MLP or RBF network (see Fig. 3d). It means 240 hidden layer outputs (60x4 HLO image) of compression MLP are now input to classification MLP with 240 input and 16 output neurons. This system recognizes 73.7 % test faces successfully (283 of the total 384). This result is shown as the method No. 9 in Fig. 12. We tried also MLPs with one hidden layer containing 16, 32, 48, 96, and 144 neurons and also two hidden layers containing 96 and 48 neurons. The results varied from 61.2 % to 71.61 %.

In the case of RBF network classifier of configuration 240-48-16 gives recognition success 82.29 % (316 of 384 test faces). This result is shown as the method No. 2 in Fig. 12. Other RBF configurations with 16, 32, 96, and 144 hidden neurons gave results from 68.23 % to 80.73 %.

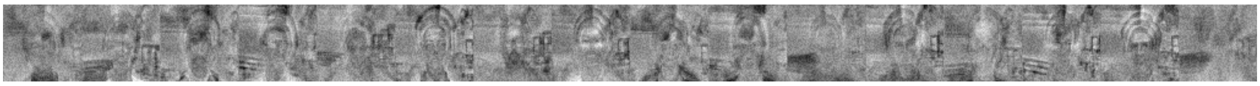


Fig. 4. Receptive fields of output neurons of MLP classifier 64x60-16.

Fig. 5. Receptive fields of 48 hidden neurons of RBF classifier 64x60-48-16.

e. In order to compare results of recognition using compression networks for feature extraction, we present also non-block compression MLP working in autoassociative mode [15], [16] followed by MLP or RBF network classifier (Fig. 3e). The training set for compression MLP again consisted of 48 faces (identical with the training set in method a). The configuration of compression MLP was 64x60-48-64x60 (MLPs with 16 and 96 hidden neurons were also examined, but reconstruction results were of lower quality). Fig. 9 shows reconstructions of a subset of training and test sets by such compression MLP. Its receptive and projective fields are shown in Fig. 10. Hidden layer outputs serve as input to classification networks. The best classification results were obtained by MLP 48-16 (74.74 %, i.e. 287 of 384 faces were recognized successfully) and RBF network 48-32-16 (72.40 %, i.e. 278 of 384). These results correspond to the methods No. 8 and 10 in Fig. 12. Other MLP and RBF network configurations gave the results from 46.09 % to 72.14 %.

f. Our last method is based on self-organizing systems with competitive learning. This method uses feature extraction method from image data, which is based on vector quantization (VQ) of images using Kohonen self-organizing map for codebook design. The indexes used for image transmission are used to recognize faces. This method is described in detail in [17]. We perform vector quantization on 64x60 face images dividing original images to 4x4 blocks. For image vector quantization, we used the configuration of the self-organizing map of 16x16 neurons with 16-dimensional weight vectors, what corresponds to bit rate 0.5 bit/pixel compared to 8 bit/pixel original images. For training this map, first twelve 64x60 images from Fig. 1 divided to 4x4 blocks were used. Remaining four images from Fig. 1 were used for testing.

Each face image is after vector quantization represented by 240 eight-bit indexes, we form them to 16x15 eight bit/pixel image (examples of such index images corresponding to original faces from Fig. 1 are shown in Fig. 11) which then serves as the input to MLP or RBF network classifier. This is shown in Fig. 3f). Both networks had 240 (16x15) inputs. The configuration of MLP was 240-15 and configuration of RBF network was 240-48-16.

This system using RBF network recognizes 80.73 % test faces successfully (310 of 384 test faces). In the case of MLP classifier of configuration 240-48-16 gives recognition success 79.95 % (307 of total 384 test faces). These results are shown as the methods No. 4 and 5 in Fig. 12. Other configurations of MLP and RBF networks reached from 61.2 % to 78.39 %.

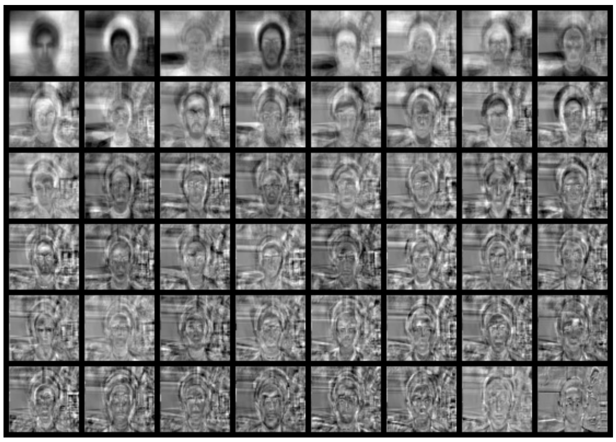


Fig. 6. First 48 eigenvectors of correlation matrix of input data (eigenfaces).

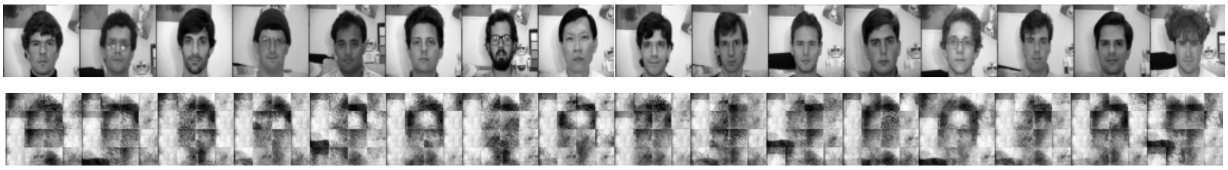


Fig. 7. Originals and reconstructions of face images from Fig. 1 by MLP 240-15-240 (left-to-right 12 training faces and 4 test faces).

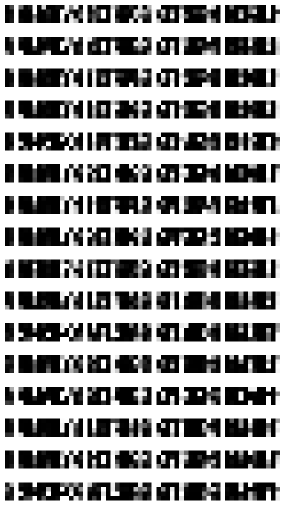


Fig. 8. Images of hidden layer outputs (HLO images) of MLP 240-15-240 for 16 faces from Fig. 1 (dimensions are 60x4 pixels).

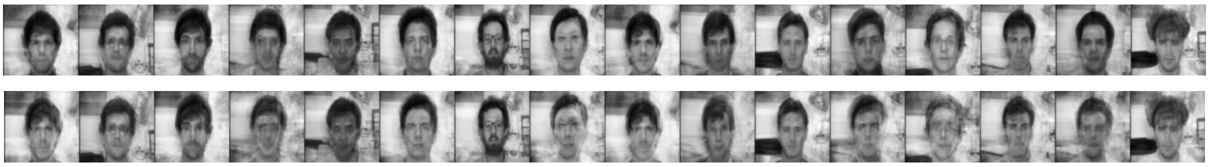


Fig. 9. Reconstruction of subset of training set (top) and subset of test set (bottom) by compression MLP 64x60-48-64x60.

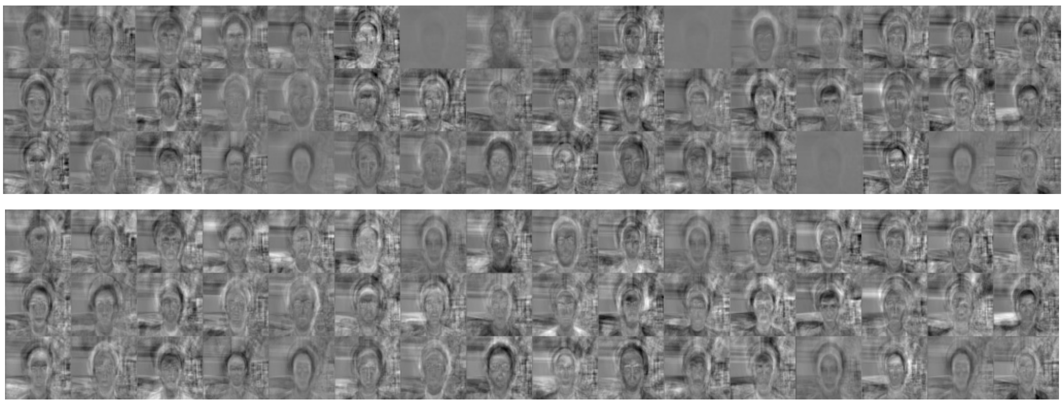


Fig. 10. Receptive and projective fields of compression MLP 64x60-48-64x60 (holons).

Fig.11. Index images (each of 16 images is 16x15 pixels) corresponding to Fig. 1, zoomed.

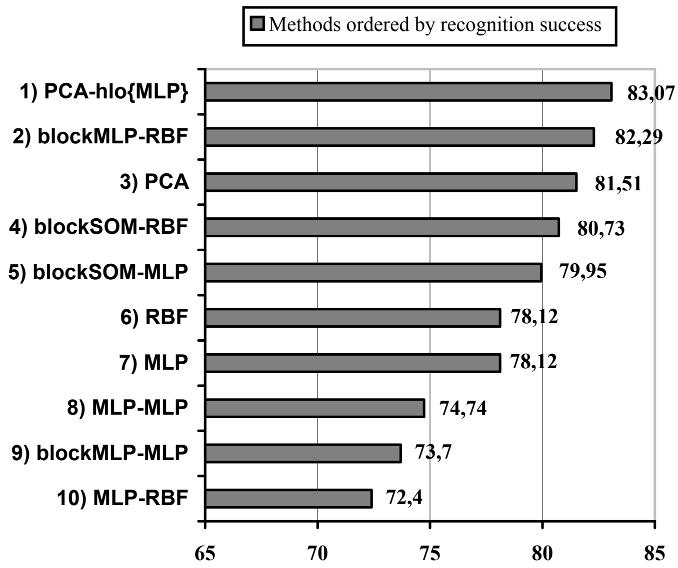


Fig. 12. Comparison of presented methods for 384 test faces (% of successfully recognized faces).

4. Conclusions

We presented the original method for internal representation of input data by MLP. It uses multilayer perceptron for block compression of image data and it is based on formation of outputs of MLP hidden layer to an image (so called HLO image-hidden layer outputs image), which is then further processed by PCA. This method is herein successfully applied in human face recognition system. Although one can note relatively poor results for reconstructed images in the MLP compression stage (Fig. 7), the proposed face recognition system gives the best results, what can be seen while comparing this method to all other presented methods. These methods cover one- and two-stage recognition systems and they include feedforward neural networks both in the role of feature extractor and classifier. Also self-organized map is used in the role of feature extractor.

Since internal representation of input data created by neural networks (Fig. 4, 5, 8, 10, 11) and reconstruction of input data is shown (Fig. 7, 9), we hope this paper gives deeper insight into face recognition systems using PCA, feedforward neural networks and self-organizing systems.

In this paper, we have not considered image preprocessing. The preprocessing could improve recognition results, its implementation is illustrated e.g. in [18], [19]. Generally, image preprocessing deals with digital image processing procedures such as image resampling, histogram equalization, color balance, etc. Other important procedures include face detection [12], i.e. localization of a face in an image with determining face size (distance from camera), rotation with following normalization of face to scale, illumination, rotation, etc.

We accent that all used methods cover the broad spectrum of tools used for face recognition purposes:

- two types of feedforward neural networks (MLP and RBF network),
- standard statistical tool – PCA, and
- Kohonen self organizing map.

It is interesting, that all these tools appeared even in 4 best methods (ordered by recognition success) in Fig. 12.

Of course, other algorithms or combination of presented methods with other methods is possible for face recognition. For example, it is possible to combine PCA with some other standard technique. In [20] a fusion of PCA with linear discriminant analysis LDA is presented. LDA was found to have useful properties – it is insensitive to large variation in lighting direction and facial expression. It is generally believed, that algorithms based on LDA are superior to those based on PCA. In [21], however, authors show that when the training data set is small, PCA can outperform LDA, and also that PCA is less sensitive to different training data sets. Such result is justified also in [22], where again combination of PCA and LDA in the form of boosted hybrid discriminant analysis is presented. Nonlinear boosting process was used for efficient parameter searching and to combine classifiers adaptively.

At present, the range of these tools becomes even broader. Kernel methods are utilized also for recognition purposes [23-27]. Kernel-based principal component analysis KPCA, kernel-based linear discriminant analysis KLDA, kernel radial basis function networks KRBF and support vector machines SVM are examples of kernel methods. They can be used for feature extraction, as well as classification. Several papers dealing with kernel methods for face recognition have appeared, e.g. [24-27]. The kernel algorithms are computationally very complex, but they seem to be promising alternative to conventional linear methods. Due to computational complexity, KPCA and KLDA are often used for input images of dimensions

28x23 pixels [24], [25] or 80x80 pixels [27].

It can be seen, that all these tools play an important role in up-to-date face recognition systems. Face recognition is considered to be a part of a biometric system. Its including into multimodal biometric systems [1] can ensure higher level of security in an open society.

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