Optik 126 (2015) 3483–3487

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

A new pose invariant face recognition system using PCA and ANFIS

Reecha Sharma*, M.S. Patterh

Department of Electronics and Communication Engineering, Punjabi University, Patiala 147002, Punjab, India

ARTICLE INFO

Article history:
Received 4 September 2014
Accepted 27 August 2015

Keywords:
Principle component analysis (PCA)
Face recognition
ANFIS
Score value

ABSTRACT

In this paper, an efficient pose invariant face recognition system using PCA and ANFIS (PCA–ANFIS) has been proposed. The features of an image under test have been extracted using PCA then neuro fuzzy based system ANFIS is used for recognition. The proposed system recognizes the face images under a variety of pose conditions by using ANFIS. The training face image dataset is processed by PCA technique to compute the score values, which are then utilized in the recognition process. The proposed face recognition technique with neuro-fuzzy system recognizes the input face images with high recognition ratio. The proposed approach is implemented in the MATLAB platform and it is evaluated by employing a variety of database images under various pose variant conditions.

1. Introduction

Face recognition is to identify or verify one or more persons in the given still or video images of a scene using a stored database of faces [1]. Face recognition can be classified into two categories; these are geometric feature-based and appearance-based [4]. The geometric feature-based methods, such as elastic bunch graph matching [5] and active appearance model [6] make use of the geometrical parameters that measure the facial parts; whereas the appearance-based methods use the intensity or intensity-derived parameters [1]. Face recognition system consists of two stages; these are face detection and the face identification [2]. In the face detection stage, facial images are localized in an input image. In the face identification stage, the localized faces are identified as individuals registered in the system. Therefore, developing both face detection algorithms and face identification algorithms is quite important [11].

The variations involved in face recognition, include illumination, pose, and identity [3], facial expression, hair style, aging, make-up, scale. It is very difficult for even humans to recognize faces correctly when the illumination varies severely, since the same person appears to be very much different [10]. A common solution to handling pose variations in face recognition is the view-based method. In this method, the face images of the individuals to be recognized are acquired from different view angles [13]. The images of the same view are used to construct an Eigen space representation for each view, and the view-specific Eigen space representations are then used for recognizing a person in different poses [12].

However the 2D image patterns of 3D face object can change dramatically due to lighting and viewing variations [7]. Recently there has been growing interest in face recognition from sets of images. Here, rather than supplying a single query image, the user supplies a set of images of the same unknown individual. In general the gallery also contains a set of images for each known individual, so the system must recover the individual whose gallery set is the best match for the given query set [9]. Recently face recognition using image-set or video sequence has attracted more and more attention within computer vision and pattern recognition community. More importantly, compared with single snapshot, a set or a sequence of images provides much more information about the variation in the appearance of the target subject [8].

The overall structure of the paper is organized as follows: Section 2 in which proposed face recognition system using PCA and ANFIS (PCA–ANFIS) is discussed. Section 3 gives the experimental results and discussions. Section 4 concludes the paper.

2. The proposed face recognition system using PCA–ANFIS

For the proposed work, the face images are taken from the ORL database. These images are first denoised using the adaptive median filter, before further processing. The denoised images are given to the next process in order to calculate the score values using principle component analysis (PCA) technique. The score values so obtained from the PCA techniques are then used by ANFIS classifier for accomplishing the training process. Based on the predefined threshold value the image under test is indicated as recognized or not recognized.

* Corresponding author. Tel.: +91 9501895500.
E-mail address: sharmareecha@gmail.com (R. Sharma).

http://dx.doi.org/10.1016/j.ijleo.2015.08.205
0030-4026/

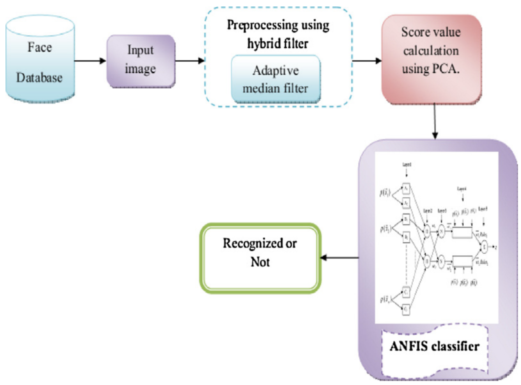

Fig. 1. Architecture of the proposed face recognition system.

The face database images are represented as

$$f_d(r,s) = \left\{ f_{d1}(r,s), f_{d2}(r,s) .. f_{di}(r,s) \right\}; \quad i = 1, 2, 3, \ldots, N, \tag{1}$$

where N is the total number of images in the database D. These numbers of face images from the database D are utilized in the recognition process. The basic structure of our proposed face recognition system is given in Fig. 1.

The proposed face detection technique consists of three stages namely

(i) Preprocessing
- Adaptive median filter

(ii) Principle component analysis.
- Score value calculation

(iii) Classification using ANFIS.

2.1. Adaptive median filter

The adaptive median filter is applied to the images $f_d(r,s)$ which is affected by the (salt and pepper) noise and acquire a noise free image as an output. The process of adaptive median filtering in noise removal is given below:

Step 1: Initialize the window w size w_z.

Step 2: Check if the center pixel $p_{\text{cen}}(r,s)$ within w is noisy. If the pixel $p_{\text{cen}}(r,s)$ is noisy go to step 3. Otherwise slide the window to the next pixel and repeat step 1.

Step 3: Sort all pixels within the window w in an ascending order and find the minimum ($p_{\min}(r,s)$), median ($p_{\text{med}}(r,s)$), and maximum ($p_{\max}(r,s)$) values.

Step 4: Compute if $p_{\text{med}}(r,s)$ is noisy,

$$(i.e.) \quad p_{\min}(r,s) < p_{\text{med}}(r,s) < p_{\max}(r,s) \tag{2}$$

If the median value range is in between the minimum and maximum means the pixel is not a noisy and go to step 5, otherwise $p_{\text{med}}(r,s)$ is a noisy pixel and go to step 6.

Step 5: Replace the corresponding centre pixel in output image with $p_{\text{med}}(r,s)$ and go to step 8.

Step 6: Check if all other pixels are noisy. If yes then expend the window size by 2 and go to step 3. Otherwise, go to step 7.

Step 7: Replace the center pixel of the image with the noise free pixel which is the closest one of the median pixel $p_{\text{med}}(r,s)$.

Step 8: Reset window size w_z and center of window to next pixel.

Step 9: Repeat the steps until all pixels are processed.

Using the above mentioned adaptive median filter algorithm the salt and pepper noise is removed. This denoised image is then given to the next process to calculate the score values using PCA technique.

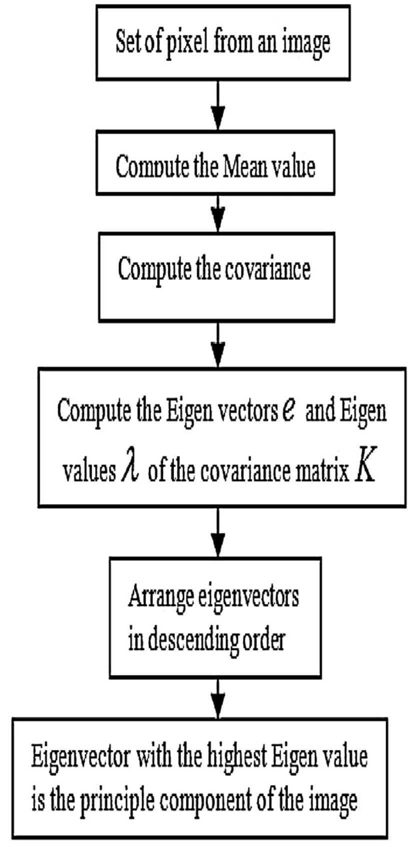

Fig. 2. Flow chart of the principle component analysis.

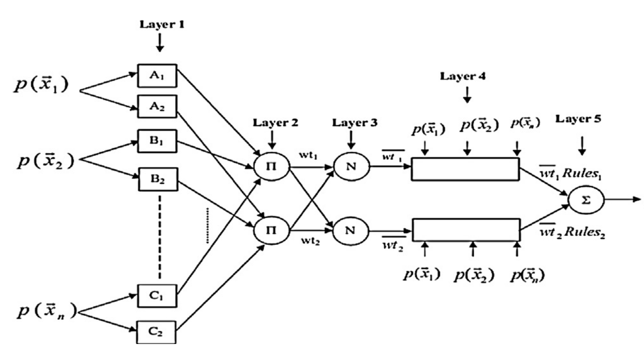

Fig. 3. Architecture of ANFIS.

2.2. Score value calculation using principle component analysis

The denoised image f'_d acquired from the adaptive median filter system is subjected to score values estimation utilizing principle component analysis [14]. Fig. 2 shows the flow chart of PCA.

In the last step of flow chart the score values $p(\vec{x}_1),\ p(\vec{x}_2)\ldots p(\vec{x}_n)$ obtained from the PCA process for different pose images are then passed into ANFIS based classification process.

2.3. Classification using ANFIS classifier

The score value $p(\vec{x}_1),\ p(\vec{x}_2)\ldots p(\vec{x}_n)$ obtained from the PCA are classified using the well known classifier named ANFIS which comprises five layers of nodes. Out of five layers, the first and the fourth layers possess adaptive nodes whereas the second, third and fifth layers possess fixed nodes. The architecture of the ANFIS is given in Fig. 3.

The learning process of ANFIS is carried out on the extracted PCA features such as Eigen vectors. The Rule basis of the ANFIS is of the form:

If $p(\vec{x}_1)$ is A_i, $p(\vec{x}_2)$ is B_i, is C_i then

$$\mathrm{Rules}_i = a_i p\left(\vec{x}_1\right) + b_i p\left(\vec{x}_2\right) + c_i p\left(\vec{x}_n\right) + f_i \tag{3}$$

where $p(\vec{x}_1), p(\vec{x}_2), p(\vec{x}_n)$ are the inputs, $A_i\, B_i$ and C_i are the fuzzy sets, Rules_i is the output within the fuzzy region specified by the fuzzy rule, a_i, b_i, c_i and f_i are the design parameters that are determined by the training process.

Layer-1: Every node i in this layer is a square node with a node function.

$$O_{1,i} = \mu_{A_i}\left(p\left(\vec{x}_1\right)\right), \quad O_{1,i} = \mu_{B_i}\left(p\left(\vec{x}_2\right)\right), \; O_{1,i} = \mu_C\left(p\left(\vec{x}_n\right)\right) \tag{4}$$

Usually $\mu_{A_i}(p(\vec{x}_1))$, $\mu_{B_i}(p(\vec{x}_2)$, $\mu_{C_i}(p(\vec{x}_n))$ are chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0 and are defined as

$$\begin{aligned}\mu_{A_i}\left(p\left(\vec{x}_1\right)\right) &= \mu_{B_i}\left(p\left(\vec{x}_2\right)\right) = \mu_C\left(p\left(\vec{x}_n\right)\right) \\ &= \frac{1}{1 + \left[\left((x - o_i)/p_i\right)^2\right]^{q_i}}\end{aligned} \tag{5}$$

where o_i, p_i, q_i is the parameter set. These parameters in this layer are referred to as premise parameters.

Layer-2: Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$O_{2,i} = \mathrm{wt}_i = \mu_{A_i}\left(p\left(\vec{x}_1\right)\right) \times \mu_{B_i}\left(p\left(\vec{x}_2\right)\right) \times \mu_{C_i}\left(p\left(\vec{x}_n\right)\right), \quad i = 1,\ 2 \tag{6}$$

Each node output represents the firing strength of a rule.

Fig. 4. Sample dataset from the ORL database.

Fig. 5. Denoised images after adaptive median filtering.

Table 1
Image denoising performance of adaptive median filter and existing average and Gaussian filtering methods.

Images	PSNR		
	Proposed adaptive median filter	Existing average filter (in dB)	Existing Gaussian filter (in dB)
1	38.64005	28.37	26.35
2	33.977	26.28	24.41
3	35.1861	26.81	26.02
4	34.54	26.19	25.52
5	33.96	26.68	25.08

Layer-3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \overline{\mathrm{wt}}_i = \frac{\mathrm{wt}_i}{(\mathrm{wt}_1 + \mathrm{wt}_2)}, \qquad i = 1,\ 2 \tag{7}$$

Layer-4: Every node i in this layer is a square node with a node function

$$O_{4,i} = \overline{\mathrm{wt}}_i.\mathrm{Rules}_i \qquad i = 1,\ 2 \tag{8}$$

where wt_i is the output of layer-3 and a_i, b_i, c_i, f_i are the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer-5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \sum_i \overline{\mathrm{wt}}_i \mathrm{Rules}_i = \frac{\sum_i \mathrm{wt}_i \mathrm{Rules}_i}{\sum_i \mathrm{wt}_i} \tag{9}$$

$$Z = \frac{\mathrm{wt}_1 \mathrm{Rules}_1 + \mathrm{wt}_2 \mathrm{Rules}_2}{\mathrm{wt}_1 + \mathrm{wt}_2} \tag{10}$$

$$Z = \overline{\mathrm{wt}}\ \ \mathrm{Rules}_1 + \overline{\mathrm{wt}}\ \ \mathrm{Rules}_2 \tag{11}$$

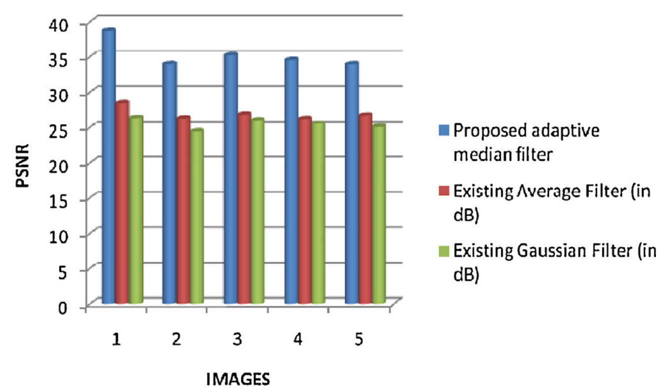

Fig. 6. Comparison of adaptive median filtering technique with the existing average and Gaussian filtering methods.

Table 2
Demonstrate the performance comparison of the proposed PCA-AFIS technique, ICA–ANFIS and LDA–ANFIS technique.

Measures	Proposed PCA–ANFIS	ICA–ANFIS	LDA–ANFIS
Accuracy	0.9666	0.713	0.68
Sensitivity	0.9729	0.728	0.6483
Specificity	0.9605	0.712	0.7288

Table 3
Illustrates the performance measures of the proposed PCA–ANFIS technique and the existing FFBNN techniques in terms of accuracy, sensitivity, specificity.

Measures	Proposed PCA–ANFIS	Existing FFBNN
Accuracy	0.9666	0.8666
Sensitivity	0.9729	0.8481
Specificity	0.9605	0.8873
FPR	0.0394	0.1126
PPV	0.96	0.8933
NPV	0.9733	0.84
FDR	0.04	0.106
MCC	0.9334	0.7343

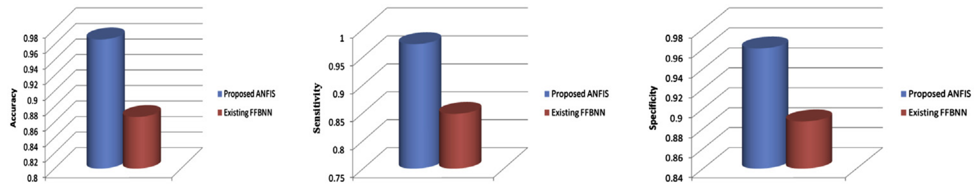

Fig. 7. Proposed PCA–ANFIS technique comparison with the existing FFBNN in terms of accuracy, sensitivity and specificity measures.

Then the predefined threshold value ω and the result of the neural network (Z) is compared which is given in the following equation:

$$\text{result} = \begin{cases} \text{recognized}, & Z \geq \omega, \\ \text{not recognized}, & Z < \omega \end{cases} \quad (12)$$

The neural network output Z greater than the threshold value ω means, the given input image is recognized and Z less than the threshold value ω mean image is not recognized. Thus the ANFIS is well trained using the score value obtained from PCA. The performance of the well trained ANFIS is tested by giving more number of different pose images.

3. Experimental results and discussions

The proposed PCA–ANFIS for different pose images is implemented using MATLAB (version 7.12) with machine configuration as follows:

- Processor: Intel core i7
- OS: Windows 7
- CPU speed: 3.20 GHz
- RAM: 4 GB

The performance of the proposed PCA–ANFIS technique for different pose images are evaluated by giving more number of images taken from the ORL database. Fig. 4 shows some sample images taken from the database.

To remove the noise from the given input face images, the images are passed through the adaptive median filter and denoised face images so obtained are shown in Fig. 5.

As can be seen from Table 1 and Fig. 6, adaptive median filter with PCA has achieved more denoising ratio than the other filtering methods. Adaptive median filter has given high PSNR value for different dataset images. For example in case of Image 3 the PSNR in case of proposed method is 35.1861 dB where as in existing average filter is 26.81 dB and in Gaussian filter is 26.02 dB.

Accordingly the denoised images acquired from the adaptive median filter are used to compute the score values utilizing the PCA based calculation. The score values in this way acquired from the principle component analysis are given as the input to the ANFIS classifier. More number of face images are used to analyze the performance of the proposed face recognition system using different statistical performance measures.

The face images from ORL database are utilized to analyze the performance of proposed PCA–ANFIS technique with the ICA–ANFIS and LDA–ANFIS techniques. The comparison results of the proposed technique, ICA–AFIS and LDA–AFIS techniques are shown in Table 2.

In Table 2, the accuracy of the proposed PCA–ANFIS technique is 0.9666 but the ICA–ANFIS and LDA–ANFIS techniques have offer only 0.713, 0.68 of accuracy. Similarly the sensitivity and specificity of the proposed PCA–ANFIS technique is 0.9729 and 0.9605 but the ICA–ANFIS and LDA–ANFIS techniques give 0.728, 0.6483 of sensitivity and 0.712, 0.7288 of specificity, respectively. Hence from the table it can be seen that proposed method recognizes the image more accurately. Moreover proposed PCA–ANFIS is also compared with the existing FFBNN technique in terms of sensitivity, specificity and accuracy measures. The results are shown in Table 3.

From the table it can be seen that the proposed PCA–ANFIS has given accuracy of 0.9666 but the existing FFBNN has given accuracy of only 0.8666. Similarly the sensitivity and the specificity of our proposed method are higher than the existing FFBNN. The comparison graph has been given in Fig. 7.

From the graph it can also be seen that the performance of the proposed PCA–ANFIS is high when compared to the existing FFBNN. Thus from the performance metrics it can be seen that the proposed PCA–ANFIS efficiently recognize the images.

4. Conclusion

In this paper a face recognition technique using PCA–ANFIS is proposed. First, the images under test are denoised by using adaptive median filter and its performance is compared with average filter and Gaussian filter. From the comparative result it has been found that adaptive median filter performs better as compared to Average and Gaussian filter. PCA is used for feature extraction and ANFIS is used for face recognition. The performance of the proposed setup (PCA–ANFIS) is compared with ICA–ANFIS and LDA–ANFIS. From the comparative results it has been found that PCA–ANFIS performs better than ICA–ANFIS and LDA–ANFIS. For example the proposed PCA–ANFIS gives accuracy of 0.9666 as compared to ICA–ANFIS which gives 0.713 and LDA–ANFIS which gives 0.68. Proposed PCA–ANFIS technique also performs better than FFBNN. It has been concluded that PCA–ANFIS set up can be used for face recognition with better accuracy.

References

[1] Wu-Jun Li, Chong-Jun Wang, Dian-Xiang Xu, Shi-Fu Chen, Illumination invariant face recognition based on neural network ensemble, in: Proceedings of 16th IEEE International Conference on Tools with Artificial Intelligence, November 2004, 2004, pp. 486–490.

[2] Rehab F. Abdel-Kader, Rabab M. Ramadan, Rawya Y. Rizk, Rotation invariant face recognition based on hybrid LPT/DCT features, Int. J. Electr. Comput. Eng. 3 (7) (2008) 488–493.

[3] Shaohua Kevin Zhou, Rama Chellappa, Image-based face recognition under illumination and pose variations, J. Opt. Soc. Am. A: Opt. Image Sci. Vis. 22 (2) (2005) 217–229.

[4] R. Brunelli, T. Poggio, Face recognition: features versus templates, IEEE Trans. Pattern Anal. Mach. Intell. 15 (10) (1993) 1042–1052.

[5] Laurenz Wiskott, Jean-Marc Fellous, Norbert Kruger, Christoph von der Malsburg, Face recognition by elastic bunch graph matching, IEEE Trans. Pattern Anal. Mach. Intell. 19 (1997) 775–779.

[6] G.J. Edwards, T.F. Cootes, C.J. Taylor, Face recognition using active appearance models, in: Computer Vision—ECCV'98, Springer, Berlin, Heidelberg, 1998, pp. 581–595.

[7] WenYi Zhao, R. Chellappa, Image based face recognition issues and methods, in: Optical Engineering, Marcel Dekker Incorporated, 2002, pp. 375–402.

[8] Xi Li, Kazuhiro Fukui, Nanning Zheng, Image-set based face recognition using boosted global and local principal angles, Lect. Notes Comput. Sci. (LNCS) (2009).

[9] Hakan Cevikalp, Bill Triggs, Face recognition based on image sets, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, San Francisco, CA, United States, 2010.

[10] Seok Cheol Kee, Kyoung Mu Lee, Sang Uk Lee, Illumination invariant face recognition using photometric stereo, IEICE Trans. Inf. Syst. E83–D (7) (2000) 1466–1474.

[11] Yasufumi Suzuki, Tadashi Shibata, Illumination-invariant face identification using edge-based feature Vectors In Pseudo-2d Hidden Markov models, in: Proceedings of the 14th European Signal Processing Conference, Florence, Italy, 2006.
[12] Hui-Fuang Ng, Pose-invariant face recognition security system, Asian J. Health Inf. Sci. 1 (1) (2006) 101–111.
[13] J. Shermina, Impact of locally linear regression and Fisher Linear discriminant analysis in pose invariant face recognition, Int. J. Comput. Sci. Netw. Secur. 10 (10) (2010) 106–110.
[14] Syed Navaz, Dhevi Sri, Pratap Mazumder, Face recognition using principal component analysis and neural networks, Int. J. Comput. Networking 3 (1) (2013) 245–256.