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Pose Invariant Face Recognition using Neuro-Fuzzy Approach

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Abstract : *In this paper a pose invariant face recognition using neuro-fuzzy approach is proposed. Here adaptive neuro fuzzy interface system (ANFIS) classifier is used as neuro-fuzzy approach for pose invariant face recognition. In the proposed approach the preprocessing of image is done by using adaptive median filter. It removes the salt pepper noise from the original images. From these denoised images features are extracted. Here Principal component analysis (PCA) is used for extracting the features of an image under test. Then ANFIS classifier is used for face recognition. PCA calculate the principal components and are used by ANFIS for further process. Here in this paper combination of PCA and ANFIS is represented as PCA+ANFIS. In the paper standard ORL face database is used for experimental results. The performance PCA+ANFIS with LDA+ANFIS and ICA+ANFIS is analyzed and compared. From experimental results it is shown that PCA+ANFIS outperforms than other two approaches. PCA+ANFIS is also compared by existing feed forward neural network (FFBNN) approach. The results show that proposed approach gives better outputs in terms of accuracy, sensitivity and specificity.*

Keywords - *Feature extraction, image denoising, image recognition, neural networks and feedforward neural network.*

I. Introduction

These days security is one of the most common and important issue. Passwords are easily hacked by hackers. So for more security unique passwords or something which only users have for authentication are necessary. Human traits are unique and more secure for identification. These days human authentication is done by biometrics. Many biometric traits are used for this purpose. One of the most common reasons of using biometric traits is that they are unique and can't be stolen, share or reproduced. Most commonly used traits are palm, iris, finger prints, voice and face. All traits except face need presence of an individual for authentication. But in case for face trait images of a person can be use for this purpose. Human can easily recognize faces but by computer vision machines and pattern recognition it is challenging task. Face recognition can hurriedly and correctly recognize target persons when the conditions are favorable. Researchers find many challenges in face recognition. The most common challenges are pose, illumination, occulation, expression etc. In this proposed research paper a pose invariant system for face recognition has been studied.

The rest of paper is organized as follows: Section II explains a brief knowledge about related work. Section III explains schematic of proposed neuro-fuzzy approach for pose invariant face recognition. Section IV gives experimental results and discussion and in section V conclusion and future scope of proposed work explained.

II. Related Work

There are two main broad categories of face recognition. They are template based or feature based. In first category i.e. template based full face is considered for recognition purpose. In second category i.e. feature based only common features are used. These features may be eyes, nose, mouth and ear etc. combination of feature is also used for improving the recognition rate [1]. The eigenfaces or Principle Components are the set of characteristic features of a face obtained by decomposing a face. Eigenface gives training phase. For recognition test image is placed into subspace called face space and recognition is done by comparing the test image with trained database in face space [2]. Neural network architecture is used for pose invariant face recognition. PCA is used for feature extraction and neural network is used for recognition [3]. It seems to be very difficult for human to recognize faces correctly when the illumination varies severely, since the same person appears to be very much different. Back propagation neural network is used for illumination invariant face recognition. The features of an image are extracted in eigenspace. Then illumination direction specific back propagation neural network trains the extracted feature and then testing is down [4]. Radial basis function (RBF) neural classifier reduces the problem of small training set of high dimensional [5]. Non linear face images give 90% of acceptance ratio when back propagation neural network is combined with PCA [6]. Combination of SOM and convolution network gives fast and automatic system for face recognition as compare to Eigen faces [7]. When PCA combined with feed forward neural network PCA-NN gives improved recognition as compare to traditional PCA. The same improvement is shown in LDA-NN [8]. FFNN improves the performance of face recognition as compare to Euclidean distance [9]. The novel architecture of the two-layer neural can recognize human face with different views. It recognizes the identity of the person and the pose variation of a face at the same time [10]. A combination of RBFNN and FHLA is used for face recognition. It provides faster training with less number of neurons in hidden layer [11]. ANFIS and SVM fuse local and global features for face verification. They fused together for better face recognition as compare to non adaptive and non fusion schemes [12]. Linear Discriminant Analysis (LDA) is just like as eigenfaces of PCA. The only difference of LDA and PCA is in the method of calculating the subspace. LDA maximize the ratio of the between class scatter matrix and within class scatter matrix [13]. One hidden layer FFNN not only reduces the hidden units but also weights. It gives better results as compare to BPNN [14]. Fusion of LDA and PCA give better results in face recognition because they are intercorrelated to each other [15]. Independent component analysis (ICA) is a generality of PCA. It separates the high order and second order moments. ICA is performed on images of face database by an unsupervised learning algorithm derived from the optimal information transfer through sigmoidal neurons [16]. ICA, PCA and rough set theory combined to make a hybrid method for face recognition. ICA and PCA are used for feature extraction and for recognition rough set rule based classifiers are used [17]. In this proposed paper we are comparing PCA+ANFIS with LDA+ANFIS, ICA+ANFIS and also with FFBNN.

III. Schematic For Neuro-Fuzzy Approach

The proposed schematic for pose invariant face recognition using neuro-fuzzy approach is discussed in this section. Here in the proposed approach PCA+ANFIS based pose invariant face recognition is done.
Proposed schematic for pose invariant face recognition using neuro-fuzzy approach have following steps.

1. The original images are taken from some standard face database. In our proposed schematic ORL face database is used. The ORL face database images are grouped as test images and training images.
2. These images are preprocessed. Here hybrid filter called adaptive median filter is used for removing salt and pepper noise from the original images.
3. These denoised images are given to PCA for feature extraction. Here principal components are calculated and saved for further use.
4. These principal components are used by ANFIS a neuro-fuzzy classifier. The proposed ANFIS have five layers. This is used for classification of images.
5. Here classified images are compared with predefined threshold value. If it greater than threshold value then it is a recognized face otherwise not.

These steps are explained in detail in further sub sections.

3.1 Adaptive median filter

The adaptive median filter is used for preprocessor for noise removal. The noised images $f_d(r,s)$ from ORL face database are given as input to the adaptive median filter. These images are affected by the impulse and salt-pepper noise. The output of adaptive median filter is noise free image. Fig.1 shows some samples of the noised images from ORL face database. Fig.2 shows noise free output of adaptive median filter.

Figure 1: Sample of noised images from the ORL face database.

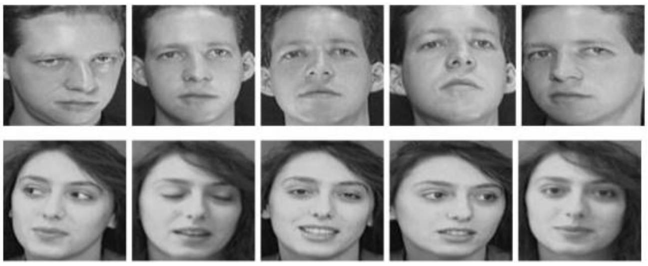

Figure 2: Denoised images after adaptive median filtering.

The working of adaptive median filter is explained in following steps:

Step 1: Initialize the window w size w_z .

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

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

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

(i.e.) $p_{\min}(r,s) < p_{med}(r,s) < p_{\max}(r,s)$ (1)

If the median value falls in the range of the minimum and maximum, it means that pixel is not a noisy pixel. Then go to step 5. Otherwise $p_{med}(r,s)$ is a noisy pixel and then go to step 6.

Step 5: Here centre pixel of output image is replaced with $p_{med}(r,s)$ and go to step 8.

Step 6: In the step check whether all other pixels are noisy. If pixels are noisy then expend the window size by 2 and go to step 3. If not, go to step 7.

Step 7: Center pixel of noisy image is replaced with the noise free pixel which is the closest one of the median pixel $p_{med}(r,s)$.

Step 8: Reset window w_z size. Center of window is changed to next pixel.

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

The table 1 shows the experimental results of noise removal filters. Average filter and Gaussian filter are traditional filters used for noise removal but here in this work we are using adaptive median filter for noise removal. The adaptive median filter is performed in spatial domain to find which pixels of an image are affected by salt-pepper noise or impulse noise. In this each pixel is compared by neighbor pixels. The size of neighborhood and threshold are adjustable. A pixel that is different from other neighborhood pixels is considered as noise. These detected noise are replaced by median filter.

The main advantages of using adaptive median filter are as follow:

1. Remove impulse noise.
2. Smoothing of other noises
3. Reduces distortion of excessive thinning or thickening of boundaries.

In table 1, peak signal to noise ratio (PSNR) are calculated of some sample images. It is seen that PSNR of adaptive median filter is better as compare to average filter and Gaussian filter. Here only few sample images are taken for comparison.

Table 1 PSNR performance of Adaptive median filter, Average and Gaussian filter.

Images	PSNR		
	Adaptive Median Filter (in dB)	Average Filter(in dB)	Gaussian Filter (in dB)
1	38.64	28.37	26.53
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

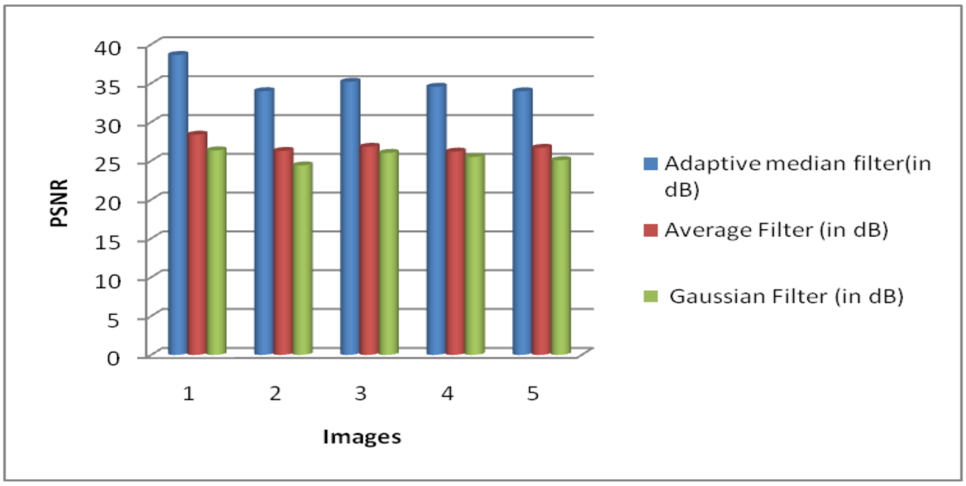

Figure 3: Illustration of PSNR of sample images for adaptive median filter, average filter and Gaussian filter.

Fig.3 shows the illustration of PSNR of sample images for adaptive median filter, average filter and Gaussian filter. The five sample images are taken to represent PSNR graphically. Adaptive median filter shows highs peak.

3.2 Principal components calculation using PCA

The noise free images which are obtained from adaptive median filter as output are used for feature extraction. Here feature extraction is done by PCA. The principal components are calculated here. The common steps for PCA are given below:

1. Taking the whole dataset ignoring the class labels.
2. Computing the d-dimensional mean vector.
3. Compute the covariance matrix.
4. Computing eigenvectors and corresponding eigenvalues.
5. Sorting the eigenvectors by decreasing eigenvalues
6. Transforming the samples onto the new subspace
7. The Eigenvectors with highest eigenvalues are principal components of an image.

$pca(x_1)$, $pca(x_2)$, $pca(x_3)$…………… $pca(x_n)$ are principal components obtained from the PCA process. These principal components are then passed into neuro-fuzzy based ANFIS classifier for classification process.

3.3 Neuro-fuzzy ANFIS classifier

The principal components $pca(x_1)$, $pca(x_2)$, $pca(x_3)$…………… $pca(x_n)$ calculated from the PCA are classified using neuro-fuzzy ANFIS classifier. The architecture of proposed neuro-fuzzy ANFIS consists of five layers of nodes. From these five layers, the first and the fourth layers have adaptive nodes whereas the second, third and fifth layers possess fixed nodes. The architecture of the ANFIS for pose invariant face recognition is given in fig.4

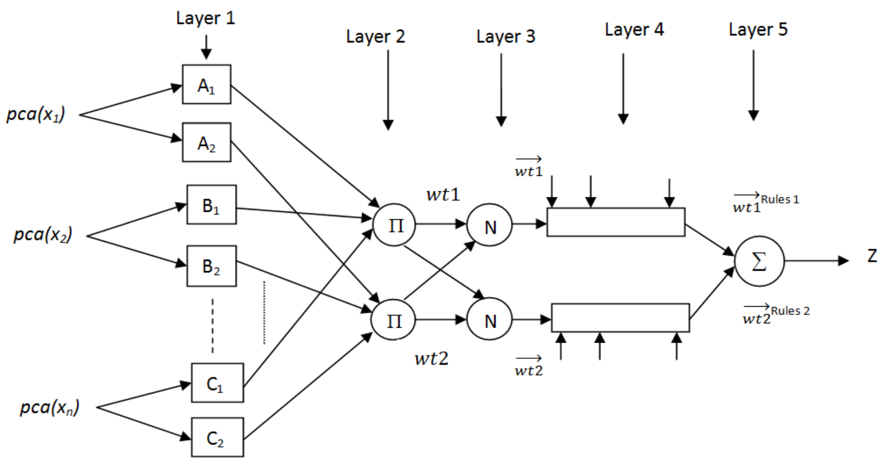

Figure 4: Architecture of ANFIS for pose invariant face recognition.

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

If pca(x_1) is A_i, pca(x_1) is B_i and pca(x_n) is C_i then

$$Rules_i = a_i pca(x_1) + b_i pca(x_2) + c_i pca(x_n) + f_i \tag{2}$$

Where pca(x_1), pca(x_2), pca(x_3)…………… pca(x_n) are the inputs. A_i B_i & 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.

$$O_{1,i} = \mu_{A_i}(pca(x_1)),\ O_{1,i} = \mu_{B_i}(pca(x_2)), O_{1,i} = \mu_C(pca(x_n)) \tag{3}$$

Usually $\mu_{A_i}(pca(x_1))$, $\mu_{B_i}(pca(x_2)$, $\mu_{C_i}(pca(x_n))$ are chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0 and are defined as

$$\mu_{A_i}(pca(x_1)) = \mu_{B_i}(pca(x_2)) = \mu_C(pca(x_n)) = \frac{1}{1 + \left[\left(\frac{x - o_i}{pca_i}\right)^2\right]^{q_i}} \tag{4}$$

Where o_i, pca_i, q_i are the parameter set. These are main parameters in this layer.

Layer-2: Layer 2 has circle nodes labeled by Π. It multiplies the incoming signals and sends the product output. For instance,

$$\begin{aligned} O_{2,i} &= wt_i \\ &= \mu_{A_i}(pca(x_1)) \times \mu_{B_i}(pca(x_2)) \times \mu_{C_i}(pca(x_n)), \\ i &= 1, 2 \end{aligned} \tag{5}$$

Each node output represents the firing strength of a rule.

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

$$O_{3,i} = \overline{wt}_i = wt_i / (wt_1 + wt_2), \quad i = 1, 2 \tag{6}$$

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

$$O_{4,i} = \overline{wt}_i . Rules_i \quad i = 1, 2 \tag{7}$$

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:

$$O_{5,i} = \sum_i \overline{wt}_i Rules_i = \frac{\sum_i wt_i Rules_i}{\sum_i wt_i} \tag{8}$$

$$z = \frac{wt_1 Rules_1 + wt_2 Rules_2}{wt_1 + wt_2} \tag{9}$$

$$Z = \overline{wt} Rules_1 + \overline{wt} Rules_2 \tag{10}$$

Then the predefined threshold value ω and the result of the neural network (Z) is compared which is given in Eq. (11).

$$result = \begin{cases} recognized\,, Z \geq \omega, \\ not\,recognized\,, Z < \omega \end{cases} \tag{11}$$

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.

IV. Experimental Results And Discussions

The proposed schematic for pose invariant face recognition using neuro-fuzzy is implemented in MATLAB. Here we compare the performance of filters for better noise removal. A sample image is denoised by three filters. These are adaptive median filter, average filter and Gaussian filter. The results on ORL face database shows that adaptive median filter gives high PSNR as compare to other two. Adaptive median filter gives 38.64005 dB PSNR and on the other hand average filter gives 28.37dB and Gaussian filter gives 26.35dB. Here results of PSNR shows that choice of adaptive median filter for noise removal is better as compare to other filters.

Accordingly the denoised images acquired from the adaptive median filter are used to calculate the principal components utilizing the PCA based calculation. The principal components in this way acquired from the PCA are given as the input to the ANFIS classifier. More number of face images is 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 neuro-fuzzy based PCA+ANFIS approach with the ICA+ANFIS and LDA+ANFIS approach. The comparison results of the proposed PCA+ANFIS, ICA+AFIS and LDA+ANFIS approach are shown in the table 1.

Table 2: Demonstrate the Performance comparison of the proposed neuro-fuzzy based PCA+ANFIS, ICA+ANFIS and LDA+ANFIS.

Measures	**Proposed PCA+ANFIS (%)**	**ICA+ANFIS (%)**	**LDA+ANFIS (%)**
Accuracy	96.66	71.3	68
Sensitivity	97.29	72.8	64.83
Specificity	96.05	71.2	72.88

In table 2 the accuracy of the proposed PCA+ANFIS approach is 96.66% but the ICA+ANFIS and LDA+ANFIS approaches have offer only 71.3%, 68% of accuracy respectively. Similarly the sensitivity and specificity of the proposed PCA+ANFIS approach is 97.29% and 96.05% but the ICA+ANFIS and LDA+ANFIS approach give 72.8%, 64.83% of sensitivity and 71.2%, 72.88% of specificity respectively. Hence from the table it can be seen that proposed approach recognizes the image more accurately.

Moreover proposed PCA+ANFIS is also compared with the existing FFBNN technique in terms of sensitivity, specificity and accuracy and many more measures. In this approach the measurements are taken in terms of true positive (TP) is correctly identified images by the approaches used for comparison, true negative (TN) is correctly rejected images, false positive (FP) is incorrectly identify images and false negative (FN) is incorrectly rejected images.

Here accuracy as also called true positive rate (TPR) and is given by

$$TPR = \frac{TP}{(TP+FN)} \tag{12}$$

Specificity or true negative rate (TNR) is given by

$$Specificity = TNR = \frac{TN}{FP+TN} \tag{13}$$

False positive rate (FPR) is given by

$$FPR = \frac{FP}{FP+TN} \tag{14}$$

Positive predictive value (PPV) is given by

$$PPV = \frac{TP}{TP+FP} \tag{15}$$

Negative predictive value (NPV) is given by

$$NPV = \frac{TN}{TN+FN} \tag{16}$$

The results are shown below in table 3.
Table 3: Illustrates the performance measures of the proposed PCA+ANFIS approach and the existing FFBNN approach in terms of accuracy, sensitivity and 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

From the table 3 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. Fig.8 shows the illustrations of all measurement of PCA+ANFIS and existing FFBNN.

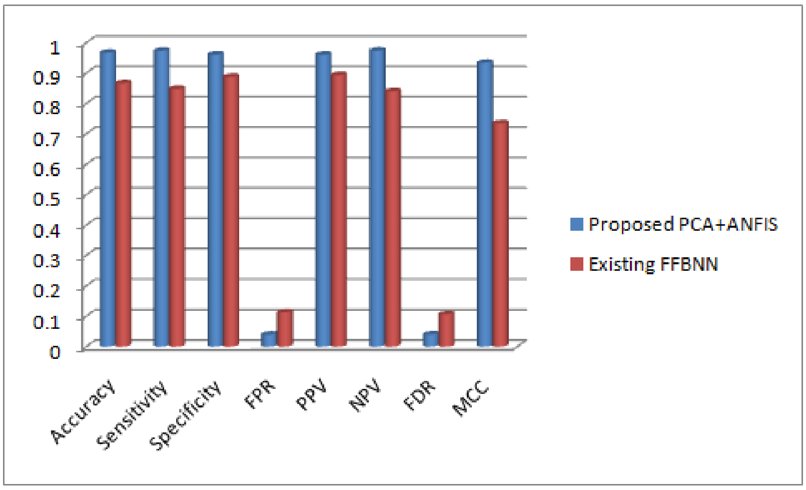

Figure 8: Illustration of comparison of accuracies of proposed neuro-fuzzy based PCA+ANFIS approach with ICA+ANFIS and LDA+ANFIS.

V. Conclusions

In this paper pose invariant face recognition using neuro-fuzzy approach 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 PCA+ANFIS is compared with ICA+ANFIS and LDA+ANFIS. From the comparative results it has been found that PCA+ANFIS perform better than ICA+ANFIS and LDA+ANFIS. For example the proposed PCA+ANFIS give accuracy of 96.66% as compared to ICA+ANFIS which gives 71.3% and LDA+ANFIS which gives 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. The proposed technique can further improve in future for other parameters like illumination, occulation or age.

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