ISSN 2229-5518

Modular PCA Based Fuzzy Neural Network Approach for Illumination and Expression invariant 3D Face recognition

Nita M. Thakare, V. M. Thakare

Abstract— In this paper a Modular PCA based fuzzy neural network approach for face recognition is proposed. The proposed technique improves the efficiency of face recognition; it performs well under varying illumination and expression conditions and its performance is better as compared to the traditional PCA methods. In this method the face image is divided into three horizontal strips thus the face image is divided into three sub-images. On these three horizontal modules the Modular PCA is applied for feature extraction. Due to the extraction of features using three horizontal strips, the effect of variations in expressions is minimized and because of the use of depth-map images the proposed algorithm gives better recognition rate even in varying illumination conditions. The performance of the proposed technique is evaluated under varying f illumination and expression. The experiments were carried out on the the face images with varying light effects and expressions from two standard face databases; CASIA 3D and GAVA DB databases.

Index Terms— Face Recognition, Modular PCA, Feature Extraction, Fuzzy Neural Network

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1 Introduction

Face Recognition is the most essential technique to cope up with the todays threatening scenarios. It has also proved to be one of the difficult problems because of the similar structure of faces and the envioronmental effects. The uncontrolled environmental conditions results into the more number of falsly accepted and falsly rejected facial images. The variations in expressions and uncontrolled lighting effects are prone to the wrongly recognized, within-class matches also. To handle this problem this proposed system uses the modular PCA based fuzzy neural network on depth maps generated from the 3D Images. The depth map contains the depth information of the 3D face image. Since the input images contain the depth information the input to the fuzzy neural network is illumination invariant.

Despite significant advances in Face recognition technology, it has yet to put wide use in commercial and security applications. Even though face recognition is the most non-intrusive and easy biometric methodology, the error rates are too high. The changes in the lighting condition, facial orientation and facial expression increase both false rejection rates (FRR) and false acceptance rates (FAR). In most of the cases the computerized face recognition systems outperform human results because human's face recognition capability depends on the external factors like motivation fatigues, training and speed [1]. Still humans are able to use extra information while recognizing the face of the subject.

The capability of human-being to use extra, correlated information helps in minimizing the effect of environmental changes and therefore humans have the ability to recognize the known faces in varying lighting conditions, and facial expresions. The computerized face recognition system must be robust to cope up with such unexpected and uncontrolled environmental changes and should be capable to act like human recognition system. In the proposed system the automatic face recognition system works well in varying illumination conditions and its performance is compatible to human recognition system when evaluated on face images with varying expressions.

The efficiency of Principal component algorithm decreases while working with the face images taken in uncontrolled environment. And generally the applications of face recognition system grabs the human face images in uncontrolled invironment, specially while dealing with the security systems , the effect of uncontrolled lighting effect and varied expressions can not be avoided.

To improve the performance of PCA algorithm, in this proposed system the horizontal strips of face image are considered as the indiavidual images representing the horizontal region of face. The effect of expressions on particular regions specifically eyes and lower parts of face deteriots the performance of face recognition system. By applying the modular PCA approach the result of proposed system is considerably improved.

This paper is organized as follows: Section 2 explains 3D databases and 3D face recognition methodology it also discusses the related work on Modular PCA approach. Section 3 describe the outline of the algorithm and illustrates the normalization and division of face image into three regions. Section 4 describes the process of fuzzy neural network and classification process. Section 5 duscusses the results obtained by applying the PCA method on whole face , modular PCA method on three face regions on the images from both the databases.

- *Author Nita M. Thakare is currently pursuing PhD in computer science andEngineering in S.G.B. University,Amravati, India, E-mail:nitathakre@yahoo.com*
- *Co-Author Dr. V. M. Thakare has done his PhD in Computer Science and Engineering and currently working as Head, Ddepartment of Computer Science and Engineerng in S.G.B. University,Amravati, India E-mail: Vilthakare@yahoo.co.in*

ISSN 2229-5518

2 Modular approach for 3D face recognition

2.1 3-D Face Recognition

A facial recognition is the process of automatically identifying or verifying a person from a digital image or a video frame and has been a recent area of research. Nowadays face recognition is becoming more and more necessary due to increasing demand of high- security systems [2]. To make the face recognition more efficient, the robustness, higher recognition rates, tolerance for ambiguity and uncertainty should be considered as essential factors for implementation. Even though face recognition is the most non-intrusive and easy biometric methodology, the error rates are too high. The changes in the lighting condition, facial orientation and facial expression increase both False rejection rates (FRR) and false acceptance rates (FAR). In most of the cases the computerized face recognition system outperforms human results because human's face recognition capability depends on the external factors like motivation fatigues, training and speed [3]. Still humans are able to use extra information while recognizing the face of the subject. The drawback of 2D face recognition is its inability to provide the less information of facial structure. Generally most of the applications use the 2D face recognition systems, but these systems are prone to various factors like pose, expression, lighting conditions, etc. Nowadays 3D face recognition has become a ever-growing and promising technique because of its robust features [4].

The 3D facial data can provide a promising way to understand the characteristics of the human face in 3D domain, and has potential possibility to improve the performance of the recognition system. And more and more researchers focus on 3D face recognition in the past few years. However, since the 3D cameras are not as common as 2D cameras, it is expensive to build a public 3D face database, which brings the difficulty to validate the proposed methods in a uniform platform. CASIA 3D face database [5] is one of the important 3D databases. This database contains 2D as well as 3D face images and it is created by Chinese Academy of Sciences.

The images were collected using a non-contact 3D digitizer, Minolta VIVID 910, working on Fast Mode. This database contains 4624 scans of 123 subjects, with each subject having 37 or 38 images. The database is divided into three subsets, that is, the training set, the gallery set and the probe set. The images in this database are VRML images. These are also referred to as *world* files having extension *wrl.* The CASIA 3D face database contains the images taken in varying light effects and with changing expressions. Another database is Gavab Database [6] containing face images of 61 individuals, and for each individual there are 9 images with varied rotations and different geustures. The file format of this database is also VRML format.

To make the system invariant to illumination and expressions this approach proposes to use depth maps generated from these 3D images. From the CASIA database the 15 images per person are taken with expression and light variations.whereas from GavabDB the 5 images per person are taken with variation in expressions. All the images with frontal pose are considered. The depth map is generated from each of these images to represent the feature of face image.

The depth maps are used as 2D representation of 3D image , containing the depth information of each point in the 3D image. It is simply an image with depth information as shown in Fig. 1-b. In other words, a depth map is an array of numbers where the numbers quantify the distances from the focal plane of the sensor to the surfaces of objects within the field of view. The closest point has the highest value. And therefore the closest point appears as white and farthest point appears as black giving the gray level values to the between points. The depth images have some advantages over 3D images [7]. The most important one is that the depth maps are robust to the change of illumination and color because the value on each point represents the depth value which does not depend on illumination or color.

The 3D face images contain highly accurate data but it is not feasible to process the large amount of facial data. Because the face model of each subject model has different vertices. The processing of the large data results into the expensive computation.

Face recognition systems based on 3D facial depth information the accuracy and robustness. But have not been addressed thoroughly. Only a few works on the use of depth map have been reported. The fusion of depth map and texture map is used in [8] where Fisher face and FaceIt techniques are used and FaceIt method outperformed on fusion of depth and texture information. The fusion of depth map and curvature informaton is used in [9].

In this proposed system the depth maps containing depth information are generated from the available 3D face images. The training data set contains the normalized depth maps of all the subjects which are selected as the candidates for training datasets. Since our main objective is to evaluate the results for handling the illumination and expression variations, all frontal images with varying light are considered as the candidates for the face recognition. The depth maps handle illumination variations efficiently [10] and implementation of face recognition to handle uncontrolled lighting conditions is possible with the depth maps. Therefor for this proposed systems the depth maps are used as input to the FR system.

Figure 1. a shows the depth map generated from frontal image Figure 1.b shows the mask generated to crop the face area.

Figure 1. a) Depth map b) Mask c) Cropped face image

And the figure 1. C shows cropped image excluding hairs and neck portion of the image. The image shown in figure 1.c. is used as final image feeded to generate three region of a face. The three horizontal strips are used to represent the three regions of face. The modular PCA has been applied on these face region for feature extraction.

ISSN 2229-5518

2.2 Modular Principal Component Analysis

PCA is a way of identifying patterns in data, and expressing the data in such a way that it should highlight their similarities and differences. Since discriminant features are difficult to find in data of high dimension, PCA has proved itself as a powerful tool for analyzing data and representing discriminant feature with low dimentions [11],[12],[13]. .PCA involves the calculation of the eigenvalue decomposition or Singular value decomposition of a data set, usually after mean centering the data for each attribute.in the traditional PCA method the entire face image is considered, hence large variation in pose or illumination will affect the recognition rate profoundly. Gottumukkal and Asari has proposed the modular principal component analysis technique (MPCA) to implement the invariant face recognition method under varying illumination, pose and facial expression, [15]. The Authors have claimed that some of the local features of face did not vary with pose, direction of lighting and facial expression and, therefore, suggested dividing the face region smaller subimages.

Since in the case of modular PCA method the original face image is divided into horizontal stripes, the impact of variations in pose, illumination will affect less, i.e. only on some of the sub-bands, and in addition to the use of sub-images, this paper proposes to use the depth maps, because range images are less prone to illumination changes [14]. Hence this method has better recognition rate than the conventional PCA. Here a whole face image is subdivided into horizontal strips. PCA can independently be performed on each sub image and local sub-features can be extracted. Pentland *et al.* extended the eigenface technique to a layered representation by combining eigenfaces and other eigenmodules, such as eigeneyes, eigennoses, and eigenmouths [16]. This modular eigenface approach was also studied and extended by several other researchers.. A similar approach was proposed by Chen and Zhu [17] which was called as spPCA which was furtuer extented by Tan and Chen to specify that different parts of the human face may contribute differently to recognition and, this mthod is known as adaptively weighted subpattern PCA [18]. Geng and Zhou made a similar observation, but chose to select several regions from all possible candidates instead of weighting them [19]. Some other authers [20],[21],[22],[23] have worked on Modular PCA to demonstarte that MPCA outperforms conventional PCA.

The methodology of modular PCA can be described as follows;

In this method, each image in the training set is divided into 3 smaller images. Hence the size of each sub-image will be L/3. These sub-images can be represented mathematically as

$$I_{i,j}(m,n) = I_i(L/\sqrt{N\,(j-1)+\ m,L/\sqrt{N\,(j-1)+n})\forall i,j} \quad (1)$$

where i varies from 1 to M,
M being the number of images in the training set,
j varies from 1 to N, N being the number of sub-images and m and n vary from 1 to $L/\sqrt{N}$.
The face image is divided into three smaller images as shown in figure 2.

Thus for N =3.
The average image of all the training sub-images is computed as

$$A = (1/M.N)\sum_1^M \sum_1^N I_{ij} \quad (2)$$

The next step is to normalize each training subimage by subtracting it from the mean as

$$Y_{ij} = I_{ij} - A \;\forall i,j \quad (3)$$

From the normalized sub-images the covariance matrix is computed as

$$C=(1/M.N)\sum_1^M \sum_1^N Y_{ij}.Y_{ij}^T \quad (4)$$

Next we find the eigenvectors of C that are associated with the 'X' largest eigenvalues.We represent the eigenvectors as E1; E2; . . . ; EX.
The weights are computed from the eigenvectors as shown below:

$$\boldsymbol{W_{pnJK}}=\boldsymbol{E_{K.}^T}(\boldsymbol{I_{pnj}}\text{-A}) \quad \forall \boldsymbol{p},\boldsymbol{n},\text{J,K} \quad (5)$$

where K changes from 1; 2; . . . X, n varies from 1 to C, C being the number of images per individual, and p varies from 1 to P, P being the number of individuals in the training set.
Weights are also computed for the test sub-images using the eigenvectors as shown in the next equation:

$$W_{test\,JK}=E_{K.}^T(I_{test\,j}\text{-A}) \quad \forall J,K \quad (6)$$

Mean weight set of each class in the training set is computed from the weight sets of the class as shown below:

$$T_{p,j,K} = \left(\frac{1}{\tau}\right)\sum_{K=1}^{M^1}\sum_{n=1}^{\tau} W_{pnJK} \quad \forall P,J \quad (7)$$

These weight set s representing the weights of each class then further considered as input to the Fuzzy neural network for further classification.

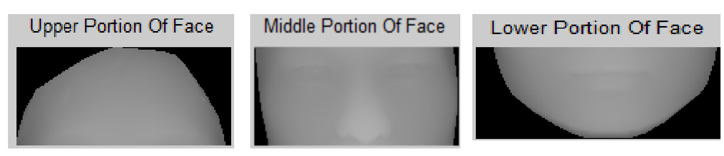

Figure 2. Showing three horizontal region of Face Image

3 Outline of Work

Thus the main approach of this proposed work is to use depth maps as the 2D representation of 3D face image and then subdivide each face into three regions. The modular PCA is applied on each region and the three Eigen modules were generated. The methodology can be described as follows.

ISSN 2229-5518

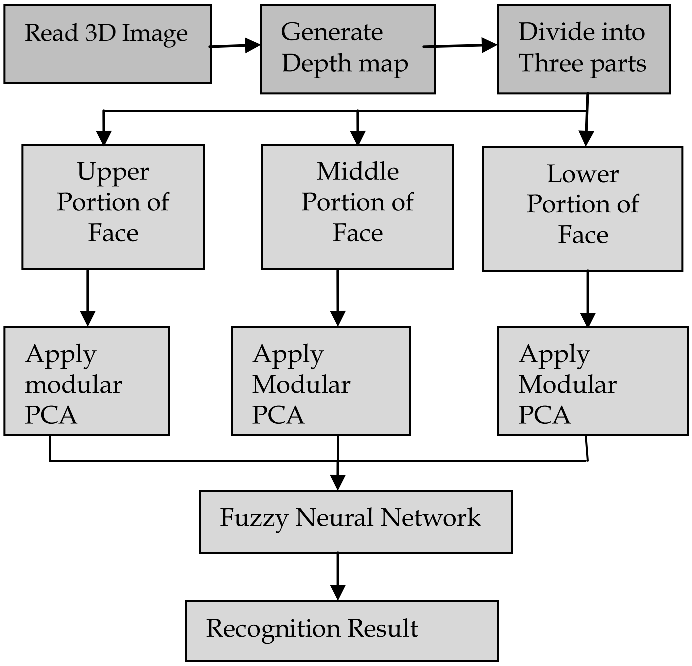

Figure 3: The steps involved to generate result

The method includes first step as reading the 3D image; the 3D images are in VRML format, during the training of the database the 3D images are read and from the training data set the depth maps are generated during the second step. These depth maps contain the depth of each pixel. The depth map is then divided into three equal horizontal regions/ strips. This division is done in third step. In fourth and parallel process the modular PCA is applied on all the three regions to represent each region in low dimension space.

The output of each sub-region will result into the Eigen module. These three Eigen modules are then considered as input to the fuzzy neural network. The fuzzy neural network considers the contribution of each region and uses fusion of classifiers for recognizing the face correctly.

4 Result and Discussion

The experiments were carried out on the images from both the databases i.e. CASIA and GAVAbDB. The CASIA database contains images with varying light effect and expression also and in GAVAbDB the images with changing expressions are available. Initially the experiments were carried out on the whole face image by using conventional PCA. And then the same images were used for implementing the modular PCA. The databases were trained on certain number of images and the results were analyzed. Initially the less number of training samples were used and it is found that MPCA outperforms the PCA. For the limited number of training samples the PCA's performance is not good. As we increase the number of training samples the PCA performance well. But in case of MPCA the performance is consistence even the number of sample are less.

Another observation about the impact of changing factors is that in case of variations in expression the performance of both the methods (PCA and MPCA) is comparatively less than that with the images taken in changing lighting effects.

TABLE 1
PCA Vs MPCA

No. of samples	PCA+Expr	PCA+light	MPCA+ expr	MPCA+light
20	70.22	73.34	93.12	93.55
40	71.45	73.88	94.44	96.77
60	73.17	76.12	95.3	97
80	80.9	82.01	95.99	97.65
100	84.54	85	96.12	98.23
120	84.67	88.34	96.34	98.9

The results demonstrate that the modular PCA handles the illumination and expression effects efficiently. But the division of face in three regions still does not handle the varying expressions properly. When observed closely the middle portion of a face image contains two face parts; eyes and nose. The eyes region changes considerably in almost all the expressions, where as the nose part remains unchanged. The extension to the propose work would be the sepeartion of these two face-parts so that the face recognition system would perform robustly. The Figure 4. Shows the graphical representation of the performance of both the methods; Principal component analysis and Modular Principal component analysis.

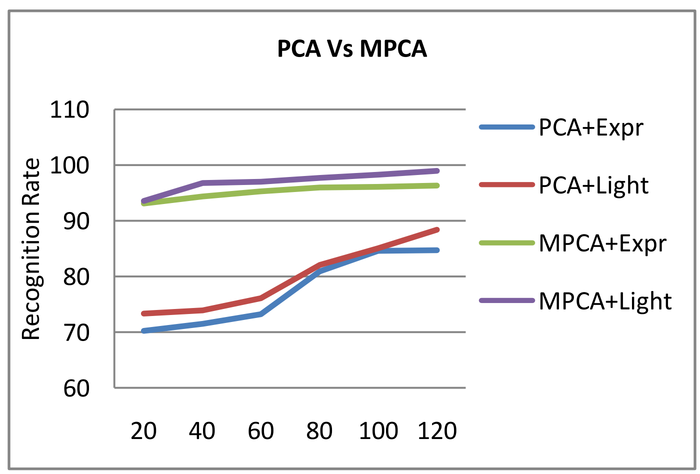

Figure 4.: No of sample Vs Recognition Rate

5 Conclusion

The proposed algorithm uses the local features to handle the effect of external factors like illumination and expressions. When compared with conventional PCA algorithm the modular PCA has an improved recognition rate for face images with large variations in lighting direction and facial expression. The PCA approach applied to each of three sub-images also handles the issue of extra storage requirement for the features extracted from these subregions. With slight extension we expect the proposed method to be able to completely cope with these variations.

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