FACE RECOGNITION BY INDEPENDENT COMPONENT ANALYSIS TO VERIFY STUDENT IDENTITY

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ABSTRACT

A face recognition application to detect student identity based on two face recognition algorithms namely Principal Component Analysis and Independent Component Analysis is presented here. An image database of 49 students was used for the evaluation. There were 100 images for each student which has been captured while the student moves up right face from left to right. Only face area was captured for each image based on Viola-Jones detection algorithm and resized to 140×140 pixels. Each student's face area is then detected, captured and resized to 140×140 pixels from a live video stream from a web cam or a laptop camera, and then found the best matched student from the database created in the previous step using Principal Component Analysis and Independent Component Analysis. Proposed solution is further capable of detecting multiple faces in the camera view in parallel. In addition to that it was also experienced that Independent Component Analysis performed better comparing to Principal Component Analysis.

***Key words*:** Face recognition, independent component analysis, ICA, principal component analysis, PCA

1. INTRODUCTION

Face recognition has gained much attention in recent years due to its applicability in automatic face detection. Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) are three widely used face recognition algorithms.

PCA is known as Eigen space Projection which is based on linearly projecting the image space to a low dimensional feature space that is called Eigen space. It tries to find the eigenvectors of the covariance matrix that correspond to the directions of the principal components of the original data [1], [2]. LDA which is known as Fisher's Discriminant Analysis searches for a linear transformation such that the feature clusters are most separable after the transformation which can be achieved through scatter matrix analysis. LDA deals directly with discrimination between classes, whereas PCA deals with the data in its entirety for the principal components analysis without paying any particular attention to the underlying class structure [3]. ICA which is a special case of redundancy reduction technique and it represents the data in terms of statistically independent variables. ICA is a method for transforming an observed multidimensional random vector into components that are statistically as independent from each other as possible [1]. J. R. Beveridge et al. found that LDA performed consistently inferior than PCA [4]. Hence PCA and its counterpart ICA were used as the main algorithms in this research. We plan to further extend this research for the other widely used face recognition algorithms as well in future.

The proposed application can be experimented and applied in many real world scenarios. One good example would be identity detection during examinations. In most educational institutes, administration staff checks students' eligibility for sitting on examinations by considering factors such as payment details, registration, identity and percentage of attendance manually. Proposed solution is further capable of detecting multiple faces in the camera view in parallel. Therefore this solution can be implemented to facilitate the above requirement in verifying the student identity.

1.1. Principal Component Analysis

PCA basis vectors are computed from a set of training images I. First, the average image is subtracted from the training images, creating a set of data samples, $i_1, i_2, \ldots, i_n \in (I - \bar{I})$. These data samples are then arrayed in a matrix X, with one column per image. XX^T is then the sample covariance matrix for the training images, and the principal components of the covariance matrix are computed by solving, $R^T (XX^T) R = \Lambda$, where Λ is the diagonal matrix of eigenvalues and R is the matrix of orthonormal eigenvectors.

Geometrically, R is a rotation matrix that rotates the original coordinate system onto the eigenvectors, where the eigenvector associated with the largest eigenvalue is the axis of maximum variance, the eigenvector associated with the second largest eigenvalue is the orthogonal axis with the second largest variance [1], [3].

1.2. Independent Component Analysis

ICA finds independent rather than pair-wise uncorrelated dimensions (Figure 1).

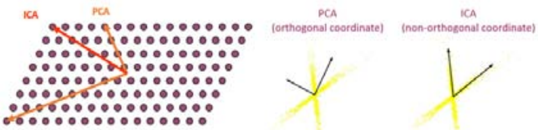

Figure 1: Difference between PCA and ICA.

While PCA de-correlates the input data using second-order statistics and thereby generates compressed data with minimum mean-squared re-projection error, ICA minimizes both second-order and higher-order dependencies in the input. ICA can be viewed as a generalization of PCA. PCA de-correlates the training data so that the sample covariance of the training data is zero [5], [6]. Based on the Architecture 1 of [1], we built our own face detection system to find the best match using ICA algorithm. This architecture used Infomax algorithm proposed by Ball and Sejnowski, which is derived from the principle of optimal information transfer in neurons with sigmoidal transfer functions.

Rest of the paper is organized as follows. Section 2 explains the methodology, Section 3 discusses experiment results and conclusions are drawn in section 4.

2. METHODOLOGY

An image database of 49 students was used for the evaluation. There were 100 images (640×480) for each student which has been captured while the student moves up right face from left to right. First faces were detected, cropped based on Viola-Jones detection algorithm in Matlab, resized to 140×140 pixels, and converted to gray scale (Figure 2). Based on the Architecture 1 [1], [7], proposed face detection system was built to find the best match using ICA.

Figure 2: Face detection, cropping and resizing.

3. RESULTS AND DISCUSSION

3.1. Experiment 1: ICA and PCA Recognition Rates for 5 Students

First 1 to 5 students were selected, divided into training and testing data, and recognition rates were calculated for ICA and PCA algorithm by changing sizes of train and test dataset. Table 1 demonstrate that recognition rate increases when training set increases.

Table 1: Recognition rates for Experiment 1

Train Set	Test set	Recognition Rate (%)	
		ICA	PCA
30	70	97.82	74.58
40	60	98.50	76.00
50	50	99.75	78.95
60	40	99.92	83.22
70	30	100.00	86.53

3.2. Experiment 2: ICA and PCA Recognition Rates for 49 Students

The recognition rate was calculated for all 49 students same as in Experiment 1. Table 2 demonstrate that the recognition rate increases with the training set size.

Table 2: Recognition rates for Experiment 2

Train Set	Test set	Recognition Rate (%)	
		ICA	PCA
30	70	86.50	72.96
40	60	90.82	75.64
50	50	92.24	77.55
60	40	94.44	81.65
70	30	96.33	84.52

3.3. Experiment 3: ICA Recognition Rate Improvement

It is identified that, faces were not cropped properly in the Experiments 1 and 2 since a fixed sized cropping rectangle of 250×250 pixels is used. Hence the default rectangle size returned in the Viola-Jones detection algorithm in Matlab was used in the Experiment 3 (Figure 3).

Figure 3: Detect the face and resize the image (student 22).

In experiment 2 the best recognition rate was 96.33% when training dataset was 70 and the testing dataset was 30. Hence the ICA recognition rate was calculated in Experiment 3 for same training and test dataset sizes, and the recognition rate was improved to 98.00%.

Then only 50 images out of 100 images were selected for each student as images 1, 3, …, 97, 99. Since previous experiments show best recognition rates when training dataset was 70 and testing dataset was 30, new training dataset and testing dataset were selected as 35 and 15 proportionally. Then an improved recognition rate for ICA was noticed as 99.72%.

3.4. Experiment 4: Recognition Rate for Random Students

To validate the recognition rates in Experiment 3, images from six random students were tested with both 100 images and 50 images datasets from Experiment 3 (Figure 4). As shown in Table 3 five out of six random images (student IDs are 1, 22, 25, 29, 35, 45) were perfectly matched with 100 image dataset, and all the images were matched in 50 images dataset, demonstrating that 50 images dataset provides better recognition.

Figure 4: Best match with randomly selected images

Table 3. Recognition results for Experiment 4.

No	Random image ID	Match image ID	
		100	50
1	1	1	1
2	22	22	22
3	25	25	25
4	29	29	29
5	35	26	35
6	45	45	45

3.5. Experiment 5: Non-Real Time Recognition of Images from a Web Cam

Only two students (22 and 25) image were captured using a USB webcam, face area was cropped based on Viola-Jones detection algorithm in Matlab, and resized to 140×140 pixels. Then the recognition was tested as in Experiment 4 with both 100 and 50 images datasets. Student 25 was perfectly recognized with both 100 and 50 images datasets. However student 22 was not recognized in 100 images dataset but was recognized in 50 images dataset (Table 4).

Table 4. Recognition results for Experiment 5.

No	Student image ID	Match image ID	
		100	50
1	22	49	22
2	25	25	25

3.6. Experiment 6: Real Time Face Detection

A real time face detection application was developed, for single face and for multiple faces as shown in Figure 5. Student ID 25 was recognized but student ID 22 was not recognized with the 50 images dataset.

Figure 5: Real time single and multiple face detection.

3.7. Experiment 7: Improved Real Time Face Detection

It was further noticed that even with the default cropping rectangle of Viola-Jones detection algorithm in Matlab detected face area contains details outside of the face area as shown in Figure 6 left. Hence face area was cropped excluding 0.1×width range from all sides of default cropping rectangle as shown in Figure 6 middle. As shown in Figure 6 right, student ID 22 was detected showing an improvement in the recognition. Then the real time application was experimented with multiple faces as shown in Figure 7 and it is clear that further adjustments are required for a better recognition.

Figure 6: Improve real time face detection by changing the default detection box.

Figure 7: Real time multiple face detection.

3.8. Experiment 8: Comparison of ICA Recognition with Different Parameters

Here a new dataset was created by cropping the faces as explained in the Experiment 7. Then ICA recognition rate was calculated by changing the size of the cropping rectangle, and number of images in the dataset. It is demonstrated that larger training dataset size and small image size in pixels provides better recognition rates (Figure 8).

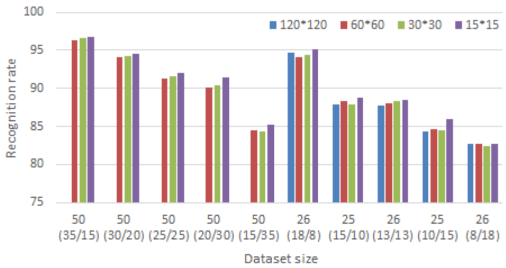

Figure 8: ICA recognition rate vs. dataset size for different image sizes.

3.9. Current Issues in Real Time Face Recognition

Following issues in the proposed application were identified. Viola-Jones detection algorithm in Matlab is sensitive to different lighting conditions, and it is observed that webcam location caused in different results in face recognition. Quality of the webcam is another factor (the used laptop webcam is 1.3 mega pixels).

4. CONCLUSION

An application for face recognition for university examinations is presented based on Principal Component Analysis and Independent Component Analysis. A dataset of 49 students with 100 images per each student was used for the experiment. Extensive set of experiments were carried out to explore the parameter values which gives the better recognition rates. It is observed that a perfect cropping around the face area, larger training dataset size, and small cropped face area, results in better recognition rates.

In future works it is planned to use randomly selected images and a user selected images as the training set to learn the changes of the recognition rate. Further it is planned to crop the face based on the locations of the face features like nose, eyes, and mouth, in order to calculate the recognition rate.

5. REFERENCES

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