Two-Dimensional Principal Component Analysis and Concurrent Self-Organizing Maps for Face Classification

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Abstract— Face recognition is one of the most widely used methods for recognition of individuals. Face recognition can classify a person through a non-intrusive process where the cooperation of the person is not necessary to capture their face. The proposed algorithm for face classification is broken down into three steps. In the first step the feature matrices are obtained using the Two-Dimensional Discrete Cosine Transform (2D-DCT) and Two-Dimensional Principal Component Analysis (2DPCA). The training of Concurrent Self-Organizing Maps (CSOM) is achieved in the second step by using the face's feature matrix. And finally, the third step extracts the feature matrix from the query image and classifies it using the CSOM network. To verify the efficiency of the algorithm, the tests have been done using the "The ORL Database of Faces" provided by the AT&T Laboratory from Cambridge University. The performance of the algorithm was satisfactory in relation to other proposed algorithms for face recognition found in the literature.

Keywords- Face recognition;DCT;2DPCA;SOM,CSOM.

I. INTRODUCTION

Face recognition has recently received significant attention, especially for the last few years, and two reasons could explain this: the first is the wide range of commercial, military and civil security applications; the second is the availability of practicable technologies after years of research.

Such as in the majority of biometric measures, the general objective of face recognition is to obtain an elevated level of performance in identifying a face presented to a system according to a known database.

The performance of the face recognition algorithm can be evaluated by a combination of factors, such as: precision in the response (in relation to false negative or false positive), robustness against adverse factors, speed of recognition, processing time and low cost of equipment.

In the last few years, many algorithms have been proposed for face recognition. In 1991, Turk and Pentland [1,2] created Eigenfaces based on the Principal component Analysis (PCA), also known as the Karhunen-Loeve expansion [3,4]. This method reduces the image's dimensions performing statistical analysis based on the image's variance and redundancy. The work of Turk and Pentland [1,2] using eigenfaces obtained a good performance in face recognition taking into consideration the variations in pose, lighting and facial expressions.

In 2004 Yang et al. [5] created a Two Dimensional PCA (2DPCA). In the use of 2DPCA they obtained many advantages over the PCA (Eigenfaces) method. The 2DPCA is simple in the extraction of the image's features, better in rate of recognition and more efficient in computation. Nevertheless, 2DPCA is not so efficient in terms of storage, because it needs to store more coefficients to represent the image.

In 2006, Moataz and Wasfy [6] presented the Transform Domain 2DPCA (TD2DPCA). The TD2DPCA reduces storage space and number of coefficients without reducing recognition rate. In the work of Moataz and Wasfy [6] the covariance matrix was found using the DCT in the difference between the image of each face and the average image of all the faces from the database. The feature matrices were found using the largest eigenvalues of the covariance matrix. The classification was achieved using the Euclidean distance between the feature matrix of the query image and the training group's feature matrices obtained from the database.

Neagoe and Ropot [7] created an algorithm for face recognition using PCA together with the Concurrent Self-Organizing Maps (CSOM). The objective of their work was to compare the efficiency between Self-Organizing Map (SOM) and CSOM. After the tests had been carried out, Neagoe [7] concluded that the CSOM network presented a greater recognition rate and also a shorter training time than the SOM network.

In spite of several researches in the last few years, face recognition remains a difficult task due to various factors that affect it, such as lighting conditions, point of view, body movement and facial expression.

Inspired by the works of Moataz and Wasfy [6] and Neagoe and Ropot [7] the proposed algorithm was broken down into three steps. The first step extracts the feature matrices from the faces (training group) using the largest eigenvalues of the 2DPCA covariance matrix. The CSOM training takes part in the second step using the feature matrices from the training group. Finally, the third step extracts the feature matrix from the query image and classifies it using the CSOM network.

This article is structured as follows: section II presents the background of 2DPCA and CSOM; section III describes the proposed algorithm; section IV presents the results obtained; and finally, section V presents the achievements and conclusions of these results.

II. 2DPCA AND CSOM BACKGROUND

A. *Two-Dimensional Principal Component Analysis (2DPCA)*

The 2DPCA method, presented by Yang et al. [5] consists of definitions of the covariance matrix S of N training images A_i of dimensions m x n (where i = 1 to N) in 2D.

The covariance matrix S of dimension n x n is calculated by (1)

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(A_i - \overline{A}\right)^T\left(A_i - \overline{A}\right) \qquad (1)$$

where: $\overline{A}$ is the average matrix of the N training images.

The set consisting of the k eigenvectors related to the largest eigenvalues of the covariance matrix, $V = [V_1, V_2, ..., V_k]$, of size n x k is obtained so that the projection of the training images about V accommodates the best dispersion. V is used to obtain the feature of each training image A_i. The feature vectors are obtained by (2).

$$Y_{j,i} = A_i V_j \qquad j = 1,2,\ldots,k \qquad i = 1,\ldots,N \qquad (2)$$

The feature vectors $Y_{j,i}$ are used to assemble the feature matrix B_i of dimensions m x k to each training image A_i.

$$B_i = \left[Y_{1,i}, Y_{2,i}, \ldots, Y_{k,i}\right] \qquad i = 1,\ldots,N \qquad (3)$$

In the classification proposed by Yang et al. [5] the similarity between the feature matrices of the images was obtained by (4).

$$d\left(B_i, B_j\right) = \sum_{d=1}^{k}\left\|Y_{d,i} - Y_{d,j}\right\| \qquad (4)$$

B. *Concurrent Self-Organizing Maps (CSOM)*

Concurrent Self-Organizing Maps (CSOM) proposed by Neagoe [7], is formed by a collection of smaller SOMs which uses the “winner-take- all” strategy.

The CSOM, opposite to SOM, has supervised training where an individual algorithm is used for each SOM network. Each SOM network is used only to correctly classify the pattern of each class. The number of SOM networks that comprise the CSOM network equals the number of classes [7].

For each n training patterns, a SOM network is used, as shown in Fig. 1.

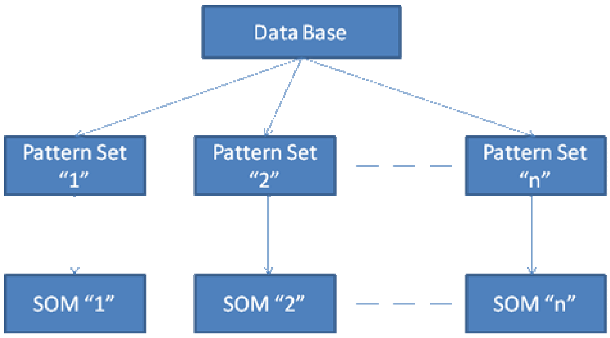

Figure 1. CSOM training model.

In classification, the class of the test pattern is the one which presents the shortest distance calculated between the test pattern and the neurons of the SOMs [7], as shown in Fig. 2.

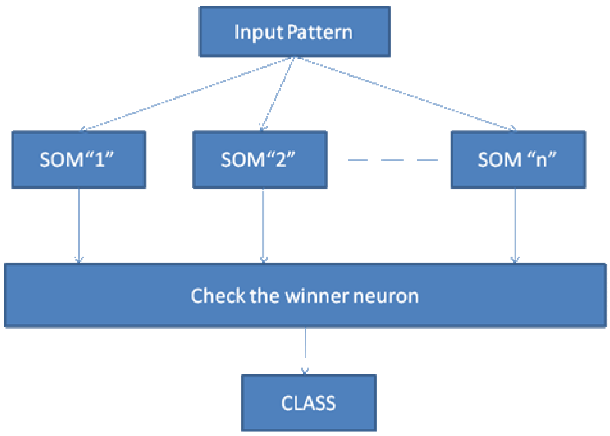

Figure 2. CSOM classification model.

Inspired by the work of Yang et al. [5] and Neagoe and Ropot [7], the proposed work applies CSOM in results obtained through 2DPCA. Moreover the proposed algorithm is tested on the data processed using the 2D Discrete Cosine Transform (2D-DCT).

III. Two-Dimensional Principal Component Analysis and Concurrent Self-Organizing Maps for Face Classification

The proposed algorithm extracts the feature matrix of each face to be used in the training and classification of the neural network. In the training stage, we applied the 2D-DCT to each image from the training set. In order to reduce the number of coefficients to represent the feature matrix of each face, we stored in a square matrix only the most significant coefficients which are located around the origin, as shown in Fig.3. This figure shows the coefficients of 2D-DCT which were applied in a face from the ORL database.

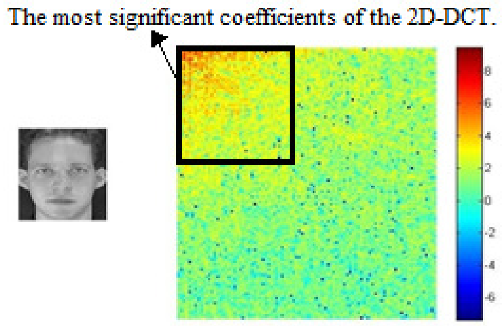

Figure 3. 2D-DCT of a face from the ORL database and the selection of the most significant coefficients.

The CSOM network formed by n SOMs is trained with feature matrices from each face. These matrices are found by applying the 2DPCA on each square matrix of the most significant coefficients of the 2D-DCT of each face of the training set.

In classification, the feature matrix of the query image is obtained in the same way as was found the feature matrices of the training images in the training stage.

Fig. 4 shows the block diagram of the proposed algorithm.

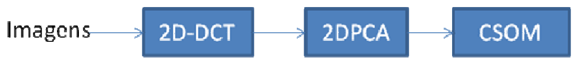

Figure 4. Block diagram of the proposed algorithm.

A. *Face database*

To verify the performance of the proposed algorithm in this article, we used the “The ORL Database of Faces” provided by the AT&T Laboratory from Cambridge University [9].

The ORL database [9] contains 400 images of 40 individuals. For each individual, 10 images from different times, lighting conditions and facial expressions were obtained with and without glasses. The size of each image is 112 x 96 pixels with 256 levels of gray. For each individual, five images were selected for training and five for classification, as shown in Fig. 5.

Figure 5. Images of an individual’s face from the ORL database. (a) Training images; (b) Query images.

IV. Experimental Results

In the training stage, the 2D-DCT was applied to each image of the training set, storing the 2D-DCT coefficients in the square matrix, as shown in Fig.3. Fig.3 shows that the most significant coefficients are grouped around to the origin. By using this attribute, only 20 x 20 coefficients of the 2D-DCT located around the origin are used. By using the selected matrix of 2D-DCT to represent each face, it is possible to reduce the runtime of the algorithm in the next steps.

With the selected 2D-DCT coefficients from each individual of the training set, we calculated the feature matrices using the largest eigenvalues from the 2DPCA covariance matrix. Because we chose to use only 20 x 20 of the 2D-DCT coefficients, there is a total of 20 eigenvalues, as illustrated in decreasing order in Fig.6.

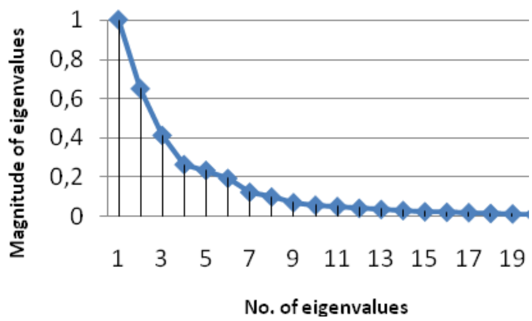

Figure 6. Eigenvalues of the training set from the ORL database.

Fig.6 shows that the most significant components are located in the first 10 eigenvalues. Therefore in the training stage and in the classification stage, the 10 largest eigenvalues of the covariance matrix were used to obtain a feature matrix for each individual, resulting in a 20 x 10 feature matrix, or a feature vector of 200 components.

The CSOM network of the proposed algorithm uses a linear configuration on each SOM network. Each SOM was trained separately to represent a specific individual from the ORL database. The CSOM network used is composed of 40 SOMs, because the database has 40 individuals.

Fig.7 shows the results of the tests performed with different numbers of neurons in the output layer of each SOM network.

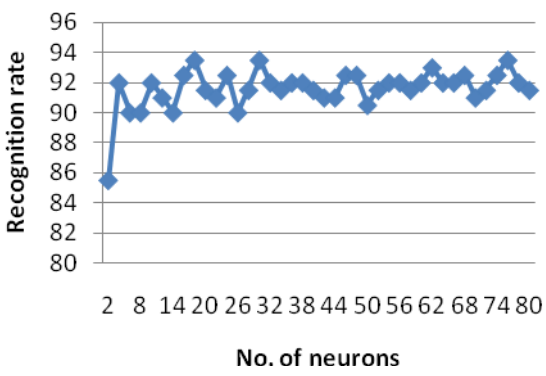

Figure 7. Results obtained using the ORL database.

Fig. 7 shows that the highest recognition rate obtained was 93.5% for 18, 30 and 76 neurons in the output layer of each SOM network belonging to the CSOM

Table I shows the recognition rate and the processing time (sum of feature extraction time and network training time) of the proposed algorithm (2D-DCT + 2DPCA + CSOM) compared with other face recognition algorithms in literature (PCA [1], PCA+CSOM [7] and 2DPCA [5]), where the results were obtained from their respective works. The objective of carrying out the tests with the 2DPCA + CSOM and DCT + 2DPCA algorithms was to verify the efficiency of the proposed algorithm.

TABLE I. COMPARISON TABLE

Algorithm	Recognition Rate %	Time (*s*)
PCA	89	391
PCA+CSOM	**91**	**406**
2DPCA	91,5	0,9602
2DPCA+CSOM	**93**	**1733**
DCT+2DPCA	92	0,0363
DCT+2DPCA+CSOM	**93,5**	**304**

Table I shows that the recognition rate was higher (93,5%) and processing time was shorter (304 s) in the proposed algorithm in comparison with other algorithms in the literature and with algorithms developed to verify the performance of the proposed algorithm. By using the 2D-DCT and 2DPCA in the proposed algorithm, good performance was achieved in extracting features of faces and there has also been a contribution in reducing processing time.

V. CONCLUSION

In addition to the tests shown in section IV, other tests were also carried out and many important characteristics were also observed. In the tests carried out on the ORL database, it is possible to verify that the result varies according to the size of the feature vector from each individual and also according to the number of neurons.

The proposed algorithm presented a better recognition rate (approximately 2% higher) in relation to all the algorithms in Table I. The increase in recognition rate occurred for two reasons: the use of 2D-DCT and 2DPCA in the feature extraction of faces, and the use of CSOM network in classification.

The CSOM network has a better recognition rate than the SOM, because each SOM of the CSOM network is trained independently for each individual. The radiuses of neighborhoods are smaller for CSOM components than for a single big SOM to classify all individuals.

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