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Face recognition and verification based on 2D circle technique

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Abstract

This paper presents, how to recognize a face of portrait photographs by applying the principal components analysis (PCA) to get the feature vector and verification algorithm based on 2D circle. PCA was applied to modify the mean which is the cut of, 5% minimum and 5% maximum of data. For verification process, each image was reduced into 2 dimension (2D). Those images of each individual in 2D are encircled with the diameter calculated form the maximum Euclidean distance between any two vectors in each pair of those images. In this paper, two experiment were conducted. We chose test image in training set, verified them by using circle and shows the results of the proposed algorithms and others in 5 distance measures for the first experiment. Then, we also chose test image, which is not in training set and verify in the same way in the second experiment. We choose some images in Essex Faces94 (Female and Male Staff) to form a training set. The proposed algorithms show the better performance than other algorithms and they have recognition rate over 89%.

Keywords: Circle, Euclidean distance, Face recognition, Principal component analysis

1. Introduction

Nowadays, there are many researchers interested in recognizing of human face or face recognition since it is used in various ways and institutions. For instance, to recognize workers' facial feature as they enter the office, or to compare known and unknown image in the database. Face recognition can be processed in many ways such as Principle Component Analysis or PCA [1], which face images are projected into a lower dimensional space which each image is represented by a vector, Linear Discriminant Analysis or LDA [2] which is proposed by Zhao, Chellappa and Krishnaswamy to help evaluate the importance of varied facial features in relation to their discriminant power and Multi-linear Principal component Analysis or MPCA [3], which is proposed by Haiping Lu, Plataniotis and Venetsanopoulos. MPCA method is a modification of PCA using multi-linear algebra, while PCA uses only one vector. In MPCA, the number of transformation vectors are used. Both PCA and LDA were presented to Euclidean distance measurement, which is conveniently used as a benchmark.

In 2012, Dinesh, Pawar [4] presented a new way to recognize the face using facial recognition software together with neural network methods and used this facial recognition system to protect frauds and terrorists. In the same year, Abdullah, Wazza and Bo-saeed [5] conducted a study to optimize the time complexity of PCA (eigenfaces) that does not affects the recognition performance. They minimized the participated eigenvectors which consequently decrease the computational time. A comparison was done to compare the differences between the recognition time in the original algorithm and in the enhanced algorithm.

In 2015, Schroff, Kalenichenko and Philbin presented system FaceNet [6]. Their method was based on learning a Euclidean embedding per image using a deep convolutional network. The network is trained such that the squared L2 distances.

In this paper, two algorithms for face verification and recognition was presented based on PCA. We used PCA to find a subset of principle component in a set of training faces, then we projected faces into principal components space and gathered the feature vectors. Comparison was performed by calculating the distance between these vectors. Normally, the comparison of face images is performed by calculating the Euclidean distance between these feature vectors.

Mathematical formulation of this recognition algorithm is presented as follows:
Let $\boldsymbol{X}, \boldsymbol{Y}$ be eigenfeature vectors of length $\boldsymbol{n}$ such that $\boldsymbol{X} = [\boldsymbol{x_1}\ \boldsymbol{x_2} \ldots \boldsymbol{x_n}], \boldsymbol{Y} = [\boldsymbol{y_1}\ \boldsymbol{y_2} \ldots \boldsymbol{y_n}]$. The Minkowski distance $(\boldsymbol{p} > \boldsymbol{0})$ is defined

$$\mathbf{d_p(X,Y)} = \left(\sum_{\mathbf{i=1}}^{\mathbf{n}} |\mathbf{x_i} - \mathbf{y_i}|^{\mathbf{p}}\right)^{\mathbf{1/p}}.$$

Particularly, the Manhattan and Euclidean distances are $\boldsymbol{d_1(X,Y)}$ and $\boldsymbol{d_2(X,Y)}$, respectively. The Angle-based and Canberra distances are defined

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$$\mathrm{d_A(X,Y)} = -\sum_{i=1}^{n} x_i y_i \Bigg/ \sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}$$

and $d_C(X,Y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|}$, respectively.

2. Materials and methods

2.1 Principle Component Analysis (PCA)

The principle component analysis approach was described by Turk and Pentland [4] in 1991. The training database contains $\boldsymbol{M}$ images which are represented as the same size of matrix. Each image matrix is normalized by converting to the equivalent image vector (column matrix)$\boldsymbol{x_i}$. The training matrix $\boldsymbol{X}$ contains the image vectors as $\boldsymbol{X} = [\boldsymbol{x_1}\ \ \boldsymbol{x_2}\ \dots\ \boldsymbol{x_M}]$. The process of PCA is described as follows:

Step 1. Set $\mathbf{x_i}$ be the image vector of $\mathbf{i^{th}}$ image and calculate the mean face defined by

$$\bar{\boldsymbol{x}} = \frac{\boldsymbol{1}}{\boldsymbol{M}} \sum_{i=1}^{M} \boldsymbol{x_i}.$$

Step 2. Calculate the covariance matrix $\boldsymbol{C}$ of the training image matrix by $\boldsymbol{C} = \frac{1}{M}\boldsymbol{A}\boldsymbol{A}^{\boldsymbol{T}}$, where

$$\boldsymbol{A} = [\ (\boldsymbol{x_1} - \bar{\boldsymbol{x}})\ \ (\boldsymbol{x_2} - \bar{\boldsymbol{x}}) \dots (\boldsymbol{x_M} - \bar{\boldsymbol{x}})\ ].$$

Step 3. Since the matrix $\boldsymbol{C}$ is high dimension, the eigenvectors of $\boldsymbol{C}$ are considered by the matrix $\boldsymbol{L} = \frac{1}{M}\boldsymbol{A^T A}$ of size $\boldsymbol{M} \times \boldsymbol{M}$ (if $\boldsymbol{\lambda}$ is eigenvalue of $\boldsymbol{L}$, then $\boldsymbol{\lambda}$ is also eigenvalue of $\boldsymbol{C}$). Let $\boldsymbol{V_i}$ be the eigenvector of matrix $\boldsymbol{L}$ corresponding to the eigenvalue $\boldsymbol{\lambda_i}$ where $|\boldsymbol{\lambda_1}| \geq |\boldsymbol{\lambda_2}| \geq \dots \geq |\boldsymbol{\lambda_m}|$. Thus, $\boldsymbol{U_i} = \boldsymbol{A}\boldsymbol{V_i}$ is eigenvector of $\boldsymbol{C}$ corresponding to the eigenvalue $\boldsymbol{\lambda_i}$. The eigenfaces is defined by $\boldsymbol{U} = [\boldsymbol{U_1}\ \ \boldsymbol{U_2}\ \ \boldsymbol{U_3} \dots \boldsymbol{U_M}]$.

Step 4. (Return to Vector Conversion) The weight of each eigenvector $\boldsymbol{z_i}$ represents the image in the eigenface space as given by $\boldsymbol{z_i} = \boldsymbol{U^T}(\boldsymbol{x_i} - \bar{\boldsymbol{x}})$, where $\boldsymbol{U}$ is the eigenfaces.

Next, we propose human face verification technique using Euclidean distance and circle as follows.

2.2 Proposed algorithms

2.2.1 Verification of proposed algorithm

As mentioned in section 2.1, let $\boldsymbol{P_2}$ be 2D projection mapping and $\boldsymbol{z_i} = [\boldsymbol{\xi_1}\ \ \boldsymbol{\xi_2}\ \dots\ \boldsymbol{\xi_M}]$. We set the projection of $\boldsymbol{z_i}$ into 2D as $\boldsymbol{y_i} = \boldsymbol{P_2}(\boldsymbol{z_i}) = [\boldsymbol{\xi_1}\ \ \boldsymbol{\xi_2}]$.

Step 1. Create the circle to cover an image vector of $\boldsymbol{n^{th}}$ person (one person has $\boldsymbol{m}$ images), which radius is calculated by $\boldsymbol{R_n} = \frac{1}{2}\mathbf{max}\{\boldsymbol{d_2}(\boldsymbol{y_i}, \boldsymbol{y_j}): \boldsymbol{i}, \boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\}$, where $\boldsymbol{m}$ is the number of images per person. The center $(\boldsymbol{C_n})$ is calculated from the center of the two vectors of the radius as shown in Figure 1.

Step 2. (*Test image verification*)

Let circle with the radius and the center represents the image of each person, and let $\boldsymbol{y_0}$ be the test image.

Step 2.1. If the test image $\boldsymbol{y_0} = [\boldsymbol{h_0}\ \ \boldsymbol{k_0}]$ is in one circle of $\boldsymbol{i^{th}}$ person, the test image is in the group of $\boldsymbol{i^{th}}$ person. That is

$$\boldsymbol{d_2}(\boldsymbol{y_0}, \boldsymbol{C_i}) = \sqrt{(\boldsymbol{h_0} - \boldsymbol{h_i})^2 + (\boldsymbol{k_0} - \boldsymbol{k_i})^2} \leq \boldsymbol{R_i}\ ,$$

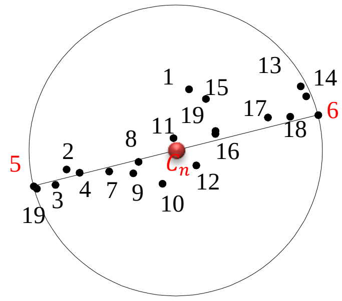
where $\boldsymbol{C_i} = [\boldsymbol{h_i}\ \ \boldsymbol{k_i}]$ and $\boldsymbol{R_i}$ are the center and the radius of $\boldsymbol{i^{th}}$ image, respectively as shown in Figure 2.

Step 2.2. If test image is not in any circle or in more than one circle, we check the minimum Euclidean distance between $\boldsymbol{y_0}$ and the center of each person, i.e., the test image is in the group of $\boldsymbol{n^{th}}$ person when

$$\boldsymbol{n} = \mathbf{arg\,min}\{\boldsymbol{d_2}(\boldsymbol{y_0}, \boldsymbol{C_i}): \boldsymbol{i} = \boldsymbol{1}, \boldsymbol{2}, \boldsymbol{3}, \dots, \boldsymbol{k}\},$$

where $\boldsymbol{k}$ is the number of subjects in databases and $\boldsymbol{d_2}(\boldsymbol{y_0}, \boldsymbol{C_n}) \leq \boldsymbol{1.5R_n}$ as shown in Figure 3. In the case $\boldsymbol{d_2}(\boldsymbol{y_0}, \boldsymbol{C_n}) > \boldsymbol{1.5R_n}$, the test image is unknown person.

In verification, we used various distance measures to compare and gave the mean of each individual. Then, we represented the image of each individual and considered the minimum of distance between the mean of each individual and the test image.



$$\boldsymbol{R_n} = \frac{\boldsymbol{1}}{\boldsymbol{2}}\mathbf{max}\{\boldsymbol{d_2}(\boldsymbol{y_i}, \boldsymbol{y_j}): \boldsymbol{i}, \boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{18}\}$$
$$= \frac{\boldsymbol{1}}{\boldsymbol{2}}\boldsymbol{d_2}\ (\boldsymbol{y_5}, \boldsymbol{y_6})$$

$\boldsymbol{C_n}$ is the middle point of $\boldsymbol{y_5}$ and $\boldsymbol{y_6}$

Figure 1 Shows how to find the radius and the center, which are the representative of each individual

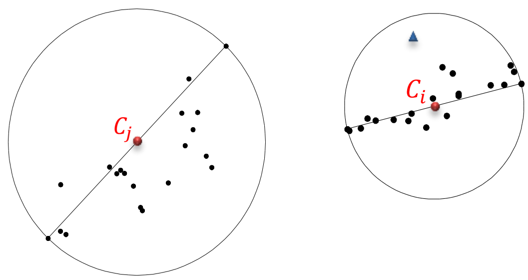


Figure 2 Show construction circles of step 2.1, where triangle is the test image.

2.2.2 Proposed algorithm 1

The training database consists of $\boldsymbol{M}$ images which are in the same size. Based on PCA, the eigenfaces are in the form of $\boldsymbol{U} = [\boldsymbol{U_1}\ \ \boldsymbol{U_2}\ \ \boldsymbol{U_3} \dots \boldsymbol{U_M}]$. We transform this into vector conversion, the weight of each eigenvector $\boldsymbol{z_i} = \boldsymbol{U^T}(\boldsymbol{x_i} - \bar{\boldsymbol{x}})$ represents the image in the eigenface space, then verified by using verification proposed algorithm as mentioned in 2.2.1.

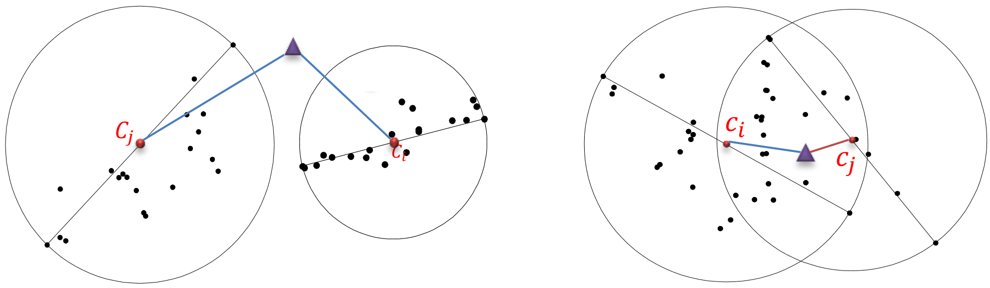


Figure 3 The left figure shows that the test image (triangle) is not in circle and the right figure shows that the test image (triangle) is in more than one circle.

2.2.3 Proposed algorithm 2

The training database includes of $\boldsymbol{M}$ images which are in the same size. The propose algorithm based on PCA can be elucidate as follows:

Step 1. Read the image, denoted by $\boldsymbol{x_i}$ which its dimension is $\boldsymbol{d} \times \boldsymbol{n}$, $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \dots, \boldsymbol{M}$. Then, transform $\boldsymbol{x_i}$ into a new column matrix. Define training set $\boldsymbol{X} = [\boldsymbol{x_1}\ \boldsymbol{x_2}\ \dots\ \boldsymbol{x_M}]$ which its dimension is $(\boldsymbol{dn}) \times \boldsymbol{M}$.

Step 2. Sort the training set $\boldsymbol{X}$ by rows, then cut 5 % of the minimum and 5 % of the maximum of image vector.

Step 3. Calculate the mean from new $\boldsymbol{X}$ in step 2 and calculate the covariance matrix $\boldsymbol{C}$ according to PCA.

Step 4. Verify by using verification proposed algorithm as mentioned in 2.2.1.

3. Experiments and results

We divided the experiment into two parts. For the first experiment, we chose a test image from the training set which consists of 20 images per person. For the second experiment, we chose a test image from the training database, thus the remaining images in the training database became a training set which consists of 19 images per person. In comparison, we gave the mean of each individual that represents the image of each individual. We use Minkowski distance, Manhattan distance, Euclidean distance, Angle-based distance and Canberra distance to verify the face recognition.

The first experiment: Image in the training set

For this experiment, the recognition results for the test image in the training set are as shown in Table 1.

Table 1 Recognition rate with test images in the training set

Distance \ Database	Recognition rate (%)		
	Essex Faces94 (Male)	**Essex Faces94 (Female)**	**Essex Faces94 (Male Staff)**
Minkowski (p=0.5)	70.80	84.21	95.00
Manhattan	71.68	89.47	95.00
Euclidean	70.80	89.47	95.00
Angle-based	37.17	52.63	95.00
Canberra	70.80	84.21	95.00
Proposed Algorithm 1	69.03	89.47	95.00
Proposed Algorithm 2	72.57	89.47	100

The second experiment: Image is not in the training set

The recognition results for the different test images in the training set are as shown in Table 2.

Table 2 Recognition rate with test images is not in the training set

Distance \ Database	Recognition rate (%)		
	Essex Faces94 (Male)	**Essex Faces94 (Female)**	**Essex Faces94 (Male Staff)**
Minkowski (p=0.5)	69.03	84.21	95.00
Manhattan	71.68	89.47	95.00
Euclidean	69.91	89.47	95.00
Angle-based	38.05	52.63	90.00
Canberra	70.80	84.21	95.00
Proposed Algorithm 1	66.37	89.47	95.00
Proposed Algorithm 2	72.57	89.47	95.00

Database description

We evaluated the proposed algorithms based on three datasets from the face94 face database [7], which is a face database constructed by Dr. Libor Spacek. It is a part of a collection of facial images. This collection contains three folders of images face94 (Male), face94 (female) and face94 (male staff) as shown in Table 3.

Table 3 Face Recognition Databases

Database	Image size	Number of subject	Number of samples per subject	Test image per subject
Essex Faces94 (Male)	180 × 200	113	20	1
Essex Faces94 (Female)	180 × 200	19	20	1
Essex Faces94 (Male Staff)	180 × 200	20	20	1

4. Discussion

Since the training set has many data of face we need to find a data that represents all of data in order to verify the accuracy of face recognition faster. We propose a new algorithm by using a circle to be representative such as the radius can compute by the maximum Euclidean distance between any two vectors in each pair of individual images and center computes from the center of the two vectors of the radius. After we obtain representative of each individual, we compared 5 distance measures with two proposed algorithms and verification algorithm based on circle. The results show that the proposed algorithm 2 is the best measure both in Table 1 and Table 2. This study also reveal the advantage of the verification algorithm that it is easier to understand, fast and high performance. However, there are still some scopes for improvement of the proposed algorithm in order to get better results in verification.

5. Conclusions

In this paper, we presented face recognition of portrait photographs which are in the same size by using Principal Components Analysis in order not only to get the feature vector and verification algorithm based on circle, but also to define a new mean face from image vector of training set. Moreover, we compare verification of recognition between the proposed algorithms and 5 distance, the results show that the proposed algorithm is the best. Whether the test image is in the training set or not.

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