Evaluation of Face Recognition Techniques for Facial Expression Analysis

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Abstract

Face recognition is an important area in the field of biometrics. It has been an active area of research for several decades, but still remains a challenging problem because of the complexity of the human face. Many recognition methods have been proposed, however, most of them are not able to make use of local salient features to effectively capture the face information. Generally, the performance of face recognition system is determined by extracting feature vector exactly and classifying them into a class accurately. Therefore, it is necessary to pay attention to feature extraction method and classifier. In this paper, we compare and analyze the Principle Component Analysis (PCA), Two Dimensional Principle Component Analysis (2DPCA) and Histogram of Oriented Gradients (HOG) based on the recognition rate and access time from the experimental results. The experiment is done on three sets of databases: the AT&T, Yale and own created face database.

Keywords- Face Recognition, Evaluation, HOG, PCA, 2DPCA

1. Introduction

Face recognition is very important in pattern recognition and image processing which gained much attractive attentions in recent years. It has many applications in a variety of fields, especially in the security systems. Given still or video images of a scene, the recognition system can identify or verify one or more person in the scene using a stored database of faces [1]. The general method of face recognition is shown in Figure 1.

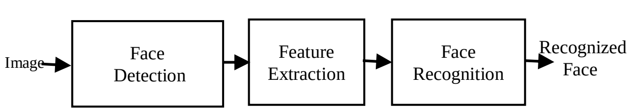

Figure 1. The general method of face recognition system

There are two kinds of algorithms in 2D face recognition field: local feature-based (face components, such as eyes, nose, mouth, etc.) and global feature-based (holistic). Global feature-based methods have been proven to be very successful in face recognition area [2]. These methods are distinctive, robust to occlusion and do not require segment the component parts from face. Many algorithms, for example, Eigenface, Fisherface, etc., are developed and performed well under some limitations, but the variation of faces, such as expression, pose, age, lighting, etc., affects the performance of recognition. HOG is very useful in face and facial expression recognition. It supports irregular shapes and partial occlusions. It is a simple but powerful approach to build robust HOG descriptors. Principal Component Analysis (PCA) [3] is a classical algorithm for face recognition [5]. Two dimensional PCA (2DPCA) [4] is an improvement of PCA in terms of both recognition rate and computation efficiency. Therefore, it's more important to evaluate the HOG algorithm with the other two algorithms using standard methodology.

The rest of this paper is organized as follows: Section 2 gives an overview of the related works. Section 3 presents background theory. Section 4 presents experimental setup. Section 5 presents experiment result and analysis. Section 6 closes with a conclusion and future work.

2. Related works

In [1], Principal Component Analysis is widely used linear subspace image based dimensionality reduction technique. Eigen features calculated here are eigenfaces. Face image, in the form of image vector, is appended column wise. Then the average vector is computed that represents a mean face. Also, a difference vector is computed for each user to qualify the differences to the mean face. Then the covariance matrix of the difference vectors is computed. Finally, principal axes can be obtained by eigen decomposition of covariance matrix. The first N eigenvectors presenting the highest eigen values will be retained and represents the most significant features of faces. Finally, each user model is represented as a linear combination (weighted sum) of coefficients corresponding to each eigenface.

In [2], Two-dimensional Principal Component Analysis (2DPCA) has been proposed and been widely applied in face recognition. Different from the classical PCA, 2DPCA takes a 2D-matrix-based representation model rather than simply the 1D-vector-based one. And image covariance matrix is constructed directly from the 2D image matrices. Since the size of image covariance matrix is much smaller, 2DPCA can evaluate the matrix accurately and computational more efficiently than PCA.

In [4], the authors examined two face recognition systems, PCA and 2DPCA algorithms. The feature projection vectors obtained through the PCA and 2DPCA methods and these vectors are applied to test image. The systems used Euclidean Distance based classifier. The results show that recognition accuracy is depended on the number of training sample and number of largest eigenvalues. Additionally, the recognition performance of 2DPCA is higher than the PCA. PCA is the high computational complexity.

In [5], the authors examined PCA and 2DPCA methods was used for face recognition and tested on face image database to evaluate the performance of two algorithms under conditions where the system will recognize faces which are invariant to expression and developing a new feature set to detect mixed emotions-such as happiness and surprise. 2DPCA is much better than PCA. 2DPCA is based on the image matrix, it is simpler and more straightforward to use for image feature extraction and is computationally more efficient than PCA and it can improve the speed of image feature extraction significantly. 2DPCA needs more coefficients for image representation than PCA.

In [6], the authors analyzed the method of Principal Component Analysis (PCA) and its performance when applied to face recognition. This algorithm creates a subspace (face space) where the faces in a database are represented using a reduced number of features called feature vectors. The PCA technique has also been used to identify various facial expressions such as happy, sad, neutral, anger, disgust, fear etc. The results show that PCA based methods provide better face recognition with reasonably low error rates. This is mainly because principal components have proven the capability to provide significant features and reduce the input size of the images.

In [7], the authors presented an overview of different face recognition techniques, studied and analyzed of the face recognition rate, failure rate, training time and recognition time of various face recognition algorithms like PCA, LDA, SVM, ICA and SVD. The results show that SVD recognition rate is highest as well as training time. But SVD consume more recognition time on comparison to PCA, LDA, ICA and SVM.

3. Background theory

3.1. Principle Component Analysis (PCA)

PCA was invented in 1901 by Karl Pearson. It involves a mathematical procedure that transforms the 2D image into 1D feature vector in subspace. This subspace is also called eigenspace in which the covariance matrix is obtained as a result of facial features. The subspace formed as a result of PCA conversion makes use of facial feature to characterize different reference images or eigenfaces from the sample dataset. PCA, also known as Karhunen-Loeve (KL) transformation or eigenspace is basically a statistical technique used in image recognition and classification. It is also used for image compression. It provides the linear arrangement of template.

The main advantage of this approach is that it is easy to implement, fast and less expensive than any other feature classifier. But it endows invariance information in the presence of varying lighting and scaling condition. The main idea of principal component analysis is to find the vectors which best account for the distribution of the face images within the entire image space. Steps for Feature Extraction:

1. The first step is to obtain a set S with M face images. Each image is transformed into a vector of size N and placed into the set.

$$S = \{ \Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M \} \quad (1)$$

2. Second step is to obtain the mean image Ψ.

Mean face: $$\Psi = \frac{1}{M}\sum_{n=1}^{M} \Gamma_n \quad (2)$$

3. Then find the difference Φ between the input image and the mean image

$$\Phi_i = \Gamma_i - \Psi \quad (3)$$

4. Next seek a set of M orthonormal vectors, μ_n, which best describes the distribution of the data. The k^{th} vector, μ_k, is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M} (\mu_k^T \Phi_n)^2 \quad (4)$$

is a maximum, subject to

$$\mu_1^T \mu_k = \delta_{1k} = \begin{cases} 1 & \text{If } 1=k \\ 0 & \text{Otherwise} \end{cases}$$

Where μ_k and λ_k are the eigenvectors and eigenvalues of the covariance matrix C

5. The covariance matrix C has been obtained in the following manner

Covariance Matrix: $$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T \quad (5)$$

$$= AA^T$$

$$A = \{\Phi_1, \Phi_2, \Phi_3, \ldots, \Phi_n\}$$

6. To find eigenvectors from the covariance matrix is a huge computational task. Since M is far less than N^2 by N^2, we can construct the M by M matrix $L= A^TA$

7. Find the M eigenvector, v_l of L.

8. These vectors (v_l) determine linear combinations of the M training set face images to form the eigenfaces μ_1

Eigenface: $\mu_1 = \sum_{k=1}^{M} v_{1k}\Phi_k \quad l = 1,2,..,M$ (6)

9. Project each of the original images into eigenspace. This gives a vector of weights representing the contribution of each eigenfaces to the reconstruction of the given image.

$$\omega_k = \mu_k^T(\Gamma - \Psi)$$

$$\Omega^T = [\omega_1, \omega_2, \omega_3, \ldots., \omega_M]$$

Where μ_k is the k[th] eigenvector and ω_k is the k[th] weight in the vector. $\Omega^T = [\omega_1, \omega_2, \omega_3, \ldots., \omega_M]$

3.2. 2D Principal Component Analysis (2DPCA)

A straightforward image projection technique called two-dimensional principal component analysis (2DPCA) is developed for image feature extraction. In contrast to PCA's covariance matrix, the image covariance matrix's size using 2DPCA is much smaller. As a result, 2DPCA has two important advantages over PCA. First, it's easier to evaluate the covariance matrix accurately. Second, less time is required to determine the corresponding eigenvectors they extract the features from the 2DPCA matrix using the optimal projection vector. The vector's size is given by the image's size and the number of coefficients.

Two Dimensional PCA (2DPCA) is an improvement of PCA. 2DPCA does not need to transform 2D face image to 1D vector. However, one disadvantage of 2DPCA (compared to PCA) is that more coefficients are needed to represent an image.

Training Algorithm:

Input: training images

Output: image features, eigenvector matrix, feature matrix

Method

a) Apply pre-processing techniques to the M training images

b) Obtain the average image A of all training samples:

$$\overline{A} = \frac{1}{M}\sum_{i=1}^{M} A_i \quad (7)$$

c) Estimate the image covariance (scatter) matrix G:

$$G_t = \frac{1}{M}\sum_{i=1}^{M}(A_i - \overline{A})^T (A_i - \overline{A}) \quad (8)$$

d) Compute d orthonormal vectors $X_1, X_2, \ldots, X_d$ corresponding to the d largest eigenvalues of G. $X_1, X_2, \ldots, X_d$ construct a d-dimensional projection subspace.

The optimal projection vectors of 2DPCA, X_1, X_2, ., X_d are used for feature extraction.

Project A_1; : : : ;A_M on each vector X_1, …, X_d to obtain the principal component vectors:

$$Y_i^j = A_j X_i \qquad i = 1; : : : ; d; j = 1; : : : ;M \quad (9)$$

3.3. Histogram of Oriented Gradients (HOG)

The Histogram of Oriented Gradients is a feature based descriptor that was initially proposed for pedestrian detection by Dalal and Triggs. HOG is very useful in facial expression recognition. It supports irregular shapes and partial occlusions. It is a simple but powerful approach to build robust HOG descriptors.

HOG algorithm consists of three steps:

1) Gradient Computation.
2) Orientation Binning.
3) Block Normalization.

Histogram of Oriented Gradients (HOG) is illumination invariant and is found by using magnitude/pixel orientation. Firstly, X and Y gradients of the image is calculated using gradient filter (G_x = [-1, 0, 1], G_y = [-1, 0, 1]). Where G_x is the horizontal kernel mask and G_y

Is the vertical kernel mask.

- Centered $f'(x) = \lim_{h\to 0}\left(\frac{f(x+h)-(f(x-h)}{2h}\right)$ (10)
- Gradient
  - Magnitude $s = \sqrt{S_x^2 + S_y^2}$ (11)
  - Orientation $\theta = \arctan(\frac{S_y}{S_x})$ (12)

Then using these gradients, corresponding magnitude and angle orientations [ranges 0°-180° (unsigned) and 0° - 360° (signed)] are calculated. The angular orientations are divided into fragments/parts which are called bins. Secondly, the resulting gradient image is divided into smaller non overlapping spatial regions called cells.

4.4. Performance formulas

Recognition performance has many measurement standards. The most important and popular formula is recognition rate in equation (14).

$$\text{Recognition rate\%} = \frac{\text{the number of recognized images}}{\text{the number of testing images}} * 100 \quad (14)$$

5. Experiment result and analysis

In order to evaluate the performance of all the 3 algorithms on the same face database and the effect for different face database.

The experiments were carried out repeatedly as follows: First, the global feature-based features were calculated in training set and testing set; Second, each testing image were matched with the training set by its distance metrics; Third, the average recognition rate and run time were calculated by testing 10 times independently. The results were analyzed in comparison to the PCA, 2DPCA and HOG.

Table 1. Comparison for the recognition rate and access time of PCA, 2DPCA and HOG on AT&T face database

Method	No. of training	No. of test	Recognition rate	Access time
PCA	200	200	78.0%	6.1 sec
2DPCA	200	200	91.5%	5.8 sec
HOG	200	200	87.5%	68.5 sec

Table 2. Comparison for the recognition rate and access time of PCA, 2DPCA and HOG on Yale face database

Method	No. of training	No. of test	Recognition rate	Access time
PCA	75	75	80%	12.5 sec
2DPCA	75	75	86.7%	10.01sec
HOG	75	75	92%	59.26 sec

Table 3. Comparison for the recognition rate and access time of PCA, 2DPCA and HOG on own created face database.

Method	No. of training	No. of test	Recognition rate	Access time
PCA	25	25	100%	1.14 sec
2DPCA	25	25	100%	0.73 sec
HOG	25	25	100%	3.55 sec

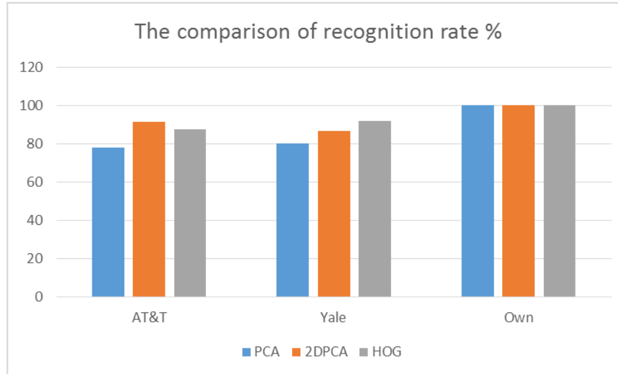

Figure 5. Recognition rate

Figure 5 illustrates the recognition accuracy of PCA, 2DPCA and HOG from each test. This figure indicates that the performance of 2DPCA and HOG are much better than PCA under conditions recognize faces which are invariant to expression and developing a new feature set to detect mixed emotions – such as happiness and surprise.

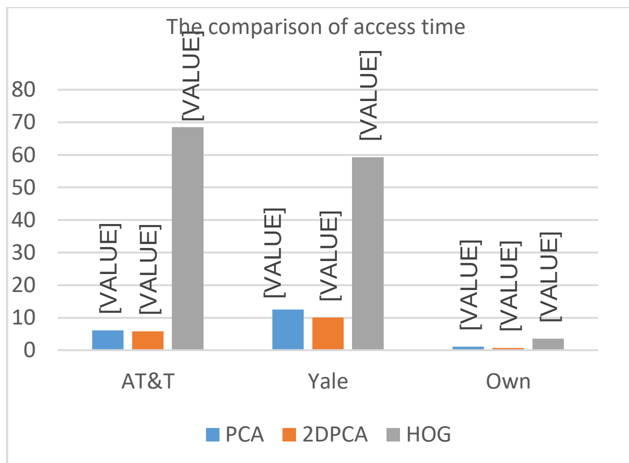

Figure 6. Access time

Figure 6 illustrates the access time of PCA, 2DPCA and HOG from each test. This figure indicates that 2DPCA is computationally more efficient than PCA and HOG. And then it can improve the speed of image feature extraction significantly.

6. Conclusion and Future Work

The paper presents three feature extraction methods: PCA, 2DPCA and HOG. The feature extracted by each of them are used to classify the faces. AT&T face database, Yale and own created datasets are used. Euclidean distance is used to recognize face. The result is compared with different datasets. Experiments demonstrated the recognition rate of HOG is nearly equal with 2DPCA but HOG needs more coefficient and more take times to

These cells can be rectangular or circular. Each pixel in the cell casts a vote that is weighted by its gradient magnitude and contributes to an orientation aligned with the closest bin in the range 0°-180° (unsigned) or 0°-360° (signed). The orientation of bins are evenly spaced and generate an orientation histogram. This step is known as Orientation Binning. After Orientation Binning, the cell histograms are normalized for better invariance to illumination and contrast. This requires grouping of cells into larger and spatially connected blocks. The Histogram of Oriented Gradients descriptor is obtained by concatenating the components of the cell histograms which are normalized from all the block regions. These blocks overlap typically, means that every cell contributes to the final descriptors at least more than once. There are two kinds of block geometries: Rectangular HOG and Circular HOG blocks. R-HOG blocks are rectangular or square grids, which are characterized by three parameters: cells per each block, pixels per each cell and channels per each histogram. In the human face detection experiment conducted by Dalal et.al., the most favorable parameters were observed to be four number of 8x8 pixel cells per each block (16x16 pixels per block) with 9 histogram channels. The R-HOG blocks are quite similar to the SIFT descriptors.

3.4. Classification

Testing image can be classified with training images by calculating the distance or similarity measures between their corresponding feature vectors X and Y; the smaller the distance between the feature vectors, the more similar are the faces. This paper define a simple similarity score to measure the extent to which the face is recognized and it is calculated as

Euclidean Distance $$d(X,Y) = \sqrt{\sum_{i=1}^{n}(X_i - Y_i)^2} \quad (13)$$

Where X, Y are in the data set X and X_i, Y_i are the i^{th} coordinates of X and Y. This measures the dissimilarity on X.

4. Experimental setup

Face recognition home page [8] supplies over 10 face databases to test the performance about different aspects of faces. In order to test the effect of the number of training images per person, a large range of images per person are needed. Therefore, the two popular and classical face database, AT&T and Yale, are selected. This paper analyzed and classified them according to the main characteristics of databases, such as pose subsets, expression subsets, etc. In this paper, experiments are based on AT&T face database, Yale face database and own created database are used.

4.1. AT&T face database

AT&T face database contains 40 distinct persons, each person having ten different face images. There are 400 face images in total, with 256 gray and the resolution of 92x112. These face images are attained in different situations, such as different time, different angles, different expression (closed eyes/open eyes, smile/surprise/angry/happy etc.) and different face details (glasses/no glasses, beard/no beard, different hair style etc.). Figure 2 shows the pictures of two persons with 10 pictures per person on AT&T database.

Figure 2. Sample face images in AT&T database.

4.2. Yale face database

There are 15 persons with 10 different poses, under 64 different illumination conditions. The size of picture is 480x640. Figure 3 shows the pictures of two persons with 11 pictures per person on Yale database.

Figure 3. Sample face images in Yale database.

4.3. Own created face database

There are 5 persons with 10 different poses, under different situations, such as different angles, different expression and illumination conditions. The size of picture is 135 x 112 . Figure 4 shows the pictures of two persons with 10 pictures per person on own face database.

Figure 4. Sample face images in own created face database.

access. Future work is to get less time for computation, reduce dimension, consume less memory and increase rate for recognition

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