Face Recognition using Principle Component Analysis with Different Distance Classifiers

Hussein Rady

El-Shorouk Academy, Higher Institute for Computer & Information Technology, Egypt.

Summary
Face recognition has received substantial attention from researchers in biometrics, pattern recognition field and computer vision communities. Face recognition can be applied in Security measure at Air ports, Passport verification, Criminals list verification in police department, Visa processing, Verification of Electoral identification and Card Security measure at ATM's. Principal Component Analysis (PCA)is a technique among the most common feature extraction techniques used in Face Recognition. In this paper, a face recognition system for personal identification and verification using Principal Component Analysis with different distance classifiers is proposed. The test results in the ORL face database produces interesting results from the point of view of recognition success, rate, and robustness of the face recognition algorithm. Different classifiers were used to match the image of a person to a class (a subject) obtained from the training data. These classifiers are: the City-Block Distance Classifier, the Euclidian distance classifier, the Squared Euclidian Distance Classifier, and the Squared Chebyshev distance Classifier. The Euclidian Distance Classifier produces a recognition rate higher than the City-Block Distance Classifier which gives a recognition rate higher than the Squared Chebyshev Distance Classifier. Also, the Euclidian Distance Classifier gives a recognition rate similar to the squared Euclidian Distance Classifier.

Keywords:
Face Recognition, Eigenfaces, Principal Component Analysis, Distance Measures.

1. Introduction

Human face recognition, as one of the most successful applications of image analysis and understanding, has received significant attention in the last decade[21]. Despite the fact that there are more reliable biometric recognition techniques such as fingerprint and iris recognition, these techniques are intrusive and their success depends highly on user cooperation, since the user must position her eye in front of the iris scanner or put her finger in the fingerprint device. On the other hand, face recognition is non-intrusive since it is based on images recorded by a distant camera, and can be very effective even if the user is not aware of the existence of the face recognition system. The human face is undoubtedly the most common characteristic used by humans to recognize other people and this is why personal identification based on facial images is considered the friendliest among all biometrics[1].

Within computer vision, pattern recognition and biometrics, face recognition has become increasingly relevant in today's society. The recent interest in face recognition can be attributed to the increase of commercial interest and the development of feasible technologies to support the development of face recognition. Major areas of commercial interest include biometrics, law enforcement and surveillance, human-computer interaction, multimedia management (for example, automatic tagging of a particular individual within a collection of digital photographs) smart cards, passport check, Criminal investigations, access control. The interest in face recognition for biometric authentication, in particular, has risen rapidly mainly due to several factors. The first one is the rising public concern for security especially in public facilities such as airports. The second factor is the rising need for verifiable identity over the internet due to the rise in internet-based e-commerce. And finally, the use of face recognition in biometric authentication is viewed to be one of the least intrusive methods while retaining a high level of accuracy. Unlike other forms of identification such as fingerprint analysis and iris scans, face recognition is user-friendly and non-intrusive. Possible scenarios of face recognition include: identification at front door for home security, recognition at ATM or in conjunction with a smart card for authentication, video surveillance for security . With the advent of electronic medium, especially computer, society is increasingly dependent on computer for processing storage and transmission of information[1, 2, 3, 4, 5, 6, 13, 17, 18, 19, 25, 32].

Principal Component Analysis (PCA) is one of the most popular appearance-based methods used mainly for dimensionality reduction in compression and recognition problem. PCA is known as Eigenspace Projection which is based on linearly Projection the image space to a low dimension feature space that is known as Eigenspace. It tries to find Eigen vectors of Covariance matrix that corresponds to the direction of Principal Components of original data[6]. The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called "eigenfaces," which may be thought of as the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the eigenfaces ("face space") and then

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classifying the face by comparing its position in face space with the positions of known individuals[19].

One of the most popular techniques for linear transformation in feature space is PCA. PCA reduces the dimensions by rotating feature vectors from a large highly correlated feature space (*image space*) to a smaller feature space (face space) that has no sample covariance between the features. After applying PCA to reduce the face space to a lower dimensional manifold, a single nearest neighbor classifier is typically used[22, 24]. PCA can not only decrease computational complexity with a linear transform, but also make the distribution of face image data more compact for classification, it have become popular feature extraction methods for face recognition[16]. On the other hand, PCA method can not only effectively reduce the dimension of human face images, but also retain its key identifying information[15].

We will now introduce some terms and notation from biometrics that will be used throughout the paper. **Subject**: A person or a subject in the training set is similar to a class or concept in data. This person can be associated with multiple images in the training set; **Training set**: The training set is defined to be all the images of subjects that are available for constructing the face space; **Gallery set**: Gallery is the set of subjects enrolled in the database and can either be the same as the training set or different. Due to a lack of enough data, the gallery images are often used as the training set for constructing the face space; **Probe set**: Probe set is the "testing" set. The images in the probe set are typically of the same subjects who are in the gallery set, but are taken at a later point in time. The goal is to project the probe set into the trained face space and correctly match it with the projected representative in the gallery[24].

The remainder of this paper is organized as follows: section 2 introduces an idea on the Face Recognition. The Principal Component Analysis is presented in Section 3. Distance Metrics for Classification are introduced in section 4. Experimental Results are discussed in section 5. The Conclusions are outlined in section 6.

2. Face Recognition

Face recognition is a form of biometric identification. A *biometric* is, "Automated methods of recognizing an individual based on their unique physical or behavioral characteristics." The process of facial recognition involves automated methods to determine identity, using facial features as essential elements of distinction. The automated methods of facial recognition, even though work very well, do not recognize subjects in the same manner as a human brain. The way we interact with other people is firmly based on our ability to recognize them. One of the main aspects of face identification is its robustness. Least obtrusive of all biometric measures, a face recognition system would allow a user to be identified by simply walking past a surveillance camera. robust face recognition scheme require both low dimensional feature representation for data compression purposes & enhanced discrimination abilities for subsequent image retrieval. The representation methods usually start with a dimensionality reduction procedure since the high dimensionality of the original visual space makes the statistical estimation very difficult & time consuming[11, 13, 27].

Face recognition is a study of how machines can recognize face, a task that humans perform naturally and effortlessly throughout lives[3]. A face recognition system identifies faces in images and videos automatically using computers. It consists of four parts: face detection, face alignment, facial feature extraction, and face classification. *Face Detection*: provides information about the location and scale of each detected face. In the case of video, the found faces may be tracked. In *face alignment*, facial components, such as eyes, nose, and mouth, and facial outline are located, and thereby the input face image is normalized in geometry and photometry. In *feature extraction*, features useful for distinguishing between different persons are extracted from the normalized face. In *face classification*, the extracted feature vector of the input face is matched against those of enrolled faces in the database, outputting the identity of the face when a match is found with a sufficient confidence or as an unknown face otherwise[28].

Depending on the application, a face recognition system can be working either on identification or verification mode. In a face identification application, the system recognizes an individual by matching the input image against images of all users in a database and finding the best match. In a face verification application the user claims an identity and the system accepts or rejects his(her) claim by matching the input image against the image that corresponds to this specific identity, which can be stored either in a database or an identification card (e.g. smart card). In other words, face identification is a one-to-many comparison that answers the question "Who is the person in the input image? Is he(she) someone in the database?", while face verification is a one-to-one comparison that answers the question "Is the person in the input image who he(she) claims to be?"[26].

A face recognition system usually consists of the following four modules[28]:

1. *Sensor module*, which captures face images of an individual. Depending on the sensor modality, the

acquisition device maybe a black and white or color camera, a 3D sensor capturing range (depth) data, or an infrared camera capturing infrared images.
2. *Face detection and feature extraction module*. The acquired face images are first scanned to detect the presence of faces and find their exact location and size. The output of face detection is an image window containing only the face area. Irrelevant information, such as background, hair, neck and shoulders, ears, etc are discarded. The resulting face image is then further processed to extract a set of salient or discriminatory, local or global features, which will be used by the face classifier to identify or verify the identity of an unknown face. Such features maybe the measurements of local facial features (such as eyes, nose, mouth, etc) characteristics or global features such as transformation coefficients of global image decomposition. These features constitute the template or signature uniquely associated with the image.
3. *Classification module*, in which the template extracted during step 2 is compared against the stored templates in the database to generate matching scores, which reveal how identical the faces in the probe and gallery images are. Then, a decision-making module either confirms (verification) or establishes (identification) the user's identity based on the matching score.
4. *System database module*, which is used to extract and store the templates of enrolled users. This module is also responsible for enrolling users in the face recognition system database. During the enrolment of an individual, the sensor module records images of his (her) face. These images are called gallery images and they are used for training the classifier that will perform face recognition. Most commonly, several frontal neutral views of an individual are recorded, but often face images depicting different facial expressions (neutral, smile, laugh, anger, etc) and presence (or non-) of glasses are also acquired.

In more details, *face detection* is the first stage of an automatic face recognition system, since a face has to be located in the input image before it is recognized. A definition of face detection could be: given an image, detect all faces in it (if any) and locate their exact positions and size. Usually, face detection is a two-step procedure: first the whole image is examined to find regions that are identified as "face". After the rough position and size of a face are estimated, a localization procedure follows which provides a more accurate estimation of the exact position and scale of the face. So while face detection is most concerned with roughly finding all the faces in large, complex images, which include many faces and much clutter, localization emphasizes spatial accuracy, usually achieved by accurate detection of facial features.

Face detection algorithms can be divided into four categories according to[1, 28]:

1. *Knowledge-based methods* are based on human knowledge of the typical human face geometry and facial features arrangement. Taking advantage of natural face symmetry and the natural top-to-bottom and left-to-right order in which features appear in the human face, these methods find rules to describe the shape, size, texture and other characteristics of facial features (such as eyes, nose, chin, eyebrows) and relationships between them (relative positions and distances).
2. *Feature invariant approaches*[26, 32] aim to find structural features that exist even when the viewpoint or lighting conditions vary and then use these to locate faces. Different structural features are being used: facial local features, texture, and shape and skin color. Local features such as eyes, eyebrows, nose, and mouth are extracted using multi-resolution or derivative filters, edge detectors, morphological operations or thresholding. Skin color is another powerful cue for detection, because color scene segmentation is computationally fast, while being robust to changes in viewpoint, scale, shading, to partial occlusion and complex backgrounds. The color-based approach labels each pixel according to its similarity to skin color, and subsequently labels each sub-region as a face if it contains a large blob of skin color pixels . There are also techniques that combine several features to improve the detection accuracy. Usually, they use features such as texture, shape and skin color to find face candidates and then use local facial features such as eyes, nose and mouth to verify the existence of a face.
3. *Template-based methods*. To detect a face in a new image, first the head outline, which is fairly consistently roughly elliptical is detected using filters, edge detectors, or silhouettes. Then the contours of local facial features are extracted in the same way, exploiting knowledge of face and feature geometry. Finally, the correlation between features extracted from the input image and predefined stored templates of face and facial features is computed to determine whether there is face present in the image.
4. *Appearance-based methods*[6, 10, 14]. While template-matching methods rely on a predefined template or model, appearance-based methods use large numbers of examples (images of faces and \ or facial features) depicting different variations (face shape, skin color, eye color, open\closed mouth, etc).

Face detection can be viewed as a pattern classification problem with two classes: “face” and “non-face”. The “non-face” class contains images that may depict anything that is not a face, while the “face” class contains all face images. Well-known appearance-based methods used for face detection are eigenfaces ,neural networks, support vector machines and hidden Markov models.

The process of face recognition mainly contains two steps. The first one is face detection and localization, in which faces have to be found in the input image and separated from the background. The second one is face feature extraction and recognition. Face feature extraction is very difficult because of variable situations such as expression, location, direction and light etc[20].

3. Principle Component Analysis

Feature extraction for face representation is one of the central issues to face recognition system. Among various solutions to the problem, the most successful seems to be those appearance-based approaches, which generally operate directly on images or appearances of face objects and process the image as two-dimensional patterns. The main trend in feature extraction has been representing the data in a lower dimensional space computed through a linear or non-linear transformation satisfying certain properties. Statistical techniques have been widely used for face recognition and in facial analysis to extract the abstract features of the face patterns. Principal Component Analysis is a main technique used for data reduction and feature extraction in the appearance-based approaches. Eigenfaces built based on these technique, has been proved to be very successful[14].

Principal Component Analysis is one of the most valuable results from applied linear algebra. PCA is used abundantly in all forms of analysis – from neuroscience to computer graphics – because it is simple, non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified structure that often underlie it [26]. It is one of the most successful techniques that have been used in image recognition and compression. PCA is a statistical method under the broad title of *factor analysis*. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables.

PCA is a statistical dimensionality-reduction method, which produces the optimal linear least-squares decomposition of a training set[9]. PCA is appropriate when we have obtained measures on a number of observed variables and wish to develop a smaller number of unknown variables that will account for most of the variance in the observed variables. PCA generates a set of orthogonal axes of projections known as the eigenvectors, of the input data distribution in the order of decreasing variances[18]. The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors)[8].

The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory, communications, etc[20].

3.1 The Eigenface approach

In the language of information theory, we want to extract the relevant information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded similarly. A simple approach to extracting the information contained in an image of a face is to somehow capture the variation in a collection of face images, independent of any judgment of features, and use this information to encode and compare individual face images. In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as a point (or vector) in a very high dimensional space. The eigenvectors are ordered, each one accounting for a different amount of the variation among the face images. These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as a sort of ghostly face which we call an eigenface. Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can also be approximated using only the "best" eigenfaces – those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images. The best M eigenfaces span an M-dimensional subspace – "face space" – of all possible images[7, 19, 23, 26].

On the other hand, the PCA approach transforms face images into a small set of characteristic feature images called "eigen faces", which are principal components of the initial training set of face images. Eigen faces are nothing but a set of basic vectors. Each of these basic vectors can be displayed as a ghostly face; often referred to as an eigen face. Concepts of eigen faces can be extended to eigen features, such as eigen eye, eigen mouth and eigen nose. In the Eigen feature representation the equivalent distance from the feature space is effectively used for detection of features. In case of a new input image, the distance from the feature space is computed at each pixel, and the minimum of the distance map is considered as the best match. However, Eigen feature approaches commonly assume that the images in low dimension cannot scale up properly[26].

3.2 The PCA algorithm

PCA method can not only effectively reduce the dimension of human face images, but also retain its key identifying information[15]. In mathematical terms, recognition of images using PCA takes three basic steps. The transformation matrix is first created using the training images. Next, the training images are projected onto the matrix columns. Finally, the test images are identified by projecting these into the subspace and comparing them with the trained images in the subspace domain[11]. The PCA algorithm is shown in the following steps[7, 8, 10, 12, 23]:

1. Let a face image X(x, y) be a two dimensional m x n array of intensity values. An image may also be considering the vector of dimension m n . Let the training set of images $\{X_1, X_2, X_3, \ldots, X_N\}$. The average face of the set is defined by

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (1)$$

2. Calculate the Covariance matrix to represent the scatter degree of all feature vectors related to the average vector.
   The Covariance matrix C is defined by

$$C = \frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})(X_i - \bar{X})^T \qquad (2)$$

3. The Eigenvectors and corresponding eigenvalues are computed by using

$$CV = \lambda V \qquad (3)$$

   Where V is the set of eigenvectors associated with its eigenvalue λ.

4. Sort the eigenvector according to their corresponding eigenvalues from high to low.
5. Each of the mean centered image project into eigenspace using

$$W_i = V_i^T (X_i - \bar{X}) \qquad (4)$$

6. In the testing phase each test image should be mean Centered, now project the test image into the same eigenspace as defined during the training phase.
7. This projected image is now compared with projected training image in eigenspace. Images are compared with similarity measures. The training image that is closest to the test image will be matched as used to identify.

4 Distance Classifiers

Most face recognition methods from the last decade make decisions based on a *distance measure*. Images are projected down to a lower-dimensional feature space. Distances between feature space representations are used as the basis for recognition judgments. For example in an identification task, distance-based algorithms choose the gallery feature that is nearest to the probe feature. Distance measures are the last component of facial recognition. Images are projected into an eigenspace and represented as vectors. The distance between the vectors of two images is the similarity of the images. The dissimilarity distance between the image projection and known projections is calculated, the face image is then classified as one of the faces with minimum distance. On the other hand, classification is performed by comparing the projection vectors of the training face images with the projection vector of the input face image based on one of the distance classifiers between the faces classes and the input face image.

A distance or dissimilarity function on a data set X i.e., $X \times X \rightarrow R$ where R is the set of real numbers, is defined to satisfy the following conditions[29, 30]:

- Symmetry. $d(x_i, x_j) = d(x_j, x_i)$. (5)
- Positivity. $d(x_i, x_j) \geq 0 \;\; \forall\, x_i$ and x_j. (6)
- Triangle inequality.
  $d(x_i, x_j) \leq d(x_i, x_k) + d(x_k, x_j)$ (7)
  $\forall\, x_i, x_j$, and x_k.
  and,
- Reflexivity. $d(x_i, x_j) = 0$ iff $x_i = x_j$. (8)

The most common dissimilarity measures between real-valued vectors used in practice are the weighted l_p metric dissimilarity measures, that is,

$$d_p(x,y) = \left(\sum_{i=1}^{l} w_i |x_i - y_i|^p \right)^{1/p} \quad (9)$$

Where x_i, y_i are the i[th] coordinates of x and y, i = 1,2,…, l, and $w_i \geq 0$ is the i[th] weight coefficient. They are used mainly on real-valued vectors. If $w_i = 1$, i = 1,2,…, l, we obtain the unweighted l_p metric dissimilarity measure:

$$l_p = \left(\sum_{i=1}^{l} |x_i - y_i|^p \right)^{1/p} \quad (10)$$

1) Euclidean Distance Classifier

Euclidean distance is the most common use of distance. When people talk about distance, this is what they are referring to. Euclidean distance, or simply 'distance', examines the root of square differences between the coordinates of a pair of objects. This is most generally known as the Pythagorean theorem. For testing we used the Euclidean distance classifier, for calculating the minimum distance between the test image and image to be recognized from the database. If the distance is small, we say the images are similar and we can decide which the most similar image in the database is. In simpler words, the Euclidean distance between the image projection and known projections is calculated; the face image is then classified as one of these faces with minimum Euclidean distance. Putting p = 2 in equation(10), we obtain the Euclidean distance, d_2 as follows:

$$d_2(x,y) = \sqrt{\sum_{i=1}^{l} (x_i - y_i)^2} \quad (11)$$

Where x, y in the data set X and x_i, y_i are the i[th] coordinates of x and y, respectively. This is a dissimilarity measure on X. The minimum possible distance between two vectors of X is 0 that is $d_0 = 0$ (the distance of a vector from itself).

2) The Squared Euclidean Distance Classifier

Without the square roots, we obtain the Squared Euclidean distance Classifier as follows:

$$d_2(x,y) = \sum_{i=1}^{l} (x_i - y_i)^2 \quad (12)$$

3) City-Block Distance Classifier

City-Block Distance Classifier, Manhattan Distance Classifier, also called, rectilinear distance, L1 distance, L1 norm, Manhattan length. It represents the distance between points in a city road grid. It examines the absolute differences between the coordinates of a pair of objects as follows:

$$d_1(x,y) = \sum_{i=1}^{l} |x_i - y_i| \quad (13)$$

4) Chebyshev Distance Classifier, maximum value distance

In mathematics, Chebyshev distance, Maximum metric, or L_∞ metric is a metric defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension. The Chebyshev distance between two vectors or points x and y, with standard coordinates x_i and y_i, respectively, is:

$$d_{Chebyshev}(x,y) = max_i\,(|x_i - y_i| \quad (14)$$

This equals the limit of the L_p metrics:

$$\lim_{k \to \infty} \left(\sum_{i=1}^{k} |x_i - y_i|^k \right)^{1/k} \quad (15)$$

Hence it is also known as the L_∞ metric.

Taking the squares of equation (14), we obtain the squared Chebyshev Distance Classifier.

Chebyshev distance is also called the Maximum value distance, defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension. In other words, it examines the absolute magnitude of the differences between the coordinates of a pair of objects.

5 Experimental Results

Two factors are important in the process of testing face recognition algorithm. First is the number of classes (different subjects) used for the creation of the face space and second is the number of images of each class used for training. We have performed the experiment with a stored face images and built a system to locate and recognize faces. We have conducted our experiment to assess the performance under known variations of lighting, scale, and orientation.

5.1 Dataset

All face recognition techniques are data set dependent. This is because of the statistical nature of the problem. A technique might perform better under a given set of conditions and may perform poorly for another set of conditions. Therefore, it is necessary to describe the database that is used for the testing of an algorithm.

The Olivetti Research Lab (ORL) Database[4, 17, 20] of face images provided by the AT&T Laboratories from

Fig.1 Part of the Training and testing image set.

Cambridge University has been used for the experiment. It contains slight variations in illumination, facial expression (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses)[31]. It is of 300 images, corresponding to 30 subjects (namely, 10 images for each class). Each image has the size of 112 x 92 pixels with 256 gray levels. Some face images from the ORL database are shown in Figure(1). In this experiment, face recognition with different kinds of poses (views), expressions, varying lighting conditions, accessories and backgrounds are verified.

Figure (2) shows three images such that, the first image is the frontal image, while the second and third are the images of the same subject with different scaling and orientation.

Fig. 2 frontal, different scaling and orientation for the same image.

5.2 Results and Discussion

Figure (3) shows a Schematic diagram of a face recognizer. This illustrated as follows: In the recognition phase (or, testing phase), given a test image of a known person. As in the training phase, we should compute the feature vector of this person using PCA, then compute the

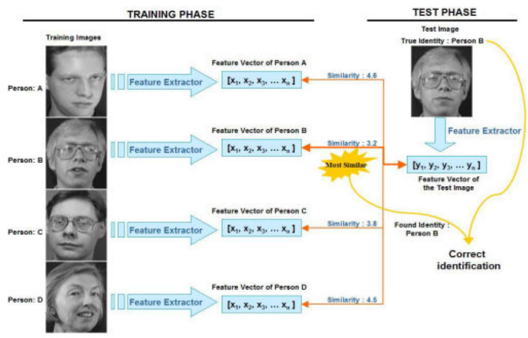

Fig. 3 Schematic diagram of a face recognizer.

similarities between the feature vector of a test image and all the feature vectors in the raining set. The similarities between feature vectors were computed using the 4 distance classifiers discussed in the previous section. On the other hand, recognition is performed by projecting a new image into the subspace spanned by the eigenfaces and then classifying the face by comparing its position in the face space with the positions of the known individuals.

Trained Images

(A) City- Block Distance Classifier.

(B) Euclidian Distance Classifier.

(C): Chebyshev Distance Classifier (squared).

Figure(4): Screen Shots displays full recognitions with the nearest three projected distances. The three images in the right identified from the trained Database.

(A): City-Block Distance Classifier.

(B): Euclidian Distance Classifier.

(C): Chebyshev Distance Classifier (squared).

Figure(5): Screen Shots displays an error recognition in some samples. The three images in the right identified from the trained Database.

In Figure(4), the 4 distance classifier are applied and the verification and recognition was done for the tested image from the testing database in the trained database using the first three consecutive nearest neighbor distances. The identification and recognition occurs with different kinds of poses (views), expressions, varying lighting conditions, accessories and backgrounds.

Figure(5) shows an identification and recognition of two trained images and one of the three images not recognized.Using the City-Block distance classifier, the second trained image were not recognized while using the Euclidian distance classifier and squared Chebysev distance classifier, the third image were not recognized.

From the test set that contains 90 sample (image), these sample was tested using the 4 distance classifiers namely; the City-Block distance classifier, the Squared Euclidian distance classifier, the Euclidian distance classifier, and the squared Chebyshev distance classifier i.e., the test set contain 90*4 = 360 test for all distance classifiers. Table(1) represents the four different nearest Neighbor classifiers, the number of identified images and the recognition rate.

Table(1): the Recognition rate and the number of images identified for all the different classifiers.

NNC	No. of images identified	Recognition Rate
City-Block	78	94.3%
Euclidian	80	95.2%
S. Euclidian	80	95.2%
S.Chebyshev	76	93.3%

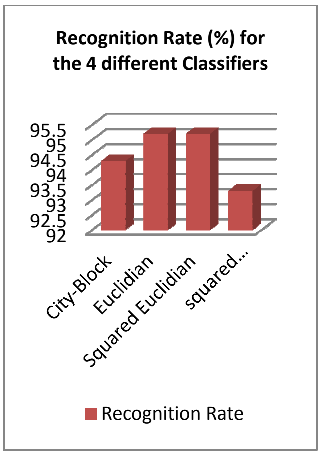

Fig.6 the Recognition Rate for all different Classifiers.

Figure(6) shows a comparison among all different classifiers. It shows that the Euclidian distance classifier and the squared Euclidean distance classifier represents the same recognitions rate and are both better than using the City-Block distance classifier which is better than the squared Chebyshev distance classifier.

The images that were poorly identified by the four different classifiers are shown in figure(7). These images takes the numbers (3), (15), (29), (30), (35), (46), (56), (58), (83) and (84) in the test database that consists of 90 image (sample). All the other images are highly identified for all classifiers.

Figure(7): Images that were poorly identified by the classifiers.

Excluding these images from our calculations (from the test database) we obtain a better results than the results in table(1).

6 Conclusions

Face recognition can be applied in Security measure at Air Ports, Passport verification, Criminals list verification in police department, Visa Processing, Verification of Electoral identification and Card Security measure at ATM's. Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities.

In this paper, face recognition using principal component analysis was implemented using 4 distance classifiers on the ORL database were used to see the performance of the Principal Component Analysis based face recognition system. A system that uses different distance measures for each image will perform better than a system that only uses one. The experiment show that PCA gave better results with Euclidian distance classifier and the squared Euclidian distance classifier than the City-Block distance classifier, which gives better results than the squared Chebyshev distance classifier. On the other hand, the recognition rate using the Euclidian and the

Squared Euclidian distance classifier are the same and is higher than the recognition rate using City-Block distance classifier which is higher than its counterpart using the squared Chebyshev distance classifier.

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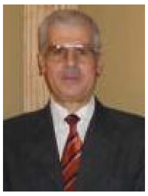

Hussein Rady received the B.Sc degree in Pure Math and Mathematical Statistics 1976, Faculty of Science, Ain Shams Univ. and a Postgraduate diploma in Computer Science 1986, M.Sc degree in computer Science 1991, and PhD degree in Computer Science 2002, ISSR, Cairo University. He is interested in Artificial Intelligence, Machine Learning, Neural Networks, Pattern Recognition, Intelligent Agents, Expert Systems, Mathematics, Statistics.