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EFFECT OF DISTANCE MEASURES IN PCA BASED FACE RECOGNITION

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Abstract— With the growth of information technology there is a greater need of high security, so biometric authentication systems are gaining importance. Face recognition is more used because it's easy and non intrusive method during acquisition procedure. Various methods are used for facial recognition. Principal component analysis (PCA) based systems are used often. In this paper we study 4 distance measures on the FERRET database to see the performance of the principal component analysis (PCA) based face recognition system.

Keywords— Distance measures, Face recognition, ICA, LDA, PCA

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INTRODUCTION

Face recognition is one of the most important biometric which seems to be a good compromise between actuality and social reception and balances security and privacy well. It has a variety of potential applications in information security, law enforcement, and access controls. Facial recognitions systems are used as an additional and mass security measure and are comparable to the other biometric security systems available today such as retina scanners, fingerprint scanners, etc. Research on this technology started in the mid 1960s.

Face recognition system fall into two categories: verification and identification. Face verification is a 1:1 match that compares a face images against a template face images, whose identity is being claimed. On the contrary, face identification is a 1: N problem that compares a query face image against all image templates in a face database. Face localization, feature extraction, and modelling are the major issues in automatic facial recognition.

The first important factor in facial recognition systems is its ability to differentiate between the background and the face. This is especially important when the system has to identify a face within a crowd. The system then makes use of a person's facial features - its peaks and valleys and landmarks and treats these as nodes that can be measured and compared against those that are stored in the system's database. While this information characterizes the underlying physical processes well, it is not available in all cases and is often difficult to compute from images or videos alone. Facial recognition systems are computer programs that are used for automatically identifying a person. This technology works by using several facial features in a person's image and comparing these with existing images in the database.

FACE RECONGNITION TECHNIQUES

The method for acquiring face images depends upon the underlying application. For instance, surveillance applications may best be served by capturing face images by means of a video camera while image database investigations may require static intensity images taken by a standard camera. Some other applications, such as access to top security domains, may even necessitate the forgoing of the nonintrusive quality of face recognition by requiring the user to stand in front of a 3D scanner or an infra-red sensor.

Therefore, depending on the face data acquisition methodology, face recognition techniques can be broadly divided into three categories:

- Those that operate on intensity images,
- Those that deal with video sequences,
- Those that require other sensory data such as 3D information or infra-red imagery.

FACE RECONGNITION FROM INTENSITY IMAGES

There are two face recognition methods for intensity images: feature-based and holistic.

A FEATURED-BASED

In feature-based approaches[15,16,17] first we process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducial marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements. The main advantage offered by the featured-based techniques is that since the extraction of the feature points precedes the analysis done for matching the image to that of a known individual, such methods are relatively robust to position variations in the input image. In principle, feature-based schemes can be made invariant to size, orientation and/or lighting. Other benefits of these schemes include the compactness of representation of the face images and high speed matching. The major disadvantage of these approaches is the difficulty of automatic feature detection and the fact that the implementer of any of these techniques has to make arbitrary decisions about which features are important. After all, if the feature set lacks discrimination ability, no amount of subsequent processing can compensate for that intrinsic deficiency.

B HOLISTIC

Holistic approaches attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. These schemes can be subdivided into two groups: statistical and AI approaches.

Statistical:
In the simplest version of the holistic approaches, the image is represented as a 2D array of intensity values and recognition is performed by direct correlation comparisons between the input face and all the other faces in the database. Though this approach has been shown to work under limited circumstances (i.e., equal illumination, scale, pose, etc.), it is computationally very expensive and suffers from the usual shortcomings of straightforward correlation-based approaches, such as sensitivity to face orientation, size, variable lighting conditions, background clutter, and noise. The major hindrance to the direct matching methods is that they attempt to perform classification in a space of very high dimensionality. To counter this curse of dimensionality, several other schemes have been proposed that employ statistical dimensionality reduction methods to obtain and retain the most meaningful feature dimensions before performing recognition.

Sirovich and Kirby [9,14] were the first to utilize Principal Components Analysis (PCA) to economically represent face images. They demonstrated that any particular face can be efficiently represented along the eigen pictures coordinate space, and that any face can be approximately reconstructed by using just a small collection of eigenpictures and the corresponding projections ('coefficients') along each eigenpicture. Turk and Pentland realized [15] based on Sirovich and Kirby's [9,14] findings, that projections along eigenpictures could be used as classification features to recognize faces. They employed this reasoning to develop a face recognition system that builds eigenfaces, which correspond to the eigenvectors associated with the dominant eigenvalues of the known face (patterns) covariance matrix, and then recognizes particular faces by comparing their projections along the eigenfaces to those of the face images of the known individuals. The eigenfaces define a feature space that drastically reduces the dimensionality of the original space, and face identification is carried out in this reduced space. PCA appears to work well when a single image of each individual is available, but when multiple images per person are present, then Belhumeur et al. argue that by choosing the projection which maximizes total scatter, PCA retains unwanted variations due to lighting and facial expression.

Moses et al. propose Fisher's Linear Discriminant Analysis [18,19] which maximizes the ratio of the between-class scatter and the within-class scatter and is thus purportedly better for classification than PCA method called Fisherfaces, uses subspace projection prior to LDA projection (to prevent the within-class scatter matrix from becoming degenerate), is better at simultaneously handling variations in lighting and expression. Some recent work shows that when the training data set is small, PCA can outperform LDA and also that PCA is less sensitive to different training sets. The standard eigenfaces and the Fisherfaces approaches assume the existence of an optimal projection that projects the face images to distinct non-overlapping regions in the reduced subspace where each of these regions corresponds to a unique subject. However, in reality, that assumption may not necessarily

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be true since images of different people may frequently map to the same region in the face space and, thus, the regions corresponding to different individuals may not always be disjoint. Numerous variations on and extensions to the standard eigenfaces and the Fisherfaces approaches have been suggested since their introduction. Some recent advances in PCA-based algorithms include multi-linear subspace analysis, symmetrical PCA, two-dimensional PCA , eigenbands , adaptively weighted subpattern PCA , weighted modular PCA , Kernel PCA and diagonal PCA . Examples of recent LDA-based algorithms include Direct LDA , Direct-weighted LDA , Nullspace LDA , Dual-space LDA , Pair-wise LDA , Regularized Discriminant Analysis , Generalized Singular Value Decomposition , Direct Fractional-Step LDA , Boosting LDA , Discriminant Local Feature Analysis , Kernel PCA/LDA , Kernel Scatter-Difference-based Discriminant Analysis , 2DLDA , Fourier-LDA , Gabor-LDA , Block LDA , Enhanced FLD , Component-based Cascade LDA , and incremental LDA . All these methods purportedly obtain better recognition results than the baseline techniques. One main drawback of the PCA and LDA methods is that these techniques effectively see only the Euclidean structure and fail to discover the underlying structure if the face images lie on a non-linear submanifold in the image space. Since it has been shown that face images possibly reside on a nonlinear submanifold the eigenvectors found by PCA depend only on pair wise relationships between the pixels in the image database.

However, other methods exist that can find basis vectors that depend on higher-order relationships among the pixels, and it seems reasonable to expect that utilizing such techniques would yield even better recognition results. Independent component analysis (ICA) [13,20] a generalization of PCA, is one such method that has been employed for the face recognition task. ICA aims to find an independent, rather than an uncorrelated, image decomposition and representation. Bartlett et al. performed ICA on images in the FERET database under two different architectures: one treated the images as random variables and the pixels as outcomes; conversely, the second treated the pixels as the random variables and the images as outcomes. Both ICA representations outperformed PCA representations for recognizing faces across days and changes in expression. A classifier that combined both ICA representations gave the best performance.

AI:

AI approaches utilize tools such as neural networks and machine learning techniques to recognize faces. In 50 principal components were extracted and an auto-associative neural network was used to reduce those components to five dimensions. A standard multi-layer perception was exploited to classify the resulting representation. Though favorable results were received, the database used for training and testing was quite simple: the pictures were manually aligned, there was no lighting variation, tilting, or rotation, and there were only 20 people in the database. Weng et al. made use of a hierarchical neural network which was grown automatically and not trained on the traditional gradient descent method. They reported good results on a database of 10 subjects.

The main advantage of the holistic approaches is that they do not destroy any of the information in the images by concentrating on only limited regions or points of interest. This same property is their greatest drawback too, since most of these approaches start out with the basic assumption that all the pixels in the image are equally important. Consequently, these techniques are not only computationally expensive but require a high degree of correlation between the test and training images, and do not perform effectively under large variations in pose, scale and illumination. Several of these algorithms have been modified and/or enhanced to compensate for such variations, and dimensionality reduction techniques have been exploited as a result of which these approaches appear to produce better recognition results than the feature-based ones in general.

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PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (Karhunen-Loeve or Hotelling transform) – is one of the most valuable results from applied linear algebra [1, 2, 3]. PCA is used abundantly in all forms of analysis - from neuroscience to computer graphics - because it is a 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.

The principal component analysis is a statistical approach used to extract facial features for face recognition. This 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 basis vectors. Each of these basis 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. These “eigen features” are used for the detection of features such as eyes, mouth and 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.

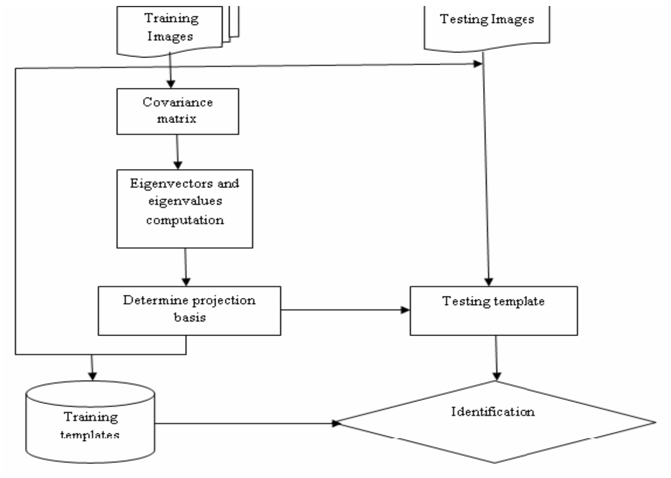

Figure 2. Simple flow chart of PCA algorithm

PCA algorithm:

- X ← Create N x d data matrix, with one row vector x_n per data point
- X subtract mean *x* from each row vector x_n in X
- Σ ← covariance matrix of X
- Find eigenvectors and eigenvalues of Σ
- PC's ← the M eigenvectors with largest eigenvalues

Over the past few years, several face recognition systems have been proposed based on principal components analysis (PCA) these systems have the same pre-processing and run-time steps. During pre-processing, they register a gallery of *m* training images to each other and unroll each image into a vector of *n* pixel values. Next, the mean image for the gallery is subtracted from each and the resulting "centered" images are placed in a gallery matrix *M*. Element [*i*; *j*] of *M* is the *i*th pixel from the *j*th image.

A covariance matrix W = *MMT* characterizes the distribution of the *m* images. Subsets of the Eigenvectors of W are used as the basis vectors for a subspace in which to compare gallery and novel probe images. When sorted by decreasing Eigenvalue, the full set of unit length Eigenvectors represent an orthonormal basis where the first direction corresponds to the direction of maximum variance in the images, the second the next largest variance, etc. These basis vectors are the Principle Components of the gallery images. Once the Eigenspace is computed, the centered gallery images are projected into this subspace. At run-time, recognition is accomplished by projecting a centered probe image into the subspace and the nearest gallery image to the probe image is selected as its match. There are many differences in the systems referenced. Some systems assume that the images are registered prior to face recognition; among the rest, a variety of techniques are used to identify facial features and register them to each other. Different systems may use different distance measures when matching probe images to the nearest gallery image.

DISTANCE MEASURES

Let X, Y be eigenfeature vectors of length n. Then we can calculate the following distances between these feature vectors

City Block Distance

$$d(x,y) = |x-y| = \sum_{i=1}^{k} |x_i - y_i|$$

Euclidean Distance (Squared)

$$d(x,y) = \|x-y\|^2 = \sum_{i=1}^{K} (x_i - y_i)^2$$

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Angle Negative Angle Between Image Vectors

$$d(x,y) = -\frac{x \cdot y}{\|x\|\,\|y\|} = -\frac{\sum_{i=1}^{k} x_i y_i}{\sqrt{\sum_{i=1}^{k} (x_i)^2 \sum_{i=1}^{k} (y_i)^2}}$$

Mahalanobis Mahalanobis Distance

$$d(x,y) = -\sum_{i=1}^{k} \frac{1}{\sqrt{\lambda_i}} x_i y_i$$

Where l*i* is the *i*th Eigenvalue corresponding to the *i*th Eigenvector. This is a simplification of Moon's definition:

$$d(x,y) = -\sum_{i=1}^{k} z_i x_i y_i \text{ where } z_i = \sqrt{\frac{\lambda_i}{\lambda_i + \alpha^2}} \simeq \frac{1}{\sqrt{\lambda_i}} \text{ and } \alpha = 0.25$$

EXPERIMENTS AND RESULTS

We experimented on the FERET database. The FERET database [10] contains images of 1,196 individuals, with up to 5 different images captured for each individual. The images are separated into two sets: gallery images and probes images. Gallery images are images with known labels, while probe images are matched to gallery images for identification. The database is broken into four categories:

FB Two images were taken of an individual, one after the other. In one image, the individual has a neutral facial expression, while in the other they have non-neutral expressions. One of the images is placed into the gallery file while the other is used as a probe. In this category, the gallery contains 1,196 images and the probe set has 1,195 images.

Duplicate I The only restriction of this category is that the gallery and probe images are different. In this category, the gallery consists of the same 1,196 images as the FB gallery while the probe set contains 722 images.

FC Images in the probe set are taken with a different camera and under different lighting than the images in the gallery set. The gallery contains the same 1196 images as the FB & Duplicate I galleries, while the probe set contains 194 images.

Duplicate II Images in the probe set were taken at least 1 year after the images in the gallery. The gallery contains 864 images, while the probe set has 234 images.

PCA gave better results with Mahalanobis distance rather than the other three distances (City Block Distance, Euclidean Distance (Squared), Angle Negative Angle between Image Vectors).

Distance used	**Duplicate I**	**FB**
City Block Distance	35	**77**
Euclidean Distance (Squared)	**33**	**72**
Angle negative Angle Between Image Vectors	**34**	**71**

Mahalanobis Mahalanobis Distance	**41**	**75**

Fig 2: Different distances measured on FERET database.

CONCLUSION

In this experiment we used 4 distance measures on the FERRET database to see the performance of the Principal Component Analysis (PCA) based face recognition system**.** The experiment show that PCA gave better results with Mahalanobis distance rather than the other three distances (City Block Distance, Euclidean Distance (Squared), Angle Negative Angle between Image Vectors).

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