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Face Recognition Based on Factor Analysis Technique

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Abstract **-** *In this work we are developing a code for matching the given image with the pre given image and displaying the information about it while keeping the error limitations in mind or displaying a negation remark. This is being done by the help of matlab simple and user friendly features. Thus making it simple, efficient and providing wide applications. It is based on information theory concepts, a computational model that best describes a face, by extracting the most relevant information contained in that face. Eigenfaces approach is a principle component analysis method, in which a small set of characteristic picture are used to describe the variation between face images. Goal is to find out the eigenvectors (eigenfaces) of the covariance matrix of the distribution, spanner by a training set of face images [1].*

Later, every face image is represented by a linear combination of these eigenvectors. Evaluations of these eigenvectors are quite difficult for typical image sizes but, an approximation that is suitable for practical purpose is also presented.

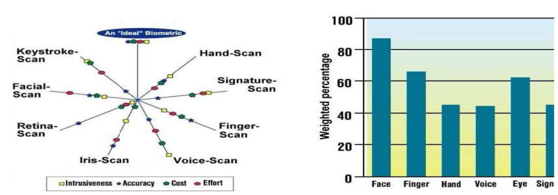
Recognition is performed by projecting a new image into the subspace spanned by the eigenfaces and then classifying the face by comparing its position in face space with the position of known individuals.

A face recognition system, based on the eigenfaces approach is proposed. Eigenfaces approach seems to be an adequate method to be used in face recognition due to its simplicity, speed and learning capability. Experimental results are given to demonstrate the viability of the proposed face recognition method.

Keywords*: Factor analysis, Eigen values,PCA*

I. Introduction

Facial scan is an effective biometric attribute/indicator. Different biometric indicators are suited for different kinds of identification applications due to their variations in intrusiveness, accuracy, cost, and ease of sensing (see Figure1.3 (a))[2]. Among the six biometric indicators considered in facial features scored the highest compatibility, shown in Figure1.3 (b), in a machine readable travel documents (MRTD) system based on a number of evaluation factors.



(a) (b)

Fig.1. Comparison of various biometric features:
(a) based on zephyr analysis;
(b) based on MRTD compatibility.

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II. Existing Methods of Face Recognition

The basic question relevant for face classification is that; what form the structural code (for encoding the face) should take to achieve face recognition. Two major approaches are used for machine identification of human faces; geometrical local feature based methods, and holistic template matching based systems. Also, combinations of these two methods, namely hybrid methods, are used. Whichever method is used, the most important problem in face recognition is the curse of dimensionality problem. Appropriate methods should be applied to reduce the dimension of the studied space. Working on higher dimension causes over fitting where the system starts to memorise. Also, computational complexity would be an important problem when working on large databases. The recognition techniques are grouped as statistical and neural based approaches.

PCA is a form of appearance based method of face recognition as shown in the figure 2 .

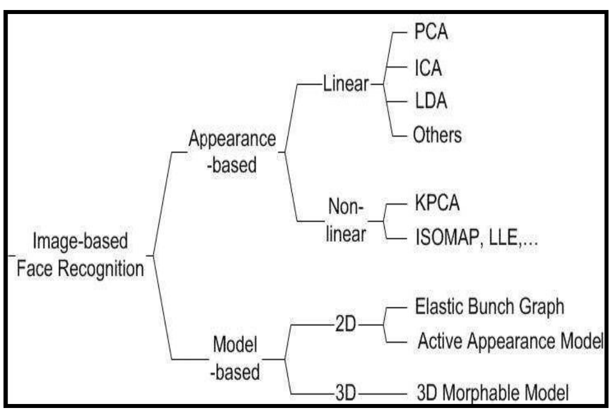

Fig. 2 Face recognition algorithms

III. Principal Component Analysis

The Principal Component Analysis (PCA) 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 dataspace (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data.

In the language of information theory, the relevant information in a face image is extracted, encoded as efficiently as possible, and then compared 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 economically. This is the case when there is a strong correlation between observed variables.

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).

Before getting to a description of PCA, this chapter first introduces mathematical concepts that will be used in PCA. It covers standard deviation, covariance, eigenvectors and eigenvalues. This background knowledge is meant to make the understanding of PCA very straightforward.

IV. Background Mathematics and Definitions

IV.1 Statistics

The entire subject of statistics is based around the idea that we have this big set of data, and we want to analyze that set in terms of the relationships between the individual points in that data set.

IV.2 Standard Deviation.

To understand standard deviation, we need a data set. Statisticians are usually concerned with taking a *sample* of a population. To use election polls as an example, the population is all the people in the country, whereas a sample is a subset of the population that the statisticians measure. The great thing about statistics is that by only measuring (in this case by doing a phone survey or similar) a sample of the population, you can work out what is most likely to be the measurement if you used the entire population. Here's an example set:

X= [1 2 4 6 12 15 25 45 68 67 65 98]

X refer to this entire set of numbers. The mean of the sample is given by the formula

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

Unfortunately, the mean doesn't tell us a lot about the data except for a sort of middle point. For example, these two data sets have exactly the same mean (10), but are obviously quite different:

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[0 8 12 20] and [8 9 11 12]

It is the spread of the data that is different. The Standard Deviation (SD) of a data set is a measure of how spread out the data is. SD is given by the formula

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{(n-1)}}$$

SD is the average distance from the mean of the data set to a point. The data set given below

[10 10 10 10]

has a mean of 10, but its standard deviation is 0, because all the numbers are the same None of them deviate from the mean.

IV.3. Variance.

Variance is another measure of the spread of data in a data set. In fact it is almost identical to the standard deviation. The formula is simply the SD squared.

$$s^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{(n-1)}$$

IV.4 Covariance.

The last two measures we have looked at are purely 1-dimensional. However many data sets have more than one dimension, and the aim of the statistical analysis of these data sets is usually to see if there is any relationship between the dimensions.

Covariance is such a measure. Covariance is always measured between two dimensions. If you calculate the covariance between one dimension and itself, you get the variance. So, if you had a three-dimensional data set (x,y,z), then you could measure the covariance between x and y dimensions , the x and z dimensions and the y and z dimensions The formula for covariance is very similar to the formula for variance. The formula for variance could also be written like this

$$var(X) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})}{(n-1)}$$

The formula for covariance is given by

$$cov(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

The exact value of covariance is not as important as it's sign (ie. Positive or negative). If the value is positive, then it indicates that both dimensions increase together. If the value is negative, then as one dimension increases, the other decreases. If the covariance is zero, it indicates that the two dimensions are independent of each other.

IV.5. The Covariance Matrix.

Covariance (cov) is always measured between two dimensions. If we have a data set with more than two dimensions, there is more than one cov measurement that can be calculated. For example, from a three dimensional data set (dimensions x,y,z) you could calculate cov (x,y) , cov (y,z) , cov (y,z) . In fact, for an n dimensional data set, you can calculate

$$\frac{n!}{(n-2)! * 2}$$

different covariance values.

A useful way to get all the possible cov values between all the different dimensions is to calculate them all and put them in a matrix. So, the definition for the cov matrix for a set of data with n dimensions is :

$$C^{mxn}=(c_{i,j}\ ,\ c_{i,j} = cov(Dim_i,\ Dim_j))$$

where C^{mxn} is a matrix with *n* rows and *n* columns and Dim_x is the x^{th} dimension. The entry on row 2, column 3 is the cov value calculated between the 2^{nd} dimension and the 3^{rd} dimension.

IV.6 Eigen Vector, Eigen Value.

Transformations of space such as translation (or shifting the origin), rotation, reflection, stretching, compression, or any combination of these; other transformations could also be listed may be visualized by the effect they produce on vectors. Vectors can be visualised as arrows pointing from one point to another.

(a) Eigenvectors of transformations are vectors which are either left unaffected or simply multiplied by a scale factor after the transformation. an eigenvector of a transformation is a non-null vector whose direction is unchanged by that transformation.

(b) An eigenvector's eigenvalue is the scale factor that it has been multiplied.

(c) The geometric multiplicity of an eigenvalue is the dimension of the associated eigenspace.
(d) The spectrum of a transformation on finite dimensional vector spaces is the set of all its eigenvalues.

For instance, an eigenvecto*r* of a rotation in three dimensions is a vector located within the axis about which the rotation is performed. The corresponding eigenvalu*e* is 1 and the corresponding *eigenspace* contains all the vectors parallel to the axis. As this is a one-dimensional space, its geometric multiplicity is one. This is the only eigenvalue of the spectrum (of this rotation) that is a real number.

A standing wave in a rope fixed at its boundaries can be seen as an example of an eigenvector, or more precisely, an eigen function of the transformation corresponding to the passage of time. As time passes, the standing wave is scaled but its shape is not modified. In this case the eigenvalue is time dependent.

V. Conclusion

This work is based on eigenface approach that gives an accuracy maximum of about 92.5%. PCA algorithms may be used to obtain an optimum threshold value. There is scope for future betterment of the algorithm by using Statistical technique that can give better results.

Instead of having a constant threshold, it could be made adaptive, depending upon the conditions and the database available, so as to maximise the accuracy. The whole software is dependent on the database and the database is dependent on resolution of camera. So if good resolution digital camera or good resolution analog camera is used , the results could be considerably improved.

Many methods of making computers recognize faces were limited by the use of improvished face models and feature descriptions(matching simple distances), assuming that a face is no more than the sum of its parts, the individual features. They tend to hide much of the pertinent information in the weights that makes it difficult to modify and evaluate parts of the approach.

This particular method using Principal Component Analysis for face recognition is motivated by information theory, leading to basing face recognition on a small set of image features that best approximates the set of known face images, without regarding that they correspond to our intuitive notions of facial parts and features.

The eigenface approach provides a practical solution that is well fitted for the problem of face recognition. It is fast, relatively simple, and works well in a constrained environment. Certain issues of robustness to changes in lighting, head size, and head orientation, the tradeoffs between the number of eigenfaces necessary for unambiguous classification are matter of concern.

VI. Future Scope

The current recognition system has been designed for frontal views of the images. A neural network architecture (may be together with a feature based approach) can be implemented in which the orientation of the face is first determined, and them the most suitable recognition method is selected.

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