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EXPERIMENTAL ANALYSIS OF DIFFERENT DISTANCE MEASURES FOR FACE RECOGNITION

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ABSTRACT

In this paper the three different types of distance measures are compared with respect to the recognition performance of Principal Component Analysis (PCA) algorithm used for the feature extraction of facial images. Distance metric or matching criteria is the main tool for retrieving similar images from large image databases for the above category of search. Three distance measures used are Euclidean distance, Manhattan distance and Mahalanobis distance. In content-based image retrieval systems, Manhattan distance and Euclidean distance are typically used to determine similarities between a pair of image. Here facial images of three subjects with different expression and angles are used for classification. Experimental results are compared and the results show that the Mahalanobis distance performs better than the Manhattan Distance and Euclidean distance for the changed angle face images.

KEYWORDS: PCA, Face Recognition, Feature Extraction, Covariance Matrix, Distance Measures, Eigenvectors, FERET Database, Image Classification

INTRODUCTION

PCA is one of the popular techniques for both dimensionality reduction and face recognition since 1990’s [6]. Principal component analysis (PCA) or Karhunen–Loeve transform (KLT)-based face recognition method was proposed in (Turk and Pentland, 1991). It was studied by computer scientists (Moonand Phillips, 1998; Yilmaz and Gokmen, 2001; Navarrete and Ruiz-del-Solar, 2001, 2002) and psychologists (Abdi et al., 1995; Hancock et al., 1996), used as a baseline method for comparison of face recognition methods (Moghaddam and Pentland, 1998; Phillips et al., 2000) and implemented in commercial applications (Viisage, 2001) [1].

In this paper the three different types of distance measures are compared on the FERRET database to see the performance of the principal component analysis (PCA) based face recognition system [3] [7]. The task of identifying objects and features from image data is central in many active research fields. In this paper I address the inherent problem that a single object may give rise to many possible images, depending on factors such as the lighting conditions, the pose of the object, and its location and orientation relative to the camera [2][14]. Here the Euclidian Distance, Mahalanobis distance and Manhattan distance is employed to measure the similarity between original data and reconstructed data. The proposed classification algorithm for face recognition has been evaluated under varying illumination and poses using standard face databases [5] [9].

Results show that the Euclidian distance is good for front faces; Mahalanobis distance is good for changed angle faces and Manhattan distance is better for face images of changed complexion[3][10][14].

DISTANCE MEASURES

Let X, Y is Eigen feature vectors of length n. Then we can calculate the following distances between these feature vectors[2][8][14].

Euclidian Distance

It is also called the L2 distance. If u= (x1, y1) and v= (x2, y2) are two points, then the Euclidean distance between u and v is given by.

$$EU\ (u,v) = \sqrt{\left(x_1 - x_2\right)^2 + \left(y_1 - y_2\right)^2} \tag{1}$$

Instead of two dimensions, if the points have n- dimensions, such as $a = (x_1, x_2, \ldots, x_n)$ and $b = (y_1, y_2, \ldots, y_n)$ then, eq. 1 can be generalized by defining the Euclidean distance between a and b as.

$$EU\,(a,b) = \sqrt{\left(x_1 - y_1\right)^2 + \left(x_2 - y_2\right)^2 + \ldots + \left(x_n - y_n\right)^2}$$

$$= \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{2}$$

The Mahalanobis Distance

It is a very useful way of determining the "similarity" of a set of values from an "unknown: sample to a set of values measured from a collection of "known" samples. One of the main reasons the Mahalanobis distance method is used is that it is very sensitive to inter-variable changes in the training data. In addition, since the Mahalanobis distance is measured in terms of standard deviations from the mean of the training samples, the reported matching values give a statistical measure of how well the spectrum of the unknown sample matches (or does not match) the original training spectra.

Mahalanobis, distance (Johnson and Wichern, 1998) from

x to μ, can be written[3].

$$\Delta_{ik}^2 = (\mathbf{x}_i - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_k),$$

Where μ_k are the mean and x_i is the input vector of attributes where Σ is the covariance matrix given by

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1L} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{L1} & \sigma_{L2} & \cdots & \sigma_{LL} \end{bmatrix}$$

and the individual covariance values of Σ are computed from the outer product sum given by[5].

$$\Sigma = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_j)(x_i - \mu_j)^T$$

Manhattan Distance

It is also called the L_1 distance. If u= (x_1, y_1) and v= (x_2, y_2) are two points, then the Manhattan distance between u and v is given by

$$MH(a, b) = |x_1 - x_2| + |y_1 - y_2|$$

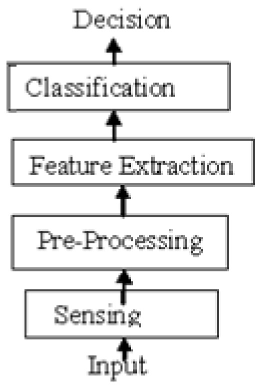
Instead of two dimensions, if the points have n- dimensions, such as $a = (x_1, x_2, \ldots, x_n)$ and $b = (y_1, y_2, \ldots, y_n)$ then, eq. 3 can be generalized by defining the Manhattan distance between a and b as.

$$MH(a, b) = |x_1 - x_2| + |y_1 - y_2| + \ldots + |x_n - y_n| = \sum_{i=1}^{n} |x_i - y_i|$$

SYSTEM DEVELOPMENT

Proposed System

Proposed system describes the following stages [4].



Sensing and Resizing (Pre-Processing)

Sensed facial images from FERET database has been taken for the experimental analysis. Size of the images is fixed. Original image size is (768*512*3), which is changed to (60*60). RGB images are converted to grayscale images. Facial images of 3 subjects (9 images for each person, 9*3=27 images) with different expression and angles are used for classification shown below [11] [12].

Figure 1: Three Different Persons Are Used and 9 Images of Each Person. Front Faces for Each Class are Used for Training and all Images of Faces With Different Angles and Expressions are Used for Testing [9]

Feature Extraction by Principal Component Analysis (PCA)

Principal Component Analysis is proposed by Turk and Pentland in 1991, which is often used for extracting features and dimension reduction. PCA aims to maximize between-class data separation. It works by finding a new coordinate system for a set of data, where the axes (or principal components) are ordered by the variance contained within the training data. A brief view of PCA is given below [4] [7].

Principal components are computed by.

$$S = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T \;, \quad \mu = \frac{1}{N}\sum_{i=1}^{N} x_i \;. \tag{3}$$

Center Data

$$x^i = \begin{bmatrix} x_1^i & \ldots & x_N^i \end{bmatrix}^T \tag{1}$$

Subtract the Mean Vector from Each Image

$$\overline{x}^i = x^i - m \text{, where } m = \frac{1}{P}\sum_{i=1}^{P} x^i \tag{2}$$

Data Matrix

Centered images are combined into a data matrix of size N×P

$$\overline{X} = \begin{bmatrix} \overline{x}^1 & | & \overline{x}^2 & | & \ldots & | & \overline{x}^P \end{bmatrix} \tag{3}$$

Where P is the number of training images and each column is a single image as shown in equation (3).

Covariance Matrix

Then covariance matrix is calculated as follows

$$\Omega - \overline{XX^T} \tag{4}$$

The Eigen Values and Eigenvectors

Then Eigen values and eigenvectors are computed as follows

$$\Omega V = \Lambda V \tag{5}$$

Where *V* is the set of eigenvectors associated with the Eigen values Λ

Order Eigenvectors

Order the eigenvectors v_i € V according to their corresponding eigenvalues λ_i € Λ *from* high to low

$$V = \left[v_1 \quad | \quad v_2 \quad | \qquad | \quad v_P \right] \tag{6}$$

This matrix of eigenvectors is the eigenspace *V*, where each column of *V* is an eigenvector

Classification, Post-Processing and Decision

Facial images are classified with the three different types of distance measures. Following results show the comparative study of the experimental analysis of Euclidian distance, Manhattan distance and Mahalanobis distance.

Here three classes (Subjects) are taken for the experiment. Every class contains the different nine images with front faces, changed angles, changed expressions and changed complexions. Distance of class 1, class 2 and class 3 is calculated with all images of three classes. Following table 1, table 2, table 3, graph 1, graph 2 and graph 3 shows the comparative study of the experimental analysis of Euclidian distance, Manhattan distance and Mahalanobis distance with respect to Principal Component Analysis (PCA) for all the classes (Persons/Subjects). Based on these results decision is made.

EXPERIMENTAL ANALYSIS

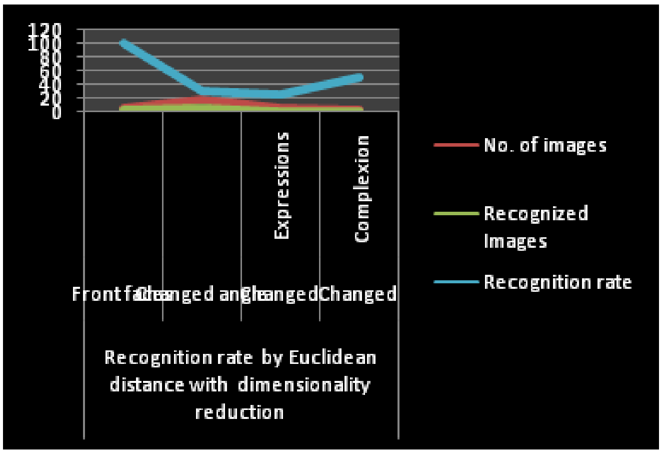
The results of the methods, the Euclidian distance, Mahalanobis distance and the Manhattan distance are compared. First the recognition rate for all three classes with different types of images is calculated by Euclidian distance, Manhattan distance method and Mahalanobis distance and then the all three results are compared with the recognition rate obtained by method for all three classes for the same types of images as used in all distance measures method. The following tables and graphs show the comparative study.

Recognition Rate Using Euclidian Distance

The table 1 shows the recognition rate obtained by Euclidian distance method. Here total images are used 27. 4 images are facing frontally, 17 images are angle changed, 4 are of changed expressions and 2 images are of changed complexions [13].

Table 1

Euclidean Distance Measure	Recognition Rate by Euclidean Distance with Dimensionality Reduction			
	Front Faces	Changed Angle	Changed Expressions	Changed Complexion
No. of images	4	17	4	2
Recognized Images	4	5	1	1
Recognition rate	100	29.41	25	50



Graph 1

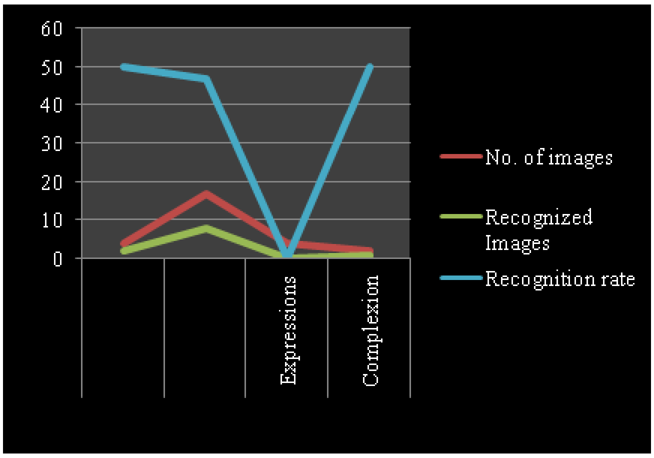
Graph 1 shows the pictorial view of table 1.

Recognition Rate Using Manhattan Distance

The table 2 shows the recognition rate obtained by Manhattan distance method. Here total images are used 27. 4 images are facing frontally, 17 images are angle changed, 4 are of changed expressions and 2 images are of changed complexions [13].

Table 2

Manhattan Distance Measure	Recognition Rate by Manhattan Distance with Dimensionality Reduction			
	Front Faces	Changed Angle	Changed Expressions	Changed Complexion
No. of images	4	17	4	2
Recognized Images	2	8	0	1
Recognition rate	50	47.05	0	50



Graph 2

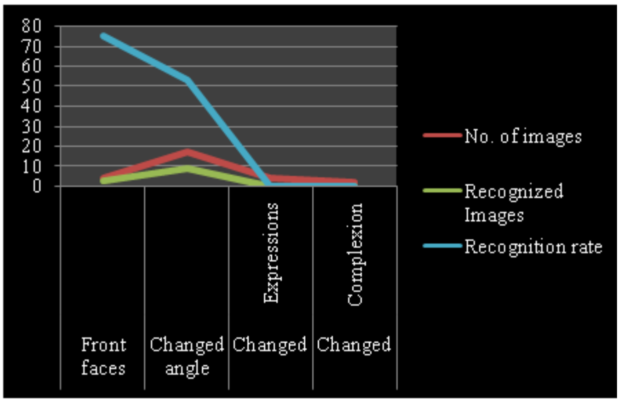
Graph 2 shows the pictorial view of table 2.

Recognition Rate Using Mahalanobis Distance

The table 3 shows the recognition rate obtained by Mahalanobis distance method. Here total images are used 27. 4 images are facing frontally, 17 images are angle changed, 4 are of changed expressions and 2 images are of changed complexions [13].

Table 3

Mahalanobis Distance Measure	Recognition Rate by Mahalanobis Distance with Dimensionality Reduction			
	Front Faces	Changed Angle	Changed Expressions	Changed Complexion
No. of images	4	17	4	2
Recognized Images	3	9	0	0
Recognition rate	75	52.94	0	0



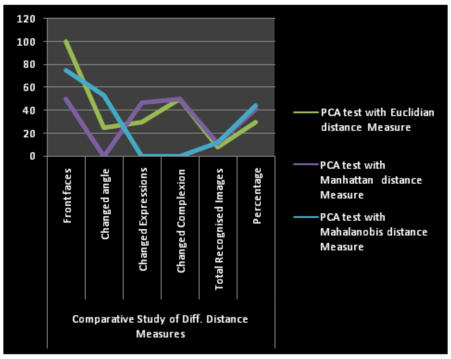
Graph 3

Graph 3 shows the pictorial view of table 3

Comparison

Table 4: Shows the Comparative Study of All Distance Measures

	Comparative Study of Diff. Distance Measures					
	Front Faces	Changed Angle	Changed Expressions	Changed Complexion	Total Recognised Images	Percentage
PCA test with Euclidian distance Measure	100	25	29.41	50	8	29.69
PCA test with Manhattan distance Measure	50	0	47.05	50	11	40.74
PCA test with Mahalanobis distance Measure	75	52.94	0	0	12	44.44



Graph 4

Graph 4 shows the pictorial view of table 4.

CONCLUSIONS

In this paper it is observed that the Mahalanobis distance gives the better results as Manhattan distance method. It has recognized total 12**(44.44%)** images out of 27 while L1 norm (Manhattan distance) has recognized total **11(40.74)** images out of 27. But Euclidian distance measure gives better results for front faces; it has recognized all front faces **(4 out of 4)**. Hence it gives 100 percent results for front faces. Using Mahalanobis distance there is an improvement in the overall performance.

FUTURE SCOPE

Every distance measure has some drawback like the drawback of the Mahalanobis distance is the equal adding up of the variance normalized squared distances of the features. Euclidian and Manhattan distance measures are not good for images with different expressions and complexions. Hence the overall performance can be improved by adding the different distance measures [1] [9] [14].

REFERENCES

1. Vytautas Perlibakas, “Distance measures for PCA-based face recognition”, Pattern Recognition Letters 25 (2004) 711–724.
2. Supriya Kapoor, Shruti Khanna, Rahul Bhatia, ”Facial Gesture recognition using correlation and Mahalanobis distance”, Vol. 7, No. 2, 2010.
3. Mahananda Malkauthekar, Shubhangi Sapkal, “Comparison of Mahalanobis and Manhattan distance measures in PCA-based face recognition”, International Journal of computer Engineering & Technology, Volume 5, Issue 5, May 2014, pp. 01-11.
4. Mini Singh Ahuja1, Sumit Chhabra2, “Effect of Distance Measures in PCA-Based Face Recognition”, International Journal of Enterprise Computing and Business Systems ISSN (Online): 2230-8849, Vol. 1 Issue 2 July 2011.
5. S. Sural, G. Qian and S. Pramanik “A Comparative Analysis of Two Distance Measures in Color Image Databases” IEEE International Conference on Image processing, vol.1, pp I-401 - I-404, 2002

6. S.Chitra, Dr. G. Balkrishanan, “A Survey of Face Recognition Feature Extraction Process of Dimensionality Reduction Techniques”, Journal of Theoretical and Applied Information Technology, Vol. 36, No.1
7. Kuldeep Singh Sodhi, Madan Lal, “Comparative Analysis of PCA-based Face Recognition System using different Distance Classifiers”, IJAIEM, Vol. 2, Issue 7, July 2013.
8. Wendy S. Yambor, “Analysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithms”, Technical Report CS 00-103, July 2000.
9. Wendy S. Yambor, Bruce A. Draper, J. Ross Beveridge, “Analyzing PCA-based Face Recognition Algorithms: Eigenvector Selection and Distance Measures”, Computer Science Department, Colorado State University, July 1, 2000.
10. M. D. Malkauthekar, “Analysis of Euclidian distance and Manhattan distance measure in face recognition”, IET, pp. 140-144.
11. M.D. Malkauthekar, ”Classifying Facial Images”, IEEE International conf. ICETECT11 Kanyakumari, Tamilnadu, 2011
12. M. D. Malkauthekar, Mrs. S. D. Sapkal and Ms. S.N. Kakarwal “Analysis of Classification Methods of Face Images using PCA and Fisher-Based Algorithms”, ICACT-2008, 26-28 Dec 2008 Hyderabad.
13. Mrs. M. D. Malkauthekar, Mrs. S. D. Sapkal and Mr. V.P. Kshirsagar, “Face Recognition Using Nearest Neighbor Method”, ICSCI-2008, Hyderabad.
14. Vadivel, A. K. M. S. S. A., A. K. Majumdar, and Shamik Sural. "Performance comparison of distance metrics in content-based image retrieval applications." In Proc. of Internat. Conf. on Information Technology, Bhubaneswar, India, pp. 159-164. 2003.