Comparative Review of LDA and MDA for Face Recognition attendance System

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Abstract - *For monitoring of student and employees, keeping a track of their attendance is of utmost importance. We need attendance system for this purpose. The problem with that is, it is not only time consuming, but also a lot of manual work. A good solution to this is face recognition attendance system. There are a lot of algorithms available for the same but dimensionality reduction algorithms help a lot to improve accuracy. In this paper we will review about two such algorithms, LDA and MDA.*

.***Key Words***: ***MDA; LDA; linear discriminant analysis; multi-linear discriminant analysis.***

1. INTRODUCTION

In previous works, object has been considered as 2-D space matrix. In order to improve the efficiency, it has been a question since past few works, whether or not using higher order tensor is beneficial. PCA, the most commonly used algorithm for Face Recognition, finds the most accurate data representation in lower dimensional space. However, some of them are directions of maximum variance which are useless for classification. This prompted us to use Fisher faces instead of Eigen faces. Fisher faces ensures that it projects to a line direction useful for data classification. Thus, the main objective of Fisher faces is to project a line such that the samples in the class are well distanced. Linear Discriminant Examination (LDA), which characterizes a projection that makes the inside class scatter littler and the between-class scatter differ by large number and outflanks PCA in FR tasks. Nonetheless, the execution of classic LDA is frequently debased by the fact that the Fisher discriminant measure characterized in the comparing LDA isn't straightforwardly identified with classification exactness in the output space [1]. MDA, unlike other approaches multiple interrelated subspaces are obtained through the optimization of the criterion where the number of the subspaces is determined by the order of the feature tensor used [2]. It spreads the tensors out into matrices along the k-th direction. Both the algorithms optimize function V, such that it minimizes the within class scatter and maximizes the between class scatter. We have tested these algorithms by implementing them on MATLAB and then comparing their accuracy against the number of images present in the face database used for the purpose of learning.

2. RELATED WORK

PCA is considered as one of the classic algorithms for face recognition. It uses orthogonal transformation. The transformations are derived in such a way that first principal component has largest possible. PCA is the simplest of the true eigenvector-based multivariate analyses. Frequently, its activity can be thought of as uncovering the inward structure of the information in a way that best clarifies the fluctuation in the information. In the event that a multivariate dataset is envisioned as an arrangement of directions in a high-dimensional information space (1 hub for each factor), PCA can supply the client with a lower-dimensional picture, a projection of this protest when seen from its most useful perspective. This is finished by utilizing just the initial couple of important segments with the goal that the dimensionality of the changed information is diminished.[3]

3. PROPOSED SYSTEM

LINEAR DISCRIMINANT ANALYSIS

It is a supervised learning algorithm which applies linear transformation on matrix. Suppose, we have got c classes. Each of them having a certain non-zero within class scatter S_w and the separation between two classes be S_b. The Fisher objective function for this is as follows[1].

$$J(X) = \frac{X^T S_b X}{X^T S_w X}$$

LDA, however tackles the problem by dimensionality reduction which is achieved by maximizing the above objective function. So, to find the projection such that samples of classes are well separated. Let, the line direction be the unit vector denoted by v, thus the projection of sample x_i onto the line direction v is given by $v^t x_i$ for sample x[4].

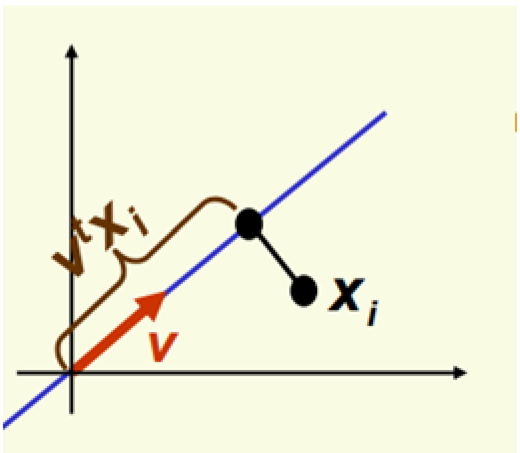

Figure 1: projection of the line

For calculating the separation between two classes let µ1 µ2 be the means of classes 1 and 2 then,[4]

$$\tilde{\mu}_1 = \frac{1}{n_1}\sum_{x_i \in C1}^{n_1} v^t x_i = v^t\left(\frac{1}{n_1}\sum_{x_i \in C1}^{n_1} x_i\right) = v^t \mu_1$$

And,

$$\tilde{\mu}_2 = v^t \mu_2$$

The major problem here, though is the fact that this measure does not consider variance of classes. Hence, the equations are normalized so that the proportionality is added to variance. The final equation that we get from the derivation suggests that there is no need to solve for the Eigen values[5].

MULTI-LINEAR DISCRIMINANT ANALYSIS

PCA or LDA, consider the objects as a 1-D vector. Since, the feature space is very large which leads to the so called curse of dimensionality dilemma. But, in computer vision, the image is represented as second or higher order tensor. MDA is basically mapping the object as a higher order tensor. In traditional subspace learning, one derives a single subspace but here, multiple subspaces are derived by using optimization and the number of subspaces is determined by the order of the feature tensor used. The tensor analysis approach used here is k-mode optimization[2].

4. IMPLEMENTATION

We implemented a system that compares both the algorithms, LDA and MDA. It is done in such a way that it compares the accuracy based on the number of images in the database. It shows the accuracy corresponding to the number of training faces data fed to the system. The result is thus tabulated in the results below. Based on the results, the algorithm is used to implement attendance system using MATLAB. The output of the system is the attendance sheet which is automatically prepared along with the timestamp and the status of 'present'.

Module 1: Face Detection

For face detection, we used the vision. Cascade Object Detector which uses the Viola-Jones algorithm for face detection. It contains several "pretrained classifiers" for detection of faces in various orientations.[1] On experimentation with various test cases required for our project, we found it reliable enough. Hence, we used this from the toolbox to detect faces.

Module 2: Face Recognition

For the purpose of recognition, we have used the dimensionality reduction algorithms mentioned in the paper. The mathematical operations on the image were carried and we have used the images from the AT & T database.

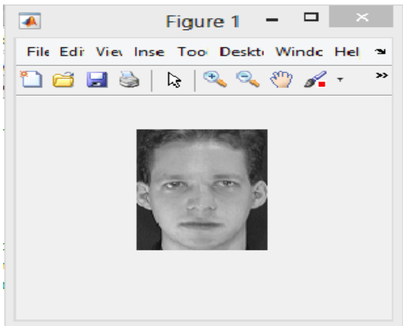

Figure 1: Selected Image for training.

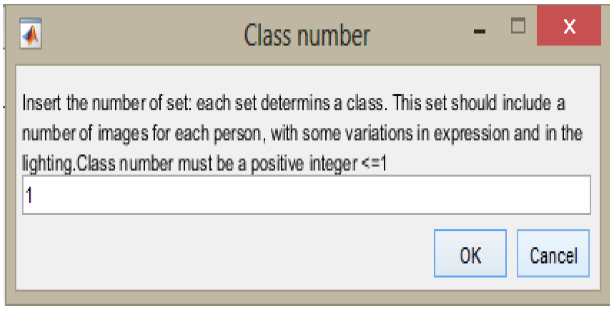

Figure 2: Insert the class number for training Image

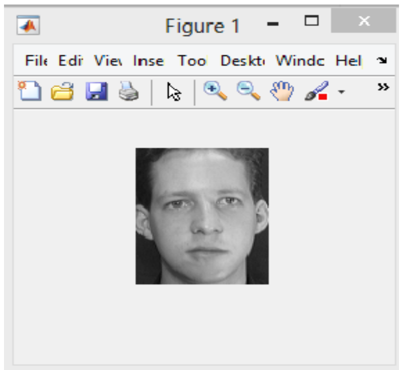

Figure 3: Recognized Face

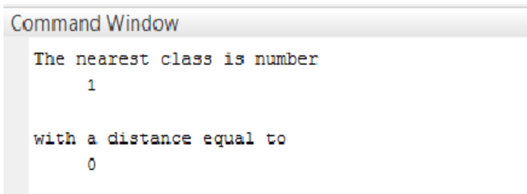

Figure 4: Nearest class number with recognized face

Module 3: Attendance Generation

The attendance generation module is dependent on the result of the last module. The detected class is fed as input to the database that contains students' name. The name and relevant details corresponding to the student is fetched and added to the sheet with the 'present' mark. This is done in every new lecture conducted.

RollNo	Name	Date	Time	Attendence
1	Tithi	16-Mar-2018	10:34:49	Present
2	Rinku	16-Mar-2018	12:46:7	Present
3	Aishwarya	16-Mar-2018	1:25:3	Present

Figure 5: Generated Attendance List

5. RESULTS:

Comparison

For comparison, we calculated the accuracy based on the number of learners present in the database. The accuracy corresponding to every new addition is calculated. This process is continued until 20 learners in the database and the final result of this review paper was successfully obtained.

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Processing FERETC80A45S6/FERETC80A45S6_32x32
Performning MDA learning
MDA learning is done
The best recognition rate for combining 1 learners is: 62.303%
The best recognition rate for combining 2 learners is: 68.1212%
The best recognition rate for combining 3 learners is: 70.303%
The best recognition rate for combining 4 learners is: 70.5455%
The best recognition rate for combining 5 learners is: 72.6061%
The best recognition rate for combining 6 learners is: 73.2121%
The best recognition rate for combining 7 learners is: 73.9394%
The best recognition rate for combining 8 learners is: 74.5455%
The best recognition rate for combining 9 learners is: 75.1515%
The best recognition rate for combining 10 learners is: 75.1515%
The best recognition rate for combining 11 learners is: 74.6667%
The best recognition rate for combining 12 learners is: 74.7879%
The best recognition rate for combining 13 learners is: 74.5455%
The best recognition rate for combining 14 learners is: 74.9091%
The best recognition rate for combining 15 learners is: 75.1515%
The best recognition rate for combining 16 learners is: 74.7879%
The best recognition rate for combining 17 learners is: 74.4242%
The best recognition rate for combining 18 learners is: 74.6667%
The best recognition rate for combining 19 learners is: 74.9091%
The best recognition rate for combining 20 learners is: 75.0303%
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Fig 1: Accuracy achived through MDA

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Performning LDA learning
LDA learning is done
The best recognition rate for combining 1 learners is: 56.3636%
The best recognition rate for combining 2 learners is: 59.8788%
The best recognition rate for combining 3 learners is: 62.303%
The best recognition rate for combining 4 learners is: 62.7879%
The best recognition rate for combining 5 learners is: 64.1212%
The best recognition rate for combining 6 learners is: 63.7576%
The best recognition rate for combining 7 learners is: 64.9697%
The best recognition rate for combining 8 learners is: 64.8485%
The best recognition rate for combining 9 learners is: 64.4848%
The best recognition rate for combining 10 learners is: 64.7273%
The best recognition rate for combining 11 learners is: 63.8788%
The best recognition rate for combining 12 learners is: 63.2727%
The best recognition rate for combining 13 learners is: 63.3939%
The best recognition rate for combining 14 learners is: 63.0303%
The best recognition rate for combining 15 learners is: 63.5152%
The best recognition rate for combining 16 learners is: 62.9091%
The best recognition rate for combining 17 learners is: 61.5758%
The best recognition rate for combining 18 learners is: 61.3333%
The best recognition rate for combining 19 learners is: 60.7273%
The best recognition rate for combining 20 learners is: 60.9697%
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Fig 2: Accuracy achived through LDA

Comparison of accuracy results		
Number of images in database	Accuracy achieved through LDA	Accuracy achieved through MDA
20	60.96%	75.63%

6. CONCLUSIONS:

Although, MDA gives higher accuracy in the results, the execution time was relatively high and the response time was slower than expected. It was due to the fact that the computation was done on order two tensors. Also that, the more images in database, the more time it takes to execute. Hence, we selected LDA for the purpose of implementing attendance system.

REFERENCES

1) Yang, Jie & Yu, Hua & Kunz, William"An Efficient LDA Algorithm for Face Recognition",2001.Available: https://www.researchgate.net/publication/2471751_An_Efficient_LDA_Algorithm_for_Face_Recognition.

2) Shuicheng Yan, Dong Xu, Qiang Yang, Lei Zhang, Xiaoou Tang, Hong-Jiang Zhang" Multilinear Discriminant Analysis for Face Recognition" IEEE Transactions on Image Processing, vol. 16, pp. 212-220, 2007, ISSN 9261414.

3) Peng Peng, Paulo Alencar, Donald Cowan" A Software Framework for PCA-Based Face Recognition" IEEE International Conference on Software Science, Technology and Engineering (SWSTE) ,pp.7-16 ,2016,ISSN 16158976.

4) Rita, "Lecture," Fisher LDA MDA. [Online]. Available: http://www.cs.haifa.ac.il/~rita/ml_course/lectures_old/Fisher.pdf. [Accessed:11-Apr-2018].

5) "Documentation," Face Detection and Tracking Using CAMShift - MATLAB & Simulink. [Online]. Available: https://in.mathworks.com/help/vision/examples/face-detection-and-tracking-using-camshift.html. [Accessed: 11-Apr-2018].