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Analysis of Regression Methods for Face Recognition System

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Abstract- Face verification has recently drawn a lot of attention as one of the best applications of image assessment and perception, particularly over the course of the last significant amount of time. Two factors, namely the wide range of corporate and legal approved applications and the openness of accessible headways after 30 years of research, speak to this example. Despite the fact that existing machine affirmation structures have made some progress, their success is still limited by the requirements of many real-world applications. For instance, the verification of facial images captured in an outside setting with variations in lighting or possibly position is still a very difficult problem. This paper present a analysis for face recognition method in comparison with PCA and LDA and suggests that LCDRC finds a discriminant subspace by maximizing collaborative between-class reconstruction error and minimizing the within-class reconstruction error simultaneously.

I.INTRODUCTION

Relapse examination is commonly used for desire and foreseeing, where its usage has critical spread with the field of AI. Relapse examination is in like manner used to appreciate which among the self-ruling factors are related to the subordinate variable, and to research the kinds of these associations. In constrained conditions, backslide examination can be used to infer causal associations between the free and ward factors. Anyway, this can provoke deceptions or bogus associations, so alert is fitting.

The execution of investigation frameworks before long depends on upon the sort of the data creating technique, and how it relates to the backslide procedure being used. Since the certified sort of the data creating technique is generally not known. These notions are to a great extent testable if a sufficient measure of data is available. Backslide models for desire are consistently useful despite when the doubts are fairly dismissed, regardless of the way that they may not perform in a perfect world. In any case, in various applications, especially with little effects or requests of causality considering observational data, backslide frameworks can give misleading outcomes.

II. LITERATURE SURVEY

In this examination [1], we propose a genuinely basic yet productive linear regression-based classification (LRC) for the issue of face recognition. Tests samples from a particular person are known to fall on a straight subspace. We utilize this idea to create class-particular models of the enrolled clients essentially utilizing the resized database pictures, along these lines characterizing the errand of face identification as an issue of linear regression. Least squares estimation is utilized to evaluate the vectors of parameters for a given test against all class models. At last, the choice tenets for the class with the most exact estimation. The described classifier can be ordered as a Nearest Subspace (NS) approach. In the worldview of perspective [2] based face identification, the decision of components for a given contextual investigation has been an arguable point. Late research has, then again, demonstrated the competency of strange components, for example, resized pictures and arbitrary projections, showing a difference from the ordinary philosophy. The LRC approach indeed fits in with this rising conviction. It has been demonstrated that with a proper decision of classifier, the resized pictures can deliver great results contrasted with the conventional methodologies. The straightforward structural planning of the proposed methodology makes it computationally productive, thusly recommending a solid nomination for sensible video-based face recognition applications. Other future bearings incorporate the strength issues identified with brightening, arbitrary pixel debasement, and stance varieties.

Different current face ID calculations use face portrayals found by solo quantifiable methods. Ordinarily these techniques find a plan of reason pictures and address stands up to as a straight mix of those photos. Head Component Analysis (PCA) is a well-known instance of such schedules. The reason pictures found by PCA rely just upon pairwise associations between pixels in the image database. In a task, for instance, face affirmation, in which fundamental information might be contained in the high-orchestrate associations among pixels, it seems, by all accounts, to be reasonable to expect that better reason pictures might be found by schedules sensitive to these high-mastermind estimations. Free segment examination (ICA) , a theory of PCA, is one such methodology. ICA was performed on face pictures in the FERET database under two unmistakable designs, one which viewed the photos as discretionary factors and the pixels as results, and a subsequent which viewed the pixels as unpredictable factors and the photos as results. The essential development displaying found spatially neighbourhood premise pictures for the faces. The second basic building made a factorial face code. Both ICA portrayals were better than portrayals considering PCA for seeing faces transversely over days and changes in expression.

III. TECHNIQUES FOR FACE RECOGNITION

Eigenface

The Eigenface strategy is one of the by and large utilized calculations for face acknowledgment. Karhunen-Loeve depends on the eigenfaces strategy in which the Principal Component Analysis (PCA) [6] is utilized. This technique is effectively used to perform dimensionality decrease. Head

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Component Analysis is utilized by face acknowledgment and location. Numerically, Eigenfaces are the foremost parts separate the face into include vectors. The element vector data can be gotten from covariance network. These Eigenvectors are utilized to evaluate the variety between numerous countenances. The countenances are portrayed by the straight blend of most noteworthy Eigen values. Each face can be considered as a straight mix of the eigenfaces. The face can be approximated by utilizing the eigenvectors having the biggest eigen values. The best M eigenfaces characterize a M dimensional space, which is called as the "face space". Head Component Analysis is likewise utilized by L. Sirovich and M. Kirby to productively speak to pictures of countenances. They characterized that a face pictures could be around recreated utilizing a little assortment of loads for each face and a standard face picture. The loads portraying each face are gotten by anticipating the face picture onto the eigen picture.

IV Face Recognition using Linear Discriminant Analysis

Fisher faces

Fisher faces are one the most successfully widely used method for face recognition. It is based on appearance method. In 1930 R.A Fisher developed linear/fisher discriminant analysis for face recognition. All used LDA [7] to find set of basis images which maximizes the ratio of between-class scatter to within-class scatter. The disadvantage of LDA is that within the class the scatter matrix is always single, since the number of pixels in images is larger than the number of images so it can increase detection of error rate if there is a variation in pose and lighting condition within same images. So to overcome this problem many algorithms has been proposed.

1.Database:

a. Consider the Orl database which consists of 40 persons of 10 each. So total images are 400.

b. Consider 200 images for training (40 persons of 5 each[1,2,4,9,3]) and other 200 images for testing (40 persons of 5 each[10,8,6,5,7]).

c. Each face image is of size 32x32, which is represented as 1024 x 1 vector.

2.Training

a. The 200 training images are represented as 1024 x 200 matrix 'A' . Each column 1024 x 1 is represented as one face image.

b. Find the mean along each row of A. This is the mean vector 'µ' of size 1024 x 1.

c. Find A1= (A- µ), Each column of matrix A is subtracted from mean vector µ. This is called as mean subtracted image, where all the common features are removed. The size of A1is 1024 x 200.

d. Find the Covariance(C) of A1. (C=A1*A1') ,1024 x 1024. The covariance has distinct features relations.

e. Find the Eigen vectors for covariance matrix 'C'.

f. The Eigen vectors are of size 1024 x 1024.

g. Along each column find the maximum value. 1x1024

h. Sort these maximum values in decending order (maximum value to minimum value).

F1	**F2**	**F3**	**F4**	**F5**	**………..**	**F198**	**F199**	**F200**
23	12	43	18	56		76	24	97

F200	**F198**	**F5**	**F3**	**F199**	**F1**	**…**			
97	76	56	43	24	23	….			

i. Now write corresponding Eigen values according to the sorted form. This is of size 1024 x 1024.

j. Consider the top 40/50/… values for further processing. Ex: 1024 x 100. These are called as Eigen faces (EF).

3.Within class Scatter matrix

a. Now project these Eigen faces (EF') 100 x 1024 on mean subtracted training faces of size 1024 x 200.

b. Atr = EF' * A1(100 x 1024 * 1024 x 200) gives 100 x 200 matrix.(reduction in dimension)

c. Each 100 x 1 column vector corresponds to face 1,2,3….200.(Atr1, Atr2, Atr3,…..Atr200)

d.

Face1 **(100x5)**	Face2 **(100x5)**	Face3**(100x5)**	….		Face40**(100x5)**
I1,I2,I3,I4,I5	I6,I7,I8,I9,I10	F11f122,f13,f14,f15,			I196,I197,I198,I199,I200
µ1	**µ2**	**µ3**	**µ4**		**µ40**

e. Aw=Atr –[**µ1, µ2, µ3,…. µ40**]; **µ1**= [µ1, µ1, µ1, µ1, µ1];
µ2= [µ2, µ2, µ2, µ2, µ2]; etc;Aw is 100 x 200 matrix.

f. Face 1 has 5 faces, find its mean µ1. Subtract µ1 from Atr1,Atr2,Atr3,Atr4,Atr5 of face1

g. Face 2 has 5 faces, find its mean µ2. Subtract µ2 from Atr6,Atr7,Atr8,Atr9,Atr10 of face2

h. Scatter matter for variable class Sw= Aw*AwT

4.Between Class Scatter matrix:

a. Consider the matrix formed in the step 3b.

b. Calculate the row wise mean of this matrix $\hat{\mu}$. (the size of $\hat{\mu}$ is 100x1)

c. Ab = Atr – repmat($\hat{\mu}$) ; repmat ($\hat{\mu}$) = [$\hat{\mu}\hat{\mu}\hat{\mu}\hat{\mu}\hat{\mu}\hat{\mu}$ …. 200].

d. Scatter Matrix for between class Sb = Ab*AbT.

e. Now calculate the Eigen values and Eigen vectors for Sb and Sw.

f. Sort the Eigen values according to the eigen vectors and create the Eigen Faces.

g. Project the training faces by multiplying the Eigen faces with the training face matrix.

h. Testing phase:

i. In the testing phase, a test image of the same size of 32×32 is taken and converted into a column vector of size 1024×1.

j. The mean face obtained in step 2b is subtracted from this test face.

k. This mean subtracted face is multiplied with the Eigen faces to form the projected test face.
l. This projected test face is matched with all the 200 projected training faces to recognize the test face.

V. LINEAR REGRESSION CLASSIFIER:

S M. Huang and J. F. Yang [2] have presented linear regression classification methodology with the help of class-specific representation where it was distinguished by Between-Class Reconstruction Error (BCRE) and Within-Class Reconstruction Error (WCRE) to find a discriminant subspace by maximizing the value of BCRE and minimizing the value of WCRE simultaneously. The main disadvantage of the LDRC is maximization of the overall between-class reconstruction error is easily dominated by some large class-specific between-class reconstruction errors, which makes the following LRC erroneous.
We denote the training face images of the ith class as $X_i \in \Re^{m \times n_i}$. Each column of X_i defined. is a dimensional face image of class i in which there are n_i training face images, and $1 \le i \ge c$ where c is the total number of classes.
Consider y is the probe face image that can be represented using X_i according to

$$y = X_i \alpha_i \text{, where } 1 \le i \ge c \qquad (1)$$

$\alpha_i \in \Re^{n_i \times 1}$ is the regression parameters; α_i can be calculated using the least-square estimation as,

$$\hat{\alpha}_i = \left(X_i^T X_i\right)^{-1} X_i^T y \text{, } 1 \le i \ge c \qquad (2)$$

The reconstruction of y by each class can be obtained as,

$$\hat{y}_i = X_i \hat{\alpha}_i = X_i \left(X_i^T X_i\right)^{-1} X_i^T y = H_i y \text{, } 1 \le i \ge c \qquad (3)$$

Where H_i is called hat matrix that maps y into $\hat{y}$ the reconstruction error of each class is calculated as

$$e_i = \left\| y - \hat{y}_i \right\|_2^2 \text{, …. } 1 \le i \ge c \qquad (4)$$

VI. LINEAR COLLABORATIVE DISCRIMINANT REGRESSION ANALYSIS [5]

S. M. Huang and J. F. Yang [4] have introduced direct relapse characterization philosophy with the assistance of class-explicit portrayal where it was recognized by Between-Class Reconstruction Error (BCRE) and Within-Class Reconstruction Error (WCRE) to discover a discriminant subspace by augmenting the estimation of BCRE and limiting the estimation of WCRE at the same time. The primary hindrance of the LDRC is expansion of the generally speaking between-class remaking mistake is effectively commanded by some huge class-explicit between-class recreation blunders, which makes the accompanying LRC incorrect. Algorithm. This paper adopts a better between-class reconstruction error measurement which is obtained using the collaborative representation instead of class-specific representation. The LCDRC [5] leads to accurate results.

$$\text{CBCRE} = \frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{ni} \left\| y_{ij} - \hat{y}_{ij}^{inter} \right\|_2^2 \qquad (5)$$

$$\text{WCRE} = \frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{ni} \left\| y_{ij} - \hat{y}_{ij}^{intra} \right\|_2^2 \qquad (6)$$

Where $\hat{y}_{ij}^{inter} = Y_{ij}^{inter} \alpha_{ij}^{inter}$ and $\hat{y}_{ij}^{intra} = Y_{ij}^{inter} \alpha_{ij}^{inter}$ (7)

The linear regression classification (LRC) algorithm was improved by a linear discriminant regression classification (LDRC) algorithm which was done by the Fisher criterion into the LRC as a discriminant regression analysis method. The LDRC used to increase the proportion of the between-class reconstruction error (BCRE) over the within-class reconstruction error (WCRE) to discover an optimum projection matrix for the LRC. The problem in the LDRC is the maximization of the overall between-class reconstruction error is easily dominated by some large class-specific between-class reconstruction errors, which makes the following LRC erroneous. In the past, LDRC was improved by the LCDRC with the aid of collaborative representation as a replacement for class-specific representation to obtain better between-class reconstruction error measurement. The LCDRC utilized the collaborative between-class reconstruction error (CBCRE) rather than BCRE. The obtained CBCRE was smaller than each class-specific between-class reconstruction error. The maximizing of CBCRE tends to better separate the WCRE and the small class-specific between-class reconstruction error than BCRE. The problem in the LCDRC is to improve the BCRE with the collaborative method, which is not used much for the WCRE. In LCDRC, the classification error happens when the true class and false class have similar small reconstruction errors. In this paper, we have planned to improve the LCDRC with our proposed methodology that can help to reduce the WCRC into as small as possible. After that WCRC is used to calculate CBCRE that helps to classify the analysis of the image accurately.

VIII. Experimental Results

The following are the results of the face recognition using PCA [6], LDA [7], LRC[4] and LCDRC [5].

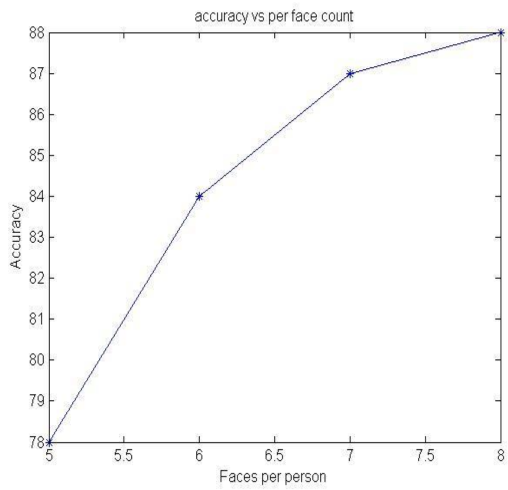

Fig 1. Accuracy of PCA. The x -axis represents number of faces for person and y axis represents the accuracy.

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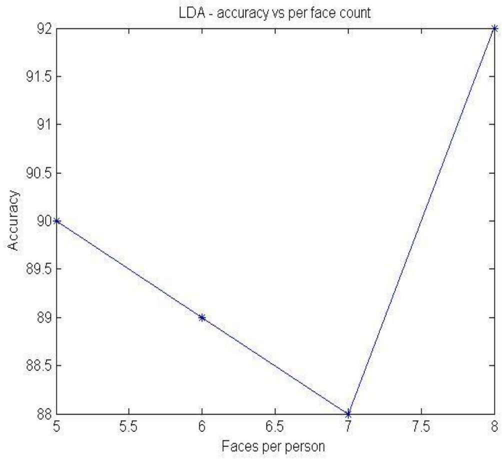

Fig 2. Accuracy of LDA. The x axis represents number of faces per person for training and y axis represents the accuracy.

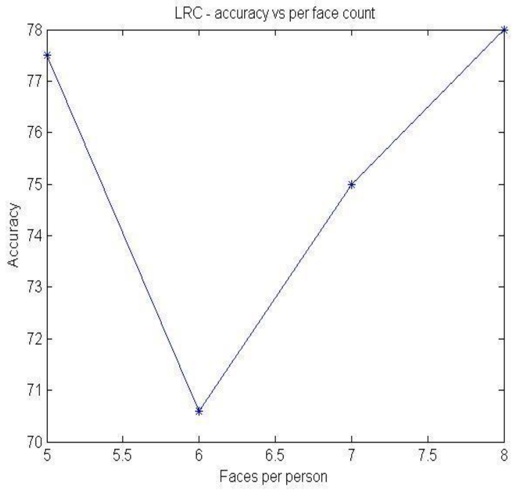

Fig 3. Accuracy of LRC. The x axis represents number of faces per person for training and y axis represents the accuracy.

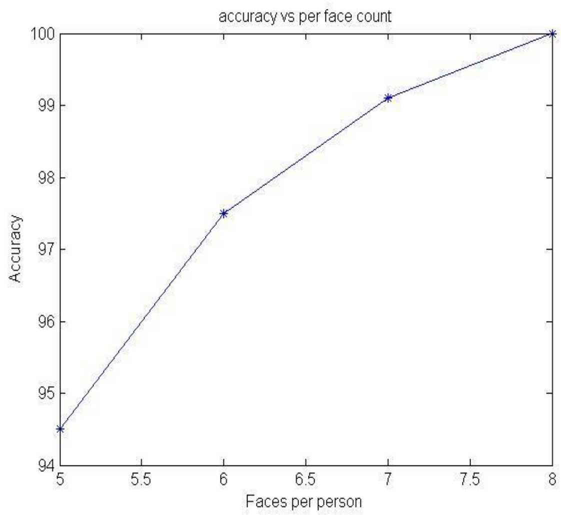

Fig 4. Accuracy of LCDRC. The x- axis represents number of faces per person for training and y axis represents the accuracy.

The ORL face database contains 400 face images of 40 individuals with 10 face images for each subject. The face images were taken under different light conditions and with different facial expressions. All the face images are cropped to be 32x32 in our experiment. Fig. 3 shows the performance of the proposed and LCDRC methods given two, and four for each class

Fig 5 Sample images for ORL dataset

Table 1. Accuracies of Different Face Recognition Techniques

Percentage (%)	PCA[6]	LDA[7]	LRC[4]	LCDRC[5]
50 %training	78.8	90.23	77.54	94.53
60%training	84.81	89.23	70.6	97.54
70%training	87.24	88.56	75.25	99.12
80 %training	88.23	92.58	78.36	98.58

The presented face recognition model was implemented within MATLAB 2015a, i3, 2.10Ghz Processor with orl database

IX .CONCLUSION

Face recognition is a challenging problem in the field of image processing and computer vision. Because of lots of application in different fields the face recognition has received great attention. In this paper different face recognition algorithms are mentioned with their advantages and disadvantages. it can also improve the efficiency of the discussed algorithms and improve the performance.

X. FUTURE SCOPE:

The optimization techniques which are used to find the optimal solutions will definitely boost up the accuracy of the recognition rate. The main aim is to suggest that optimization with regression methods will improve the performance of face recognition. Datasets.

REFERENCES

[1] Imran Naseem, Roberto Togneri, Mohammed Bennamoun, “Linear Regression for Face Recognition”, IEEE transactions on pattern analysis and machine intelligence, vol. 32, no. 11, november 2010.

[2] Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection ”, IEEE transactions on pattern analysis and machine intelligence, vol. 19, no. 7, july 1997.

[3] Wenfei Gu, ChengXiang, Y.V.Venkatesh, DongHuang, HaiLin, “Facial expression recognition using radial encoding of local Gabor features and classifier synthesis”, Pattern Recognition 45 (2012) 80–91.

Website: ijetms.in Issue:5, Volume No.4, September-2020 DOI: 10.46647/ijetms.2020.v04i05.022

[4] S.-M. Huang and J.-F. Yang, "Linear discriminant regression classification for face recognition,"Signal Processing Letters, IEEE, vol. 20, no. 1, pp. 91–94, 2013.

[5] Xiaochao Qu, Suah Kim, Run Cui, HyoungJoong Kim, "Linear collaborative discriminant regression classification for face recognition", Journal of Visual Communication and Image Representation, Vol. 31, pp. 312–319, 2015

[6] Eigenfaces for recognition By Matthew Turk and Alex Pentaland , vision and Modelling Group, The media laboratory Massachusetts Institute of Technology, Journel of cognitive Neuroscience vol3,Number1, https://www.facerec.org/algorithms/PCA/jcn.pdf

[7] Gang Xu, Shengli Zhang, YunyunLiang," Using Linear Regression Analysis for Face Recognition Based on PCA and LDA", IEEE transactions on image processing, 2010.