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Effect of Varying Training Images on Performance of Face Recognition: A Study

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Abstract - **One of the problems in face recognition is the limited number of images per person available for training. In this paper, we investigate the performance of popular feature extraction methods such as Gabor wavelets, Discrete wavelet transform, Multi-view canonical correlation analysis, Linear discriminant analysis, Generalized uncorrelated linear discriminant analysis and Supervised canonical correlation analysis for face recognition with variation in the number of training images per person. The performance is measured in terms of classification accuracy. Experimental results on four publicly available datasets viz., AR, ORL, CMU-PIE and YALE demonstrate that the classification accuracy in general increases with increase in the number of training images per person with few exceptions.**

Keywords: **- Discriminant, correlation, wavelet, accuracy, comparison.**

I. INTRODUCTION

Face recognition [1] has come up as one of the important research areas in recent past due to its large number of real time applications such as access control, surveillance, criminal investigations, and terrorist control [2] etc. The performance of face recognition systems have achieved satisfactory performance in controlled environment i.e. with frontal images, normal illumination etc., but it is difficult to have controlled environment in real life scenario. Therefore, face recognition systems are confronted with many challenges such as illumination variation, pose variation, occlusion, facial expression [3] etc. Another challenge for face recognition systems is number of training images per person available for training. Face recognition systems generally perform poor with only few available training images.

Subspace analysis has been used extensively as a popular feature extraction method for face recognition. Principal Component Analysis (PCA) [4] and Linear Discriminant Analysis (LDA) [5][6] have been the most popular subspace methods in face recognition. PCA is based on the principle of transforming the face image into a subspace spanned by the first few dominant eigenvectors of the covariance matrix of the training data samples. As PCA is based on unsupervised learning, it does not perform well on face recognition which is inherently a classification problem. To exploit the class information and simultaneously reducing the dimensionality, LDA has been proposed in literature. This is a supervised technique whose objective is to maximize the between-class scatter while simultaneously minimizing the within-class scatter. Although LDA has been one of the benchmark techniques, it suffers from the problem known as curse of dimensionality [6], also called small sample size (SSS) problem in literature. This problem occurs when the dimensionality of the data is quite large in comparison to the number of available data samples. Due to this reason, the estimated within-class scatter matrix becomes singular and results in poor performance.

Many techniques have been used to tackle the small sample size problem or curse of dimensionality. In this paper we investigate the performance of popular feature extraction methods for face recognition viz. Gabor wavelets, Discrete wavelet transform, Multi-view canonical correlation analysis, Generalized Uncorrelated Linear Discriminant Analysis, Linear Discriminant Analysis and Supervised Canonical Correlation Analysis. The performance is evaluated on four publicly available face databases AR, CMU-PIE, ORL and YALE. The performance is evaluated in terms of average classification accuracy. The rest of the paper is organized as follows: Section 2 provides a brief overview of the feature extraction methods used for face recognition. In Section 3, we describe experimental setup and results on four publically available face datasets. Some concluding remarks are given at the end.

II. FEATURE EXTRACTION METHODS

In this section, we briefly describe the feature extraction methods used in this paper. Let us suppose that all the face images are of size $m \times w$.

A. Gabor - Feature extraction

When we apply Gabor filter [7] to a face image, we get the filtered image whose size is equal to that of original image. By employing Gabor wavelets with 3

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scales and 8 orientations (24 filters), we get 24 Gabor filtered images. Afterwards, we have taken the average of these 24 filtered images for each image for feature extraction. Thus, features extracted from each image are of size $m \times w$.

B. Discrete Wavelet Transform (DWT)

In DWT [8] with Haar Wavelet, the features extracted are the approximation part. As DWT reduces the size of image by 4, the features extracted are $(m \times w) / 4$ e.g. For a face image of size 32 x 32, there will be 256 features.

C. Multiview Canonical Correlation Analysis (MVCCA)

In MVCCA [9], the Gabor features (same as discussed above, say X) and DWT features (same as discussed above, say Y) are treated as two different representations. These representations/features and then transformed to another space where correlation between these representations are maximized (which is the objective of CCA). This is implemented through cancorr ( ) function in MATLAB.

D. Linear Discriminant Analysis (LDA)

LDA [5] aims at maximizing the between class scatter while minimizing the within class scatter simultaneously. LDA suffers from small sample size problem. To overcome this, PCA is used at the first step to reduce the dimensionlity of images then LDA is applied.

E. Generalized Uncorrelated LDA(GULDA)

In GULDA [10], the transformation matrix W is determined as follows:

(i) Determine the eigenvector corresponding to the highest eigenvalue (say e_1).

(ii) Determine the next eigenvector which is perpendicular to e_1 (suppose this is vector e_2).

(iii) Determine the next vector which is perpendicular to both e_1 and e_2 (suppose this is vector e3) and so on.

Hence, $\boldsymbol{W} = [e_1\ e_2\ .....\ e_n]$ (1)

F. Supervised Canonical Correlation Analysis (SCCA)

. In SCCA [11], one of the representations (Y) is defined in terms of its class values. So that the correlation between the data samples within the same class is maximized. As class information is employed in this Canonical Correlation Analysis, it is referred to as SCCA.

III. EXPERIMENTAL SETUP AND RESULTS

The AR face dataset [12] consists of a total of 2600 images of 100 identities captured in two sessions. The facial images have varying illumination, expression and occlusion. The illumination subset is selected for the experiments resulting into 800 images. The original cropped images of size 120 × 100 were resized to 32 × 32. CMU-PIE face dataset [13] comprised of41,368 images of 68 identities with 13 different poses, 43 illumination conditions and 4 expressions. The facial images with varying lighting conditions are captured with both the back-ground light off and on. We have selected the images of 65 persons with varying illumination variation and background light off with 21 images of each person. The original images were first cropped and then resized to 32 × 32. Yale face dataset [14] has 165 gray scale images of 15 persons with 11 images for each person. Each image in the dataset was first cropped and then rescaled to 32 × 32. The ORL face dataset [15] consists of 400 images of 40 subjects each with 10 images per person. The facial images contain slight variations in pose and illumination. We have used whole ORL dataset for our experiments. The original images of 112×92 were resized to 32×32.

The number of training images are varied from 2 to 7 on all datasets. The experiments are repeated 20 times to obtain the average classification accuracy. The results on all four datasets are given in Tables I-IV for AR, ORL, PIE and Yale datasets respectively. The corresponding bar graphs are shown in Fig. 1-4 respectively.

A. Observations

(i) In general performance of all the methods on four face databases improve with number of training images per person with exception of MVCC and LDA.
(ii) No methods is clear winner on all four databases.
(iii) GULDA performs best AR and PIE databases.
(iv) DWT performs best on YALE database when number of training images per person is 2, 3 and 4 else GULDA performs best.
(v) On ORL face database, DWT based method performs the best.

TABLE I: Average Classification Accuracy on AR Face Dataset

Training/ Person	**2**	**3**	**4**	**5**	**6**	**7**
Gabor	78.97	84.40	85.03	86.20	85.55	87.10

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DWT	61.32	65.26	68.93	72.60	72.50	73.40
MVCCA	11.38	20.34	32.73	36.43	34.75	40.10
LDA	34.58	38.90	59.55	57.27	58.50	63.00
GULDA	**85.88**	**94.80**	**99.13**	**99.33**	**99.10**	**99.60**
SCCA	12.45	19.36	25.25	28.9	25.20	33.50

Fig. 1: Bar Graph showing classification accuracy on AR Face Dataset

TABLE II: Average Classification Accuracy on ORL Face Dataset

Training /Person	2	3	4	5	6	7
Gabor	80.81	87.96	91.04	93.50	94.25	95.75
DWT	**81.50**	**88.79**	**91.75**	**94.25**	**95.06**	**97.08**
MVCCA	24.31	20.04	18.96	11.45	8.25	26.42
LDA	30.53	35.82	36.04	33.90	34.56	36.75
GULDA	81.16	86.43	88.67	90.50	90.63	91.92
SCCA	9.88	10.39	16.21	15.65	17.00	16.50

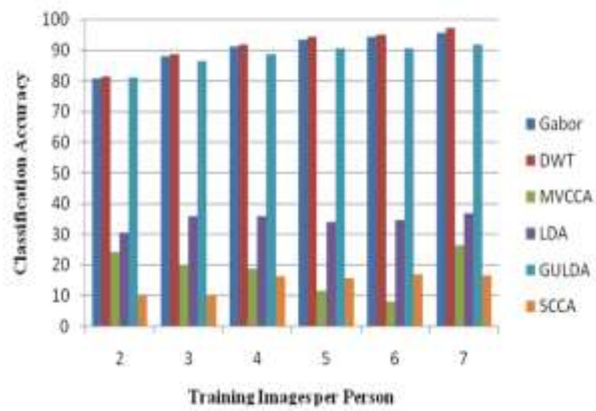

Fig. 2: Bar Graph showing classification accuracy on ORL Face Dataset

TABLE III: Average Classification Accuracy on PIE Face Dataset

Training/ Person	2	3	4	5	6	7
Gabor	63.81	74.07	80.14	85.27	86.85	89.03
DWT	53.20	61.84	69.29	76.33	79.58	83.37
MVCCA	34.93	20.55	14.76	59.90	63.16	66.96
LDA	49.30	60.00	64.63	70.71	70.14	72.44
GULDA	**76.30**	**84.59**	**86.55**	**90.70**	**90.64**	**92.16**
SCCA	48.62	56.71	62.30	69.92	69.63	68.11

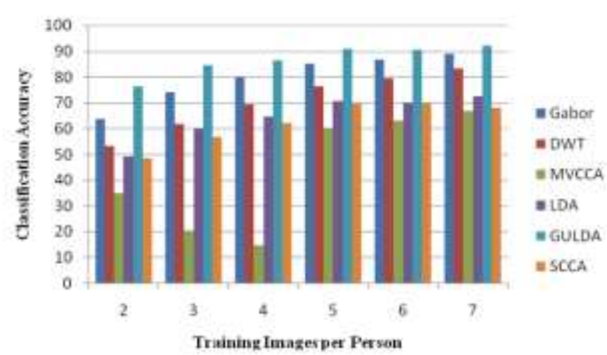

Fig. 3: Bar Graph showing classification accuracy on PIE Face Dataset

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TABLE IV: Average Classification Accuracy on YALE Face Dataset

Training/Person	2	3	4	5	6	7
Gabor	73.33	78.17	80.57	80.78	82.13	82.67
DWT	**81.26**	**84.58**	**84.38**	83.44	84.53	81.67
MVCCA	20.74	19.92	18.95	17.89	18.27	16.00
LDA	41.19	37.92	35.62	34.78	32.80	33.83
GULDA	77.26	81.00	82.95	**83.67**	**85.73**	**85.17**
SCCA	22.15	27.75	28.48	31.22	37.60	33.67

CONCLUSION

In this paper, the performance of six face recognition methods have been compared in terms of average classification accuracy. We also studied the effect of change in number of training images per person to find the methods that can perform well even with the lesser number of training images. It is observed that no method is clear winner on all face databases used. GULDA or DWT based methods perform best. In general performance improves with increase in number of training images.

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