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Face Recognition Using Gabor Feature Extraction Followed by Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA)

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ABSTRACT-

In this research paper, we narrate the different approach for face recognition system using machine learning algorithms . These techniques are based on the extraction of 2D facial image characteristics using Gabor filters, followed by using the principal component analysis (PCA) and linear discriminant analysis (LDA) on the data set. The implementation of these techniques, we can produce more precise and superior results when compared to single approach algorithm. By using this image processing algorithms, the results determined from the suggested system is advantageous for good recognition of facial images .

Keywords: Face Recognition, PCA, LDA, Gabor feature extraction

I. INTRODUCTION

Throughout the past few decades, researchers in the fields of biometrics, pattern recognition, and computer vision have paid close attention to automatic human face identification in an effort to address its unresolved problems that arise in the uncontrolled environment . It is a simple and unobtrusive way for identifying individuals because it does not involve the collaboration of the subject with the system. Due to different head postures, various environmental conditions, and face emotions, present 2D face recognition systems are still struggling to handle facial changes, which introduce huge number of variations within classes. Range images obtained from a 3D sensor expressly include information about the curvature of the facial surface. Due to variations in pose and lighting, the 3D shape information doesn't vary much, but these factors can significantly alter the image of the corresponding intensity. The effectiveness of range image-based 3D face recognition in improving face identification accuracy has been established.

This study proposes a unique method for 2D face recognition based on the feature extraction from a 2D face picture using the Gabor filters. This method chooses the most distinct characteristics to represent the face image in order to best describe the face image. The main usage of Gabor filters are due to their advantageous feature extraction characteristics, such as invariance to illumination, rotation, scale, and translation using a portion of the Gabor filter bank can significantly reduce computation and size, and in certain cases, even enhance recognition performance. We utilized PCA and LDA for feature compression and selection in order to further reduce dimensionality and get good recognition performance.

II. LITERATURE SURVEY

We concentrate on face identification using 2D face photos in this paper. Several methods have been developed to recognize faces from 2D images. When photos are sent into a feature space (referred to as "face space") that ideally encodes the variation among the face images, as described by Turk and Pent land [1], face identification using eigen faces is achieved. The "eigen faces," or eigenvectors of the set of faces, define the face space.

According to the system proposed by Omai et al. [2] based on the DCT (Discrete Cosine Transform) of the face which is being evaluated and all other DCT's in the faces database, the face which has the lowest distances likely belongs to same individual. AdaBoost Gabor feature, which is low dimensional and used by P. Yang et al [3] . The approach proposed by Bouzalmat, et al. [4] is based on the Fourier transform of Gabor filters and the method of regularized linear discriminate analysis applied to previously localized face features. The two steps that make up facial face recognition are location and recognition. The geometric model and the variation of grey level along the characteristic axis are used to determine the characteristic in the first phase. The second phase produces the feature vector by convolution of the faces.

Linlin SHEN [5] built a two-class based face recognition system employing Support Vector Machine (SVM) and optimized Gabor features. Two hundred Gabor features were initially chosen by a forward approach, and SVM was then merged with them. To improve face recognition rates, Sang-Il Choi, Chong-Ho Choi, and Nojun Kwakb [6] introduced a unique 2D image-based method that can handle illumination and position fluctuations similarly the same time. Compared to approaches based on 3D models, it is more simpler, takes a lot less computing work, and has a similar or higher recognition rate.

A face identification method based on PCA, which determines the foundation of a space symbolise by its own training vectors, was proposed by Kyungnam Kim [7]. These basis vectors—which are actually eigenvectors—were generated via PCA in the direction of the training vectors' greatest variance. A face's vector into the face space, which is created when it is projected into the face, describes the importance of each feature on each face. The eigenface coefficients of the face represent it in the face space (or weights).

III. IMPLEMENTATION

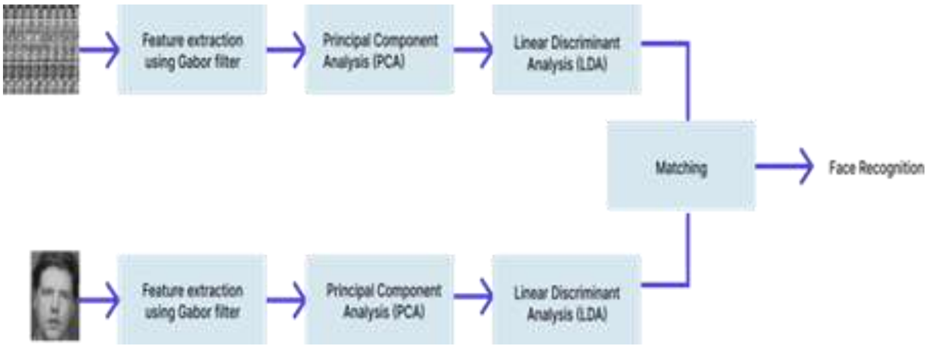

Fig1: Block diagram

A) Feature Extraction Using Gabor

Due to its superior localization capabilities in both the spatial analysis and frequency domain, the Gabor filters have been regarded as a particularly valuable tool in computer vision and image analysis. Their kernels are similar to the 2D receptive field profiles of mammalian cortex simple cells.

1) Gabor Filter

It has been discovered that gabor filters are very suitable for texture representation and discrimination. It demonstrates that the highest amount of information from local image regions may be extracted by the Gabor receptive field. Moreover, studies have demonstrated that Gabor features are different across translation, rotation, and scale when properly created.

A linear filter called the Gabor filter is used for edge detection. Gaussian kernel function modulated by a sinusoidal plane wave in the geographical domain is a 2D Gabor filter. This filter has two components which are given as below,

Real

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad \text{…. (1)}$$

Imaginary

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad \text{….(2)}$$

where,

$x' = xcos\theta + xsin$ and $y' = -xsin\theta + ycos\theta$

and where γ denotes the spatial aspect ratio, ψ is the phase offset, σ is the sigma of the Gaussian envelope, the wavelength of the sinusoidal factor is given as λ and the orientation of a Gabor function is given as θ , and the ellipticity of the Gabor function's support.

The real section of the Gabor filter are shown in below Figure with eight orientations and five frequencies for max=/2. The different frequency is shown in the rows and the different orientation is given in columns.

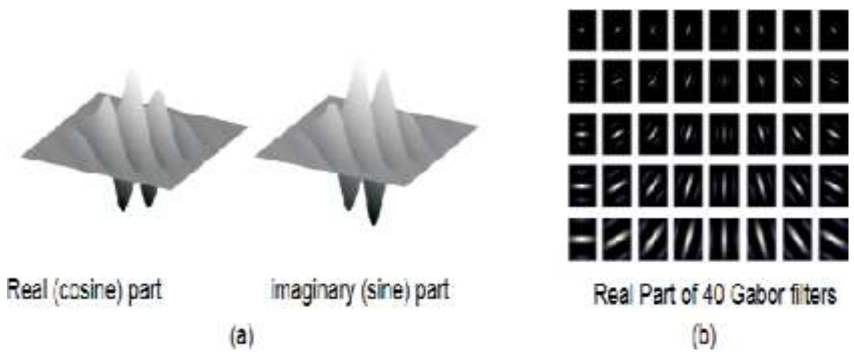

Fig2: a) Real and imaginary part b) Real part of gabor filters

A filter bank with many number of filters are generated and used to create multi-orientation and multi-scale features from the given face image which is used for feature extraction. The Gabor filters in this filter bank typically come in 5 distinct scales and 8 different orientations.

I(x, y) convolution with the bank of Gabor filters gu, v produces representation of the face's Gabor features (x, y). The outcome of the convolution is a complex value that can be divided into real and fictitious parts:

$Gu, v(x, y) = I(x, y) * gu, v(x, y)$ …(5)

$Eu, v(x, y) = Re[Gu, v(x, y)]$ …(6)

$Ou, v(x, y) = Im[Gu, v(x, y)]$ …(7)

Both the phase u,v(x, y) and the magnitude Au,v(x, y) filter responses can be estimated based on the deconstructed filtering result as follows:

$A_{u,v}(x, y) = \sqrt{E^2{}_{u,v}(x, y) + O^2{}_{u,v}(x, y)}$...(8)

$\theta_{u,v}(x, y) = arctan\left(\frac{O_{u,v}(x,y)}{E_{u,v}(x,y)}\right)$ …(9)

Gabor phase features are viewed as unstable and are typically deleted since the calculated phase responses differ dramatically even for geographical locations only a few pixels changes.

2) Principle Component Anlaysis (Pca)

It is a popular technique that is used in various applications that involves extraction of features. It is one of the best methods for facial recognition. It has been the subject of extensive research. By eliminating overlap and correlation between them, this can be utilized to reduce the number of filters that are required currently.

3) Linear Discriminant Analysis (Lda)

LDA's major objective is to carry out dimensionality reduction while retaining the most class discriminating data possible. The finest paths for separating the classes are sought after. While also taking into account the dispersal between classes as well as within classes.

Instead of looking for the vectors that best explain the data, linear discriminant analysis (LDA) looks for those that best discriminate across classes. In more formal terms, LDA builds a linear combination of the independent features that are used to characterize the data, yielding the biggest mean differences between the target classes.

B) Orl Database

This database includes a collection of faces. This database consists of 10 unique pictures of 40 different people. Images of some of the subjects were taken in several settings with somewhat different lighting, facial expressions (e.g., smiling/not smiling, eyes open/closed), and face details (glasses/no glasses).

Fig3: ORL dataset

IV. RESULTS

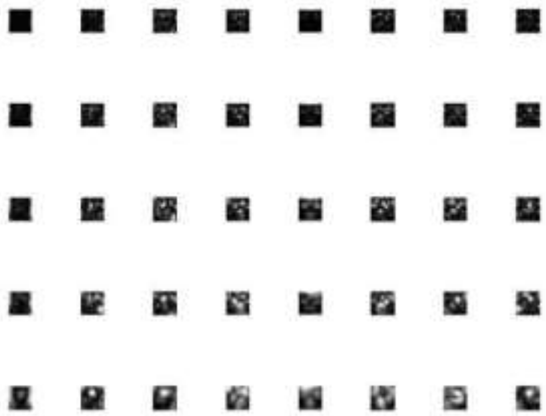

Fig: Magnetic responses of the fltering operation with gabor filter bank(no dwnsampling)

Fig: Magnetic responses of the fltering operation with gabor filter bank(downsampling factor 64)

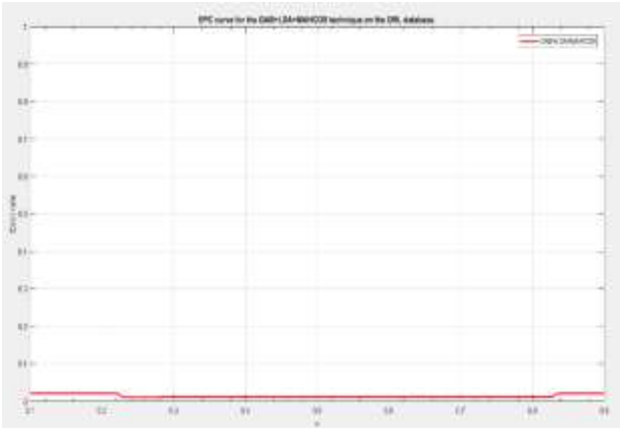

Fig: EPC curve of ORL database after using gabor extraction and Linear discriminant analysis(LDA)

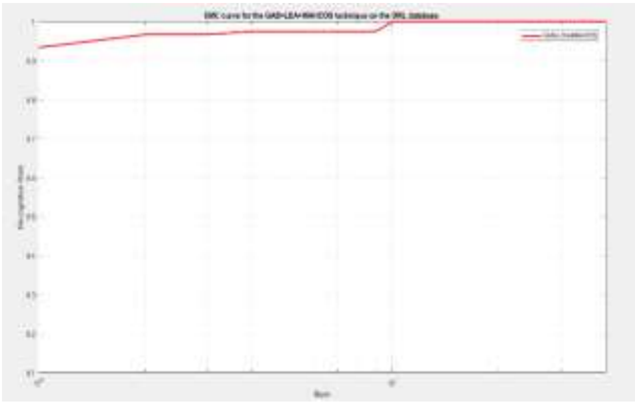

Fig: CMC curve of ORL database after using gabor extraction and Linear discriminant analysis(LDA)

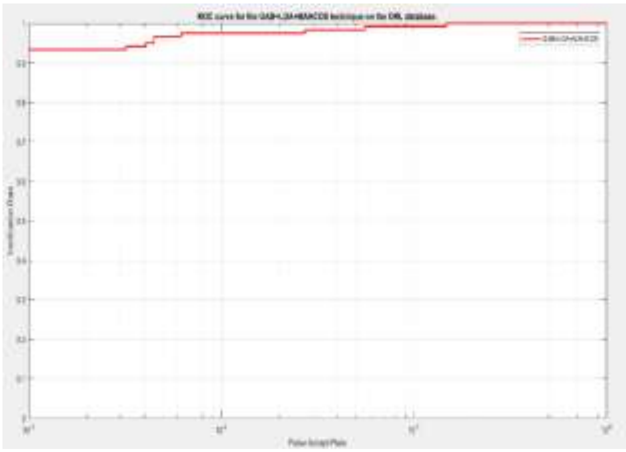

Fig: ROC curve of ORL database after using gabor extraction and Linear discriminant analysis(LDA)

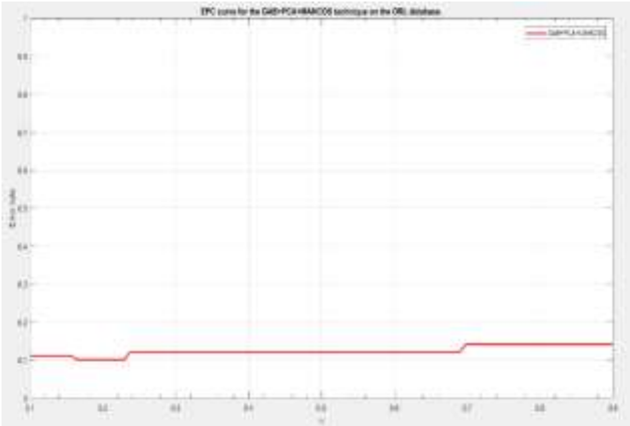

Fig: EPC curve of ORL database after using gabor extraction and Principal component analysis(PCA)

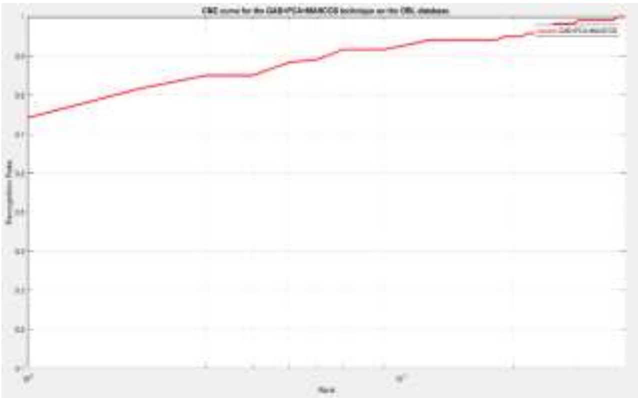

Fig: CMC curve of ORL database after using gabor extraction and Principal component analysis(PCA)

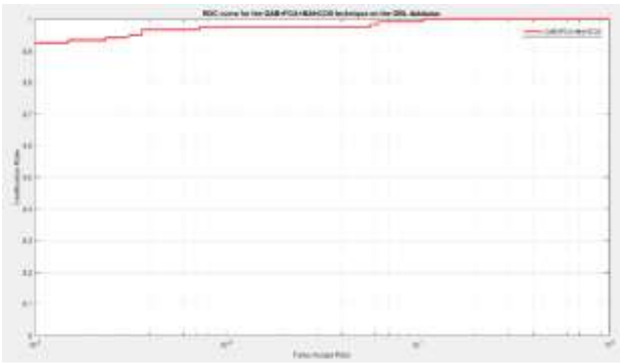

Fig: ROC curve of ORL database after using gabor extraction and Principal component analysis(PCA)

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SOME PERFORMANCE METRICS:

Identification experiments:
The rank one recognition rate of the experiments equals (in %): 93.33%

Verification/authentication experiments on the evaluation data:
The equal error rate on the evaluation set equals (in %): 2.50%
The minimal half total error rate on the evaluation set equals (in %): 1.56%
The verification rate at 1% FAR on the evaluation set equals (in %): 97.50%
The verification rate at 0.1% FAR on the evaluation set equals (in %): 93.33%
The verification rate at 0.01% FAR on the evaluation set equals (in %): 0.83%

Verification/authentication experiments on the test data (preset thresholds on evaluation data):
The verification rate at 1% FAR on the test set equals (in %): 99.38%
The verification rate at 0.1% FAR on the test set equals (in %): 91.88%
==================================================================
Finished with Step 5 (evaluation).
Finished 2D-FACE RECOGNITION USING GABOR FILTERS and LDA.
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Fig: Calculations of verification rates from command window after performing gabor feature extraction and LDA

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SOME PERFORMANCE METRICS:

Identification experiments:
The rank one recognition rate of the experiments equals (in %): 74.17%

Verification/authentication experiments on the evaluation data:
The equal error rate on the evaluation set equals (in %): 2.50%
The minimal half total error rate on the evaluation set equals (in %): 1.61%
The verification rate at 1% FAR on the evaluation set equals (in %): 97.50%
The verification rate at 0.1% FAR on the evaluation set equals (in %): 92.50%
The verification rate at 0.01% FAR on the evaluation set equals (in %): 0.83%

Verification/authentication experiments on the test data (preset thresholds on evaluation data):
The verification rate at 1% FAR on the test set equals (in %): 77.50%
The verification rate at 0.1% FAR on the test set equals (in %): 63.13%
=================================================================
Finished with Step 3 (evaluation).
Finished 2D-FACE RECOGNITION USING GABOR FILTERS and PCA.
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Fig: Calculations of verification rates from command window after performing gabor feature extraction and LDA

	Equal error rate	Minimal half error rate	Verification rate at 1%FAR	Verification rate at 0.1%FAR	Verification rate at 0.01% FAR
KPCA	4.17%	2.66%	95.00%	92.50%	0.83%
KFA	2.50%	1.85%	96.67%	93.33%	0.83%
PCA	2.50%	1.61%	97.50%	92.50%	0.83%
LDA	2.50%	1.56%	97.50%	93.33%	0.83%

Fig4: Verification rates of various algorithms on evaluation data

	Verification rate at 1%FAR	Verification rate at 0.1%FAR
KPCA	71.88%	56.88%
KFA	98.12%	93.1%
PCA	77.50%	63.13%
LDA	99.38%	91.88%

Fig4: Verification rates of various algorithms on test data

The above given tables shows the experimental results that are obtained after extracting the features of images in the ORL data set and then applying PCA and LDA to observe the ROC, EPC, CMC curves in each cases to analyze the performance. From the results it is observed that for a dataset based recognition system using LDA after Feature extraction increases performance to upto 99%.

V. CONCLUSION

We have developed a reliable, quick, and highly accurate 2D face recognition system in this research that is based on feature extraction utilizing Gabor filters, which shorten feature vectors and speed up processing. ORL Database has been used to test the system. The overall recognition outcomes show the proposed system to have a significant level of effectiveness.

VI. REFERENCES

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