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Comparative Analysis of Curvelets Based Face Recognition Methods

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Abstract—**This paper describes a comparative analysis of face recognition methods Principle Component Analysis(PCA),Linear Discriminant Analysis(LDA) and Independent Component Analysis(ICA) based on curvelet transform. Curvelet transform is multiresolution analysis method to improve directional elements with anisotropy and better ability to represent sparesely edges and other singularities along curves.This research aims to compare different face recognition techniques based on curvelet transform. All these algorithms are tested on ORL Database. The feasibility of these algorithms for human face identification is presented through experimental investigation. Face recognition algorithms are used in a wide range of applications viz., security control, crime investigation, and entrance control in buildings, access control at automatic teller machines, passport verification etc..,**

Index Terms - **Principle component analysis,face recognition, Linear Discriminant Analysis Independent Component Analysis,curvelet transform**

I. Introduction

Face recognition is a very active research area in computer vision. A survey of the research works on face recognition in the last decade can be found in [1].

Curvelet Transform is multiscale transforms to solve pattern recognition problems. It is also used to resolve image processing problems like image compression , texture classification and image denoising . Majumdar showed that curvelets can serve the basis for pattern recognition problems like character recognition [5].

Curvelet transform is defined in both continuous and digital domain and for higher dimensions curvelet transform has been used to extract features from bit quantized facial images. However, working with large number of features can be computationally expensive. This experimental study ,aims at reducing dimensionality using face recognition methods such as PCA,LDA and ICA.

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This paper describes a comparative analysis of face recognition methods PCA,LDA and ICA based on curvelet transform. It is evaluated by setting up different experiments and some of them having only one image per subject has been used as prototype. Thereafter, multiple sample images are used to increase the recognition rate. Experiments have been carried out on well-known database ORL (AT&T) Database.

The paper is organized as follows: The algorithm of face recognition methods are discussed briefly in section II; section III describes the curvelet transforms ;The result analysis is discussed in section IV and section V forms the conclusion.

II. ALGORITHM OF FACE RECOGNITION METHODS

In this section shows the face recognition algorithm discuss three different methods namely PCA,LDA and ICA

A. Principle Component Analysis

Principle Component Analysis is one of the successful technique used to the original data with lower dimensional feature vectors. This procedure that transforms a number of correlated variables into a number of uncorrelated variables called principle components.

PCA aims to maximize between-class data separation, while LDA tries to maximize between-class data separation and minimize within class data separation.

Basic steps of PCA algorithm

1. Determine PCA subspace from training data. i^{th} image vector containing N pixels is in the form
$X^i = [x_1^i, x_2^i \dots\dots x_N^i]$ Store all p images in the matrix
$X = [x^1 \dots\dots\dots\dots x^p]$ Compute covariance matrix
$\Omega = XX^T$ Compute eigenvalues and eigenvectors
$\Omega\vee = \wedge\vee$ where $\wedge$ is the vector of eigernvalues of the covariance matrix.
Order eigenvectors $\vee = [v_1, v_2, \dots\dots\dots\dots v_p]$

Order eigenvectors in $\vee$ according to their corresponding eigenvalues in descending order. Keep only the eigenvectors associated with non- zero eigenvalues. This matrix of eigenvectors forms the eigenspace $\vee$, where each column of $\vee$ is the eigenvector. Visualized eigenvectors of the covariance matrix are called eigenfaces [8] .

PCA is a powerful tool for analyzing data. The main advantage of PCA is to find the patterns in the data and reducing the number of dimensions without loss of information.

B. Linear Discriminant Analysis

Linear Discriminant Analysis(LDA) is supervised learning technique because it needs class information for each image in the training process. LDA finds an efficient way to represent the face vector space by exploiting the class information[6]. It differentiates individual faces but recognize faces of the same individual.

Basic steps of LDA algorithm

LDA considers between a class correspondences of data. It means that training images create a class for each subject, ie, one class = one subject (all his / her training images)[13]

1. Determine LDA subspace from training data. Calculate the within class scatter matrix and between class scatter matrix The following steps are performed by both methods.
2. All training images are projected onto particular method's subspace.
3. Each test image is also projected to the same sub-space and compared by distance metrics between the image and training images.

C.Independent Component Analysis

ICA minimizes both second – order and higher – order dependencies in the input data and attempt to find the basis along which the data are statistically independent.
Barlett et al (2002) provided two architecture of ICA for face recognition task: [7]
Architecture I – Statistically independent basis image.
Architecture II – factorial code representation**.**
To obtain completely independent components, which constitute complete faces. The basic idea is that any face image is a unique linear combination of these independent components.

III.CURVELET TRANSFORM

Multi-resolution analysis [6] allows for the preservation of an image according to certain levels of resolution orblurring. Broadly speaking, multi-resolution analysis allows for the zooming in and out on the underlying texture structure. Therefore, the texture extraction is not affected by the size of the pixel neighborhood. This multi-resolution quality is one of the reasons why wavelets have been useful in so many applications from image compression to image de-noising and edge detection .

Candes and Donoho [10] introduced a new system of multi-resolution analysis called the Curvelet transform. This system differs from wavelet and related systems. Curvelets take the form of basis elements, which exhibit a very high directional sensitivity and are highly anisotropic. Curvelet is one such transform that can efficiently represent edge discontinuities in images. Hence, due to its anisotropic behavior, Curvelets are elongated needle shaped structures. Owing to this needle shaped structures, curvelets approximate edges by contiguous elongated structures rather than fat dots-as was the case with wavelets. Consequently, edges can be represented by far less curvelet coefficients compared to wavelets. In other words, curvelets should be sparser than wavelets for images.

A. Curvelet feature extraction

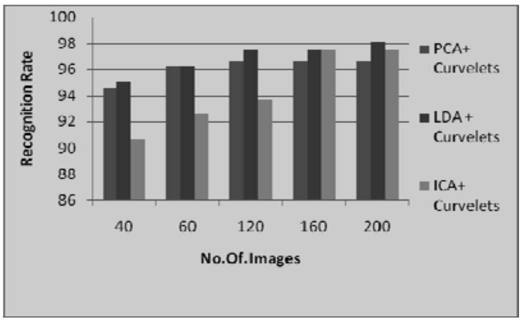
In this section the theoretical overview of curvelet transform and explained to work better than the traditional wavelet transform. Facial images are generally 8 bit i.e. they have 256 gray levels. In such images two very close regions that have differing pixel values will give rise to edges; and these edges are typically curved for faces. As curvelets are good at approximating curved singularities, they are fit for extracting crucial edge-based features from facial images more efficiently than that compared to wavelet transform. We will now describe different face recognition methodologies that employ curvelet transform for feature extraction. Typically, a face recognition system is divided into two stages: a training stage and a classification stage. In the training stage, a set of known faces (labeled data) are used to create a representative feature-set or template. In the classification stage, a unknown facial image is matched against the previously seen faces by comparing the features.

IV. ANALYSIS OF THE RESULT

To compare the curvelet transform with PCA , LDA and ICA. Table 1 shows the results are obtained from ORL database. It is clear that the comparison gives the recognition rate for PCA is 96.6%, LDA is 98.1% and recognition rate for ICA is 97.5% for the corresponding 200 images.

Tab.1.recognition accuracy for curvelet transform compared with holistic algorithms

No.of. Images	***PCA+ Curvelets***	***LDA + Curvelets***	***ICA+ Curvelets***
40	**94.6**	**95.1**	**90.63**
60	**96.2**	**96.2**	**92.64**
120	**96.6**	**97.5**	**93.75**
160	**96.6**	**97.5**	**97.50**
200	**96.6**	**98.1**	**97.50**



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V.CONCLUSION

In this paper, the three algorithms such as PCA, LDA and ICA are combined with curvelet transform. They are well known approaches for dimensionality reduction. The experiments are done with ORL face dataset, the recognition performance for all the three algorithms are evaluated and the experimental results shows that LDA based curvelet transform gives a better recognition rate and efficient dimensionality reduction technique compared with other two methods.The promising results indicate that curvelet transform can emerge as an effective solution to face recognition problem in future.

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