



Analysis of Recognition Accuracy Using Curvelet Transform

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Abstract— This paper describes a comparative analysis of recognition accuracy using feature extraction algorithm. A feature extraction algorithm is introduced for face recognition, Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and Nonnegative matrix factorization (NMF) based on curvelet transform. Mostly recognition system is capable to perform three subtasks face detection, feature extraction and classification. Digital curvelet transform is an even better method due to its directional properties, Curvelet transform is multiresolution analysis method to improve directional elements with anisotropy and better ability to represent edges and other singularities along the curves. This paper aims to compare different face recognition techniques based on curvelet transform for improving the performance of recognition accuracy. All these algorithms are based on ORL database using MATLAB. The achievability of these algorithms for human face identification is presented through new study. Face recognition algorithms are used in security control, forensic application, and access control at automatic teller machines, passport verification etc.

Keywords— Face recognition, Feature Extraction, PCA, LDA, ICA, NMF, Curvelet Transform.

I. INTRODUCTION

In the field of Image processing different types of method can be used for the analysis of image in different fields such as Denoising, Compression, Face recognition, Bio medical application etc. These analyses of images are based on different types of transforms: Fourier transform, Wavelet Transform, Curvelet transform. Now a day Wavelet and Curvelet transform is used in all fields of image processing. Face recognition has widespread applications in criminal identification, security, authentication, surveillance, Conventional ID card and password-based identification methods. The basic advantage of biometric features is that these are not prone to larceny and forfeiture and do not rely on the memory of their users. Additionally, biometrics, such as palm-print, finger-print, face, does not change significantly over time and it is difficult for a person to alter own fleshly biometric or emulate that of other person's. The main strength in appearance of faces that different images of a particular person may vary largely, while images of different persons may not necessarily vary implicitly. Furthermore, some features of the image, such as variations in brightness, position, location, measure, environment, fixtures, and age differences, make the recognition more intricate. Face recognition methods are based on extracting unique features from face images. In this respect, face recognition approaches can be classified into two main categories: holistic and texture-based [4]. Holistic or global approaches to face recognition involve encoding the entire facial image in a high-dimensional space [4]. It is expected that all faces are inhibited to particular positions, orientations, and scales and, hence, are very profound to pose disparities [7]. However, texture-based approaches trust on the detection of individual facial features and their geometric interactions earlier to execution face recognition. It is well known that while face images are exaggerated due to variations, such as non uniform illumination, expressions, and partial constrictions, facial variations are confined mostly to local regions. A local binary pattern was applied in [11] as a texture descriptor. The objective of this paper is to improve a feature extraction algorithm for face recognition using multi-resolution tools based on dominant curvelet domain features extracted from local zones instead of using the entire face image. In order to exploit the high-informative areas of a face image. Curvelet transform is defined in both continuous and digital area 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 study aims at reducing dimensionality using face recognition methods such as PCA, LDA, ICA, NMF.

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

II. CURVELET TRANSFORM

To overcome the drawback of Wavelet Transform, Curvelet Transform is developed, Curvelet Transform is very effective modal that not only consider a multi scale Time – Frequency local portion but also make use of the direction of features. It was developed by Candes and Donoho in 1999, there are two types of Curvelet transform is unequally spaced Fast Fourier Transform and wrapping based fast Curvelet Transform, in curvelet transform the width and length are related by the relation $Width \sim Length^2$ that is known as parabolic or anisotropic scaling. Moreover, frame elements in curvelet indexed by scale, location and orientation parameters in contrast to wavelets where elements have only scale

and location. This transform can be used for both continuous and digital domain. In this angle polar wedges or angle trapezoid window is used in frequency domain. Initially construction of Curvelet transform is redesigned as fast discrete Curvelet transform (FDCT) by Candes in 2006. This is second generation curvelet transform is meant to be simpler to understand and use. DCT can be implemented by wrapping based fast discrete curvelet at a given scale. At a given scale and orientation both the image and the curvelet are transformed into Fourier domain. The product of curvelet and the image are obtained in the Fourier domain. Inverse FFT is applied to the above product to obtain a set of curvelet coefficients. In order to perform IFT the trapezoidal wedge thus obtained from the frequency response of a curvelet is wrapped into a rectangular support. The spectrum inside the wedge is tilted periodically. Thus the rectangular region collects the wedge's fragmented portions by periodic tilting.

Curvelet Based Feature Extraction for Faces :

A classic face recognition system consists of some key steps, namely, input face image collection, preprocessing, feature extraction, classification, and template storage or database. In the prior section, we have presented a theoretical overview of curvelet transform and explained why it can be expected 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 conflicting 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 algorithms 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. Curvelet based feature extraction takes the raw or the preprocessed facial images as input. The images are then decomposed into curvelet subbands in different scales and orientations. Feature extraction algorithm is based on extracting spatial variations precisely from high-informative local zones of the face image instead of utilizing the entire image.

Curvelets and SVM

The first works on curvelet-based face recognition are [Zhang et al., 2007; Mandal et al.2007]. A simple application of curvelet transform in facial feature extraction can be found in [Zhang et al., 2007]. The authors have used SVM classifier directly on the curvelet decomposed faces. The curvelet based results have been compared with that of wavelets. Mandal et al. have performed 'bit quantization' before extracting curvelet features. The original 8 bit images are quantized to their 4 bit and 2 bit versions. This is based on the belief that on bit quantizing an image, only bolder curves will remain in the lower bit representations, and curvelet transform will be able to make the most out of this curved edge information. During training, all the original 8 bit gallery images and their two bit-quantized versions are decomposed into curvelet subbands. Selected curvelet coefficients are then separately fed to three different Support Vector Machine (SVM) classifiers. Final decision is achieved by fusing results of all SVMs. The selection of the curvelet coefficients is done on the basis of their variance. The recognition results for these two methods are shown below.

Average Recognition Accuracy	Curvelet + SVM	Wavelet + SVM
	90.44 %	82.57%

Table 1. Face recognition results for ORL database [Zhang et al., 2007]

III. ALGORITHM OF FACE RECOGNITION METHODS

A. Principle Component Analysis (PCA)

1. Determine PCA subspace from training data. i^{th} image vector containing N pixels is in the form

i] Store all images in the matrix

ii] Compute covariance matrix

iii] Compute eigenvalues and eigenvectors

corresponding eigenvalues in descending order. Keep only the eigenvectors associated with non- zero eigenvalues. This matrix of eigenvectors forms the eigen space, where each column of is the eigenvector. Visualized eigenvectors of the covariance matrix are called eigenfaces [4]. 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 (LDA)

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 [8]. 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) [3].

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 subspace and compared by distance metrics between the image and training images.

C. Independent Component Analysis

ICA is a statistical technique that represents a multidimensional random vector as a linear combination of nongaussian random variables ('independent components') that are as independent as possible. ICA is somewhat similar to PCA. ICA has many applications in data analysis, source separation, and feature extraction. 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. There are two architecture of ICA for face recognition task [11] 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.

D. Non-negative matrix factorization (NMF)

Non-negative matrix factorization (NMF) is a recently developed technique for finding parts, and it is based on linear representations of non-negative data. Given a non-negative data matrix X, NMF finds an approximate factorization $X=W.H$ into non-negative factors W and H. The non-negativity constraints make the representation purely additive (allowing no subtractions), in contrast to many other linear representations such as PCA or ICA. Motivation: In most real systems, the variables are non negative. PCA and ICA offer results complicated to interpret. W and H are chosen as the matrix that minimize reconstruction error. The importance of NMF is that it has capacity of obtaining significant features in collections of real biological data. When applied to X = Faces, NMF generates base vectors that are intuitive features of the faces (eyes, mouth, nose)

IV. ANALYSIS OF THE RESULT

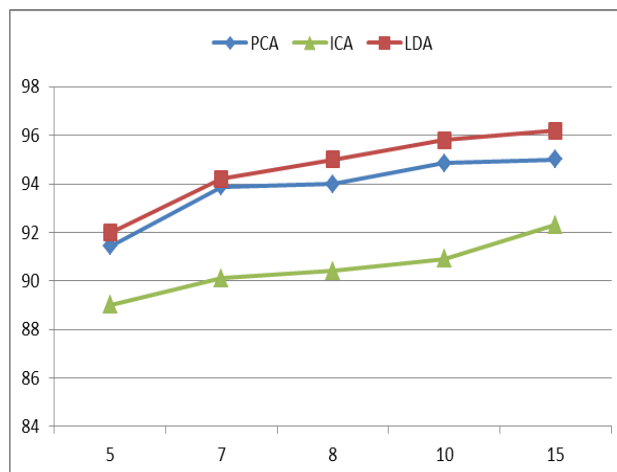
The works on face recognition accuracy using curvelet transform that exist in prose are not yet complete and do not fully understand the capability of curvelet transform for face recognition. To compare the curvelet transform with PCA, LDA and ICA NMF. In given Table 2 shows the results are obtained from ORL database. It is clear that the comparison gives the recognition rate for all algorithms based on changed images the recognition graph is shown in fig 111111 PCA is 96.6%, LDA is 98.1% and recognition rate for ICA is 97.5% for the corresponding 200 images.; hence, there is much scope of improvement in terms of both recognition accuracy and curvelet-based methodology.

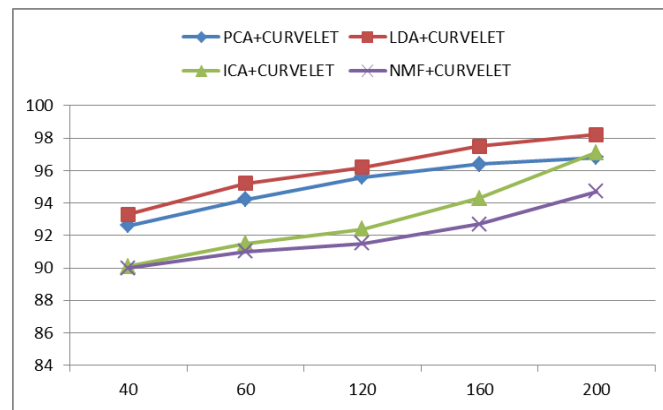
No.of Images	PCA	LDA	ICA
5	91.43	91.98	89
7	93.88	94.2	90.1
8	94.0	95	90.4
10	94.86	95.8	90.9
15	95.0	96.2	92.3

Table 2 Recognition rate of PCA, LDA, ICA

No of Images	PCA+Curvelet	LDA+Curvelet	ICA+Curvelet	NMF +Curvelet
40	92.6	93.3	90.1	90
60	94.2	95.2	91.5	91
120	95.6	96.2	92.4	91.5
160	96.4	97.5	94.3	92.7
200	96.8	98.2	97.1	94.7

Table 3 Recognition rate of PCA, LDA ,ICA, NMF with Curvelet Transform Graph Between Recognition Rate /No of Image For Table 2& 3.





V. CONCLUSIONS

In this paper two part of the result in first the three subspace projection which are PCA, LDA, and ICA are studied. In second part PCA, LDA, ICA and NMF are combined with curvelet transform. The experiments are done with ORL face dataset, recognition performance for all the algorithms is evaluated. The experimental results tell that LDA and LDA+Curvelet is a nice dimensionality reduction technique, and can be employed for face recognition very well.

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