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Face Recognition Using Curvelet Transform

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Abstract
In the era of Information Technology, openness of the information is a major concern. As the confidentiality and integrity of the information is critically important, it has to be secured from unauthorized access. Traditional security and identification are not sufficient enough; people need to find a new authentic system based on behavioral & physiological characteristics of person which is called as Biometric. Face recognition gives several advantages over the other biometrics. This paper is aimed to analyze the performance of face recognition systems using Curve let transform. One of the key issues in face recognition system is selection of features from face images. Appearance based & texture based is alternative for feature extraction stage. Here texture based curvelet feature extraction method is proposed for face recognition. In this work, we proposed face identification technique which is robust to orientation of the face image under similar illumination condition. We tested our results using CASIA database and our own captured database.

Keyword—Histogram equalization, Median Filter, PCA ,Euclidian distance.

1. Introduction

Biometrics-based person recognition is currently one of the key issues in security applications. Many biometric signals (speech, iris, fingerprint, signature, etc.) are being used in this field. Face recognition has raised extensive attention since 1990.The trend is driven by increasing demand on security application. Face recognition is best application in biometrics than fingerprint, iris recognition etc. because it has not required a physical contact like fingerprint we can acquire image from long distance at any time. So that it can be used at any security application like ATM, debit card frauds etc.

In facial recognition we are trying to recognize the face of individual person and then match with the database. A face recognition system can operate in following two modes: *Verification:* A one to one Comparison of a captured biometric with a stored template to verify that the individual is who he claims to be. *Identification*: A one to many comparisons of the captured biometric against a biometric database in attempt to identify an unknown individual. The identification only succeeds in identifying the individual if the comparison of the biometric sample to a template in the database falls within a previously set threshold

General steps in Face Recognition:

- *Capture the image*: First step is to capture the image of the person who is to be recognized by using digital camera
- *Face detection***:** Next is detection of actual face in the image.
- *Feature extraction***:** After a face has been detected, the task of feature extraction is to obtain features that are fed into a face recognition system. These features can be local features such as lines or fiducially points, or facial features such as eyes, nose and mouth or texture features.
- *Face Recognition***:** The last step is face recognition, where extracted features of input image are compared with the features in the database

This paper compares the performance of face recognition system using PCA features and Curvelet transform.

2. Background & Related work:-

Over the last few years, numerous algorithms have been proposed for face recognition. There are two approaches to face recognition, feature based and appearance based .The geometric feature based approach uses properties & relation (e.g. distance & angle) between facial features such as eyes, mouth, nose & chin to perform recognition [1]. Despite their economical representation & their insensitivity to variation in illumination & view point. It is not reliable enough for extraction and measurement of facial features. The other method used are appearance based which use low dimensional representation of images to perform recognition and is applied to either whole-face or specific regions in a face image. Among many approaches to the problem of face recognition, appearance-based subspace analysis, although one of the oldest, still gives the most promising results. Subspace analysis is done by projecting an image into a lower dimensional space (subspace) and after that recognition is performed by measuring the distances between known images and the image to be recognized The appearance based methods are as follows,

a) Eigen face by principal component analysis (PCA), a classical linear method for unsupervised

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dimensionality reduction that transforms a data set consisting of a large number of interrelated variables to a new set of uncorrelated variables [4][5][6].

b) Fisher face by linear discriminate analysis (LDA) is popular for face recognition.LDA estimate transformation matrix through maximizing ratio of between class scatter to within class scatter. Discriminative features are extracted for template matching using nearest neighbor classification rule.LDA is statistical approach for classifying sample of unknown classes based on training samples with known classes[2].

Texture is characterized by the spatial distribution of gray levels in a neighborhood. There are different methods for texture feature extraction such as DCT[7],Gabor[9][11],DWT,curvelet. Gabor filters have the ability to perform multi-resolution decomposition due to its localization both in spatial and spatial frequency domain.DWT gives only three directional features such as horizontal, vertical, diagonal.

Some of the challenges of facial recognition in the visual spectrum include reducing the impact of variable lighting and detecting a mask or photograph. Major benefits of facial recognition are that it is non-intrusive, hands-free, and continuous and accepted by most users. The main problems with authentication by face- recognition are as follow:

- The facial features depend on the angle of orientation of the face, which cannot fix.
- The features depend on the ambient.
- And the finally it changes with age, make-up, presence or absence of glasses, and even the expression on the face, like angry, happy, sad etc.

Therefore, even though the person is same, the automatic authentication system may fail. It is said that about 75% of the authentication failure is because the angle of orientation of the probe face-image. Therefore we proposed face identification technique which is robust to orientation of the face image under similar illumination condition using curve let & for dimension reduction of feature vector PCA is used.

3.Actual System Implementation

The automatic Face recognition system contains Enrollment mode & Recognition mode.

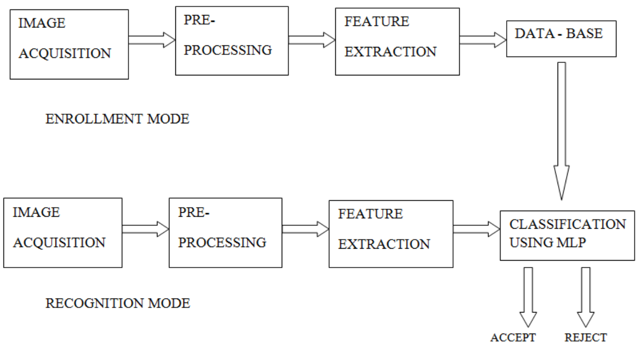


Fig 1:-System Block Diagram

- ***Image Acquisition***

This block involves taking image. Image acquisition is of two type off-line and on-line. In off-line process image is taken into paper and then transferred into computer. Since it has relatively high resolution (up to 500 dpi) face matching technique can be used. In case of online acquisition of image a low resolution and fast process can be developed and online method can be used by common man on day to day basis for securing systems and work stations. But process is costly and complicated.

So for are convenience we are going to use an offline acquisition technique for image acquisition. We have captured images of 50 persons with 6 different angle orientations with resolution 120 dpi using digital camera.

Fig 2:- Captured Images

- ***Preprocessing:-***

Face recognition algorithms have to deal with significant amounts of illumination variations between gallery and probe images. For this reason, image preprocessing algorithm that compensates for illumination variations in images is used prior to recognition.

- ***Rgb to Gray scale conversion-***

To convert from RGB to gray scale following formula used,
Luminance = (0.3xRed) + (0.59xGreen) + (0.11xBlue)
We don't use RGB images for processing since it will take three times more processing time

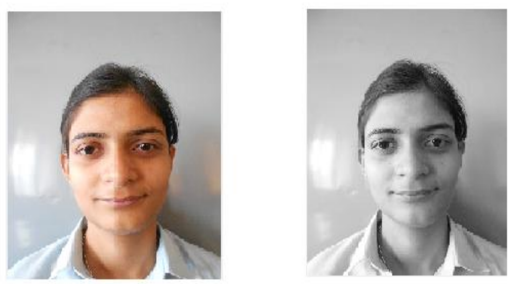


Fig. 3 :-RGB TO GRAY Conversion

- ***Noise removal***

Medial filter is applied for noise removal from images. It removes salt & pepper noise. Such noise is represented by black & white dots in image. Median filter dose better job than mean filter by preserving useful detail in image.

Fig. 4 Noise removal

➢ ***Histogram Equalization-***

Histogram equalization is used to have image with approximately the same number of pixels for all luminance. Images with equalized histogram have good contrast and it is the main reason for performing this operation.
Transformation of histogram is given by,

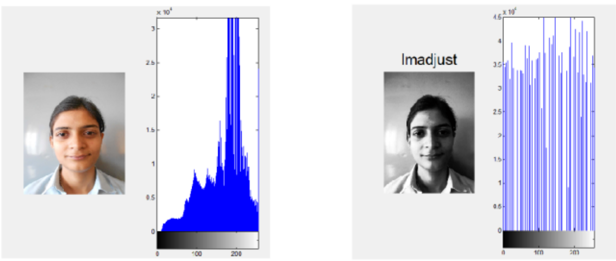
$$S=T(r)$$

Where T(r) must be single value and monotonically increasing in the interval $0 \leq r \leq 1$
Consider a discrete grayscale image {x} and let n_i be the number of occurrences of gray level i. The probability of an occurrence of a pixel of level i in the image is

$$p_x(i) = p(x = i) = \frac{n_i}{n}, \quad 0 \leq i < L$$

L being the total number of gray levels in the image, n being the total number of pixels in the image, and $p_x(i)$ being in fact the image's histogram for pixel value i, normalized to [0,1]. Cumulative distribution function corresponding to p_x is defined as,

$$cdf_x(i) = \sum_{j=0}^{i} p_x(j),$$



(a) (b)

Fig. 5 Histogram equilization

➢ ***Feature Extraction:-***

In prior to pattern matching stage a feature extraction stage is necessary, in order to obtain the face characteristics and to accomplish the recognition task. The result of this feature extraction stage, it would be desirable to have a simple and reliable representation of the input signal but retaining, at the same time, all the important cues for recognition.
Some features are more dependent on face view and less dependent on face identity whereas some features are less dependent on face view and more dependent on face identity.
In this approach for angle invariant face recognition, conceptually we need two sets of features:

- Angle features which would represent the pose/orientation of the face and
- Face image features which would faithfully represent the face identity of the person.

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. In proposed method we use curvelet transform to extract the features.
Wavelets perform well only at representing point singularities since they ignore the geometric properties of structures and do not exploit the regularity of edges. In wavelet transform the directional feature can be extracted only in three directions namely horizontal, vertical and diagonal direction whereas Curvelet transform captures all directions along wedges formed using curvelet decomposition. Curvelet take the form of basis elements ,which have elongated effective support i.e. length>width.So, curvelet transform owns very high directional sensitivity and anisotropy.The Curve let Transform includes four stages:-1)Sub-band decomposition.2)Smooth partitioning. 3)Renormalization .4)Ridge let analysis.
Second generation curvelet transform is faster and less redundant compared to its first generation version . In the new version of curvelet, the ridgelet transforms was discarded, thus reducing the amount of redundancy in the transform and increasing the speed considerably. Curvelet transforms is defined in both continuous and digital domain. Second generation curvelet transform has two different digital implementations:

- Curve lets via USFFT (Unequally Spaced Fast Fourier Transform)
- Curvelets via Wrapping.

These new discrete curvelet transforms are simpler, faster and less redundant compared to their first generation version. Both the digital implementations use the same digital colonization but differ in the choice of spatial grid.

Here we used Curvelet via Wrapping ,as this is the fastest curvelet transform currently available. Curvelet transform based on wrapping of Fourier samples takes 2-D image as input in the form of Cartesian array f[m,n] such that 0≤m<M,0≤n<N and generate number of curvelet coefficients indexed by scale j, an orientation l and two spatial location parameters(k1,k2) as a output. Discrete curvelet coefficients can be defined by,

$$C^D(j,l,k_1,k_2) = \sum_{\substack{0\le m<M \\ 0\le n<N}} f[m,n]\varphi^D_{j,l,k_1,k_2}[m,n]$$

Each $\varphi^D_{j,l,k1,k2}\,[m,n]$ is a digital curvelet transform. Wrapping based curvelet transform is multiscale transform with pyramid structure consisting of many orientation at each scale. With increase in resolution level curvelet becomes finer and smaller in the spatial domain and shows more sensitivity to curved edges which enables it to effectively capture curve in an images as shown in fig 6

Fig 6:-Second level decomposition of face image

After Curvelet, PCA is used to extract Feature vector and reduce size of feature vector.PCA is used with two main purposes. First it reduces dimensions of data to computationally feasible size. Second it extracts the most representative features out of input data so that although the size is reduced, main features remain and still be able to represent the original data. The best low-dimensional space can be determined by the "best" eigenvectors of the covariance matrix of x (i.e., the eigenvectors corresponding to the "largest" eigenvalues also called "principal components").

- ***PCA Algorithm***

Suppose $x1, x2, ..., xM$ are Nx1 vectors

Step 1: $\bar{X} = \frac{1}{M}\sum_{i=1}^{M} Xi$

Step 2: subtract the mean: $\emptyset i = xi - x$

Step 3: form the matrix $A = [\emptyset 1, \emptyset 2 \ldots \emptyset M]$ (NxM matrix), then Compute:

$C = \frac{1}{M}\sum_{i=1}^{M} \emptyset n\ \emptyset_n^T = AA^T$

(Sample **covariance** matrix, NxN, characterizes the *scatter* of the data)

Step 4: compute the eigen values of C: $\lambda 1 > \lambda 2 > \ldots > \lambda N$

Step 5: compute the eigenvectors of C: $u1, u2, \ldots, uN$

Since C is symmetric, $u1, u2, \ldots, uN$ form a basis, (i.e., any vector x or actually (x-$\bar{x}$), can be written as a linear combination of the eigenvectors):

$x - \bar{x} = b1u1 + b2u2 + \ldots + bNuN$

Step 6: (**dimensionality reduction step**) keep only the terms corresponding to the K largest eigenvalues:

$x - \bar{x} = \sum_{i=1}^{k} b_i u_i$ **where** $k \ll N$

The above steps are needed to generate the principal components of the image. Corresponding Eigen vectors are uncorrelated and have the greater variance

- ***Matching***

For Matching Euclidean Distance algorithm is used. If the value is greater than threshold then we accept it otherwise we reject it.

- **Euclidean distance**

Euclidean distance is the ordinary distance between two points. It is measure as the square root of the sum of the squares of the differences between the corresponding co-ordinates of the points. Set of Images of same user are taken and mean of these feature vectors is the Template. Template vector dimension must same as Input vector.

$$d = \sqrt{\sum_{i=1}^{L}(x_i - t_i)^2}$$

Where, d is the Euclidean distance, L is dimension of the feature vector, Xi is the ith component of the sample feature vector, Ti is the ith component of the template feature vector.

4. Results

The results were tested on standard database of CASIA & also on our own captured database, which contains 100 persons each of 6 samples. Out of 6 samples 3 were taken for training and 3 were taken for testing.

4.1 Performance measurement parameters:-

The performance of a biometric system can be measured by reporting its false accept rate (FAR) and false reject rate (FRR). These two error rates are brought together in a receiver operating characteristic (ROC) curve that plots the FAR against the GAR (1-FRR). FAR and FRR depends on threshold so EER (Equal error Rate) and Efficiency are used for comparison. For finding FAR, FRR, Efficiency we use confusion matrix.

TP	**FP**
FN	**TN**

Fig 7:-Confusion Matrix

True Positive=Correctly Identified
False Positive=Incorrectly Identified
True Negative=correctly rejected
False Negative=Incorrectly Rejected

- FAR-False Acceptance Rate.

It gives how many imposter are falsely accepted.

FAR=TP/(TP+FN)

- FRR-False Rejection Rate

It gives how many genuine are falsely rejected

FRR=TN/(FP+TN)

- **Efficiency=TP+TN/(TP+TN+FP+FN)**

Table 1:-Results of face recognition tech. for local database

Face Methods	FAR	FRR	EER in %	Efficiency
PCA	**0.8989**	**0.914**	**4**	90.3
Curvelet+PCA	**0.902**	**1**	**1.165**	**94.74**

The result table shows the efficiency obtained by Curvelet+PCA is more than PCA for local database of face.

Table 2:-Results of face recognition tech. for Casia database

Face Methods	FAR	FRR	EER in %	Efficiency
PCA	**0.868**	**0.971**	**13.9**	**88.6364**
Curvelet+ PCA	**0.8667**	**1**	**0.54**	**92.5**

The result table shows the efficiency obtained by Curvelet+PCA is more than PCA for CASIA database of face.In proposed method, efficiency obtained is 94.74 percent depending on the angle of orientation for local database and 92.5 percent for CASIA database by Curvelet+PCA algorithm.

5. Conclusion

In this paper, Eigen face technique using principal component analysis for face recognition and a multiscale representation technique for face recognition is demonstrated using Curvelet.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. However, in spite of PCA's popularity, it suffers from two major limitations: poor discriminatory power and large computational load. Discrete wavelet transform provides the time and frequency information which is not being provided by the Fourier and short time Fourier Transform. But curve discontinuities are not given by DWT.Curvelet provide the curve discontinuities well than DWT.The standard database used for employing PCA algorithm and Curvelet is the CASIA database; it is also employed using a local database consisting of 100 images with each image of a person oriented in 6 different angles. The experimental result shows that efficiency obtained using this Curvelet is more than PCA algorithm. DWT gives only three directional features (horizontal, vertical, and diagonal). The limitation of curve let transforms that transform in continuous domain and then discretize for sample data. The contourlet transform starts with discrete domain construction then studies its convergence to an expansion in continuous domain. To overcome these disadvantages in future we try to implement Contour let transform which gives multistate, multi directional features in discrete domain.

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