A Review on Iris Feature Extraction Methods

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Abstract— Iris biometry has been gaining its attention during the recent years in the various cooperative and non-cooperative environments. The stability and unique features of iris lead to its increased usage for personal recognition in various fields like airport, border security, harbors, etc. All the researches are going on in the area of iris recognition to increase its accuracy and speed of recognition. The reduced time for personal recognition improves the performance of the recognition system and reduces the amount of false recognition. The difficulty of forging and using an imposter lead to the wide acceptance of iris biometry. The various methods used in iris recognition proposed by various researches are reviewed in this paper. All these methods give importance to increase the speed of recognition.

Keywords— Iris recognition, feature extraction, Gabor, DCT, DWT, Contourlet Transform, ICA, PCA, GLCM

INTRODUCTION

Biometry is gaining more attention during the recent years. Biometrical identification refers to the physiological and behavioral characteristics of a person to recognize an individual. There are several types of biometry including voice, signature, fingerprint, face, iris, hand, keystroke dynamics, etc. The physiological characteristics include iris, face, hand, fingerprint, etc. Behavioral characteristics are voice, signature, keystroke dynamics, etc. Among all the existing biometrics, iris is the most efficient one in terms of accuracy. Iris provides unique set of features to represent an individual. These features are stable throughout the life time of an individual. Iris has distinct phase information. Iris biometry is also very reliable since it is an externally visible part of the eye and hence does not need the contact of an individual to acquire it unlike hand, fingerprint, etc.

The basic steps included in an iris recognition system are image acquisition, preprocessing, iris localization and segmentation followed by the extraction of features, and finally the formation of feature vector and identification between a genuine and an imposter image. Image acquisition implies the capturing of iris images under sufficient illumination conditions. Improper acquisition may lead to addition of noises in the acquired images. Preprocessing step includes the noise removal and pupil extraction. The pupil in an eye image does not carry any useful information, and thus can be removed which will helps in the localization of iris. Then the iris area will be identified and segmented out. This segmented iris is used to form the feature vector of an iris. After this feature extraction the feature vectors are compared using any classifiers to identify the authorized persons.

A biometric system mainly consists of two phases namely the enrollment phase and verification phase. In the enrollment phase, the images are collected and feature extracted to form the feature vector and is then stored in a database. In the verification phase, the query image which is to be tested is preprocessed and then feature extracted. Thus formed feature vector will be compared against those stored in the database to identify the authorized persons.

FEATURE EXTRACTION

Iris has a unique texture and thus can uniquely represent each of the individual. Feature extraction methods extract the distinctive features present in an iris image. Features give both the local and global information about the iris. It quantifies some significant characteristics in an iris. There exist several algorithms for efficient feature extraction. Normally feature extraction methods can be grouped as signal processing methods and statistical processing methods. The first method includes both the spatial domain and frequency domain methods. The latter one exploits the spatial dependencies between the pixels. Features can be general features or domain specific features. General features normally refer to the features like color, texture, shape, etc. they can be referred as pixel level features, local features and global features. The features that are computed pixel- wise whereas the local features are those which are computed on subdivisions of an image and global features refers to those which are computed for the entire image. Domain specific features normally refer to the features in an application specific domain such as face, fingerprint, etc. Some of the methods that are used to extract the iris features are briefly reviewed below.

a) Gabor filter

J.Daugman [17] introduced gabor filters for iris recognition and he got patent for this paper. Gabor filters can provide finest conjoint representation of signal in both space and spatial frequency. A Gabor filter is created by modulating either a sine wave or a cosine wave with a guassian. Since the sine wave is perfectly confined in frequency, but not in space, this modulation provides the optimum conjoint localization in both space and frequency. Modulation of the sine wave with a Guassian wave results in space localization, along with the loss of localization in frequency.

Quadrature pair of Gabor filters is used for the decomposition of a signal, with an imaginary part defined by a sine modulated by a Guassian and a real part defined by a cosine modulated by a Guassian. The real filters are known as the even symmetric components while the imaginary filters are known as odd symmetric components. The frequency of a sine wave specifies the center frequency of the filter, meanwhile the bandwidth is defined by the guassian bandwidth. The iris features are extracted by the application of 2D gabor filters. By varying the wavelengths and the orientation of filters, several banks of gabor filters comprising 15, 20, 25, 30, 35 filters are applied on images. 2D gabor filter can be defined as:

$$G(x, y; \theta, f) = exp\{-(1/2)[(x'^2/\partial x'^2)+ (y'^2/\partial y'^2)]\}\cos(2\pi f x') \tag{1}$$
$$x' = x\, cos\theta + y\, sin\theta \tag{2}$$
$$y' = y\, cos\theta - x\, sin\theta \tag{3}$$

where δx and δy symbolize the spatial size of the filter, θ denotes the orientation angle, f gives the frequency of the filter. Since a gabor filter possess both the real and imaginary parts, it will yield 20 real and 20 imaginary outputs when an input image is convolved with a bank of 20 filters. By combining both of these real and imaginary parts, an output feature vector of about 2048 bit length can be generated.

Gabor filters can be applied on multichannel basis in some methods. In this method, the filters will be applied locally on several parts of the image instead of applying to the entire image at once. The entire iris image is represented by the global information which is formed by combining the local information calculated from each part of the iris. This technique is done by dividing the entire original image into a number of equal parts needed to compute the local information. A number of banks of gabor filters will be applied on these divided sub images. Then the feature vector is formed by collecting information extracted from these sub-images. Thus formed feature vector will be the result of combination of local feature vectors of both the real and imaginary outputs. This resultant feature vector is then used for comparison.

b) Log-Gabor Filter

D.field [19] and P.Yao, X.Ye [20] introduced log-gabor filters which are guassian on the logarithmic scale. The normal gabor filters are the traditional choice of filters in feature extraction. Usually, they are suffered with two main restrictions; the maximum bandwidth is confined to roughly one octave and also in the case of seeking broad spectral content with maximum spatial localization, these filters are not optimal. Thus a logarithmic gabor filter called log-gabor filter is introduced as an alternative to the normal gabor filter. This log-gabor filter is based on the fact that when viewed on a logarithmic frequency scale, the natural images can be better coded using filters having Guassian transfer function. Gabor functions are having guassian transfer functions when observed on a linear frequency scale. The frequency response of a log-gabor filter can be given as:

$$G(f) = \exp\{-0.5\times\log(f/f_0)^2 / \log(\sigma/f_0)^2\} \tag{4}$$

Here f_o denotes the center frequency and σ represents the bandwidth of the filter. There are two important characteristics to be noted. Firstly, the log-gabor functions do not have a dc component, and secondly, at higher frequencies the transfer function of a log-gabor filter has an extended tail [2].

c) Discrete Cosine Transform

D. M. Monro introduced DCT for the feature extraction in [4]. Discrete cosine transform can be used for expressing a signal as a sum of sinusoids. Similar to the DFT, DCT is also meant to work on the data points which are discrete. The noticeable difference between these two is that the DCT make use of cosine functions only whereas the DFT uses both the sine and cosine functions. For very highly correlated images the DCT always shows exceptional energy compaction. DCT represents any signal or function as the sum of sinusoids for various amplitudes and frequencies.

DCT can be expressed mathematically as;

$$F(u,v) = \alpha(u)\, \alpha(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \cos(\pi(2x+1)u/2M) \cos(\pi(2y+1)v/2N) \tag{5}$$

where $\alpha(u) = \{(1/\sqrt{M})\ ,\ u = 0,$ & $\alpha(v) = \{(1/\sqrt{N})\ for\ v = 0,$
$\sqrt{(2/M)}\ ,\ u = 1,2, \ldots . M-1)$ $\sqrt{(2/N)}\ ,\ v = 1,2, \ldots . N-1)$

When DCT is applied to an image, all the low frequency coefficients will get concentrated on the top left most corners of the DCT spectrum. Thus it can be said that DCT compresses all the information present in the image and considers only those coefficients which are present at the left hand top most corners. The main unique distinguishable features of the subject are represented by these low frequency components whereas the finer details are represented by the high frequency components. For recognition based applications, usually the low frequency components which are residing on the top left most corners are extracted. It is because for such applications, these low frequency components are more than enough. The high frequency components are discarded in these cases.

The Discrete Cosine Transform requires fastest algorithms for its computation. It is real, orthogonal and separable. DCT is similar to DFT in the case of real numbers since the fourier transform of real and even function is real and even. The DCT helps in achieving a clear frequency distribution when it is applied on an image. The low frequency components possess more information than the high frequency components. The low frequency components get accumulated on the left top most corner. In order to compute 2D DCT, the 1D DCT is applied initially on the rows and then to the coloumns. The coefficients obtained after DCT is used to form the feature vector needed for comparison. For the case of basis vectors with real valued components DCT is a competent method.

d) Discrete Wavelet Transform

W. Boles and B. Boashah [21] introduced a human identification technique using the wavelet transform. Unlike DCT, Wavelet transform provides the real time representation of a signal in both time and frequency. The most significant difference is that the wavelet transform offers a flexible time frequency window. This window gets narrowed while witnessing the high frequency activities. Similarly, it gets widened while observing the low frequency activities. Thus the wavelet transform provides multiresolution analysis with the help of this window. It is said to be multiresolution since it offers good spatial resolution for higher frequencies and good frequency resolution for lower frequencies. This type of approach is more appropriate for those signals having lesser higher frequency components and more low frequency components

The DWT decomposes the image into four parts namely approximation, horizontal details, vertical details and diagonal details. The approximation part represents more information compared to the detail parts. The approximation part corresponds to the low frequency components. For further decomposition DWT is again applied on the approximation part to achieve the multiresolution. In iris recognition applications, the iris region gets decomposed to components at different resolutions. Thus the frequency data gets localized so that the features occurring at the same position and resolution become matched. Different types of wavelets are being used for this application.

e) Contourlet Transform

Amir and Hamid [23] developed an iris extraction algorithm based on contourlet transform. The main concept behind the Contourlet transform is that a sparse image expansion can be obtained by the application of multiscale transform tailed by a local directional transform. The nearby basis functions at the same scale are grouped into linear structures. The CT is obtained by the application of directional decomposition after the multiscale decomposition. Thus it offers multiple numbers of different directions at a single scale. Contourlet transform makes sense in the feature extraction applications because of its properties like directionality and antistropy. The directional energies of the curvelet coefficients in each of the sub image create the antistropic feature vector.

The Curvelet Transform is constructed by the multiscale decomposition with the Laplacian pyramid followed by the directional decomposition of sub bands using the directional filter bank. Thus the texture details from a set of directional sub bands are collected at various scales in different orientations. Thus intrinsic geometrical structures are obtained for the iris image. The contour segments detection is made possible by the local directional transform using the directional filter bank whereas the edges or point detection is made possible with the help of wavelet-like transform (Laplacian Pyramid). This combination of laplacian pyramid and double filter bank is called as pyramidial directional filter bank.

f) Principal Component Analysis

Jin-Xin Sh, and Xiao-Feng Gu [12] identified the use of principal component analysis for feature extraction. PCA is invented by Karl Pearson in 1901. This classic technique is mainly used for the suppression of higher dimensional data sets to the lower dimensions for the purpose of data analysis and visualization, compression of data and for the extraction of features. This analysis mainly involved the computation of eigen value decomposition and singular value decomposition for data covariance matrix and data matrix respectively after mean entering the data of each attribute. The features obtained after PCA are usually spatial global features. PCA thus performs the data reduction by transforming the original data into a much smaller dimensional feature space.

PCA is normally used to find patterns in the higher dimensional data. This technique involves the suppression of a larger number of correlated variables to a lesser number of uncorrelated variables. These lesser number of uncorrelated variables is called the principal components. These components usually represent the maximum variance possible and thus revealing the internal structure of the data. PCA can be considered as one of the simplest eigen vector based multivariate analyses.

The first principal component identified represents the maximum variance with the following component accounts for the remaining maximum variance possible. In such a way, the strength of variations in different directions for an image is computed. Both the eigen vectors and eigen values are computed by PCA. The principal components are those eigen vectors which are having the largest eigen value. It is also called as the discrete Karhunen-Loeve transform, the Hotelling transform or proper orthogonal decomposition (POD) depending on the application it is used. PCA find the principal components which represent the maximum variance possible by a set of linear transformed components. Thus PCA can be considered as an unsupervised linear feature extraction algorithm involving a linear mapping using the eigen vectors having the highest eigen values. The study of the eigen value decomposition of a covariance matrix is called as the Principal Component Analysis

g) Independent Component Analysis

Jin-Xin Sh and Xiao-Feng Gu [12] employed feature extraction method based on Independent Component Analysis. ICA is one of the analysis techniques for the source separation which aims at recovering the original signal from a set of known observations where each of the observations corresponds to an unknown mixture of the original signal, which is possible in case of statistically independent original signal and are under mild conditions on mixture. The ICA computes the inverse of the mixing matrix if the mixing performed is linear. Instead of the eigen vectors in PCA, ICA computes the independent source vectors. These higher dimensional vectors are a linear combination of a set of unknown independent source vectors. Using the estimates of the computed independent source vectors, ICA can reconstruct the original signal. The coefficients of expansion of ICA are taken as feature vectors for irises. Being independent the ICA source vectors are much closer to natural features present in an image and thus can easily identify the differences between irises. ICA characterizes a multidimensional random vector as a linear grouping of independent components which are random variables that are not guassian. ICA mainly depends on the correlation information between the patterns.

h) Grey Level Co-occurrence Matrix

Amir and Hamid [23] and V. V. S. Tallapragada [16] developed an iris extraction algorithm based on GLCM. A grey level co-occurence matrix defines the distribution of co-occuring values at a specified offset level. This matrix is created by considering the direction and distance between each pixel. Texture representation is done by those features which are derived from this matrix. This non-filter based technique mainly relies on the second order statistics of the pixel intensities and computes the joint probability distribution function of the grey levels present in an image. The mathematical definition of the co-occurrence matrix is the probability $P_d(i, j)$ of two pixels, with grey level values i and j respectively and are parted by a distance vector d, of an image I of size N X M is given as;

$$P_d(i, j) = (|\{((r,s)(t,v)) : I, I(t,s) = i, I(t,v) = j\}|)/NM \tag{6}$$

GLCM is a statistical measure which defines the texture by computing the frequency of occurrence of pairs of pixel in a given spatial relationship and with defined values . since the GLCM is based on the spatial relationship between the pixel of interest and the pixel to its immediate right, it is also called as grey level spatial dependence matrix. The size of the GLCM matrix represents the number of grey levels present in the corresponding image. The joint pdf of the pairs of pixels define the spatial relationship between them, which is usually described in terms of the lineal distance between pixels and the angle between them. Normally 14 features representing the visually recognizable properties of image are extracted from the GLCM matrix. These texture representing features are energy, entropy, contrast, variance, correlation, homogeneity, sum average, sum entropy, sum variance, difference variance, maximum correlation coefficient, and finally the information measures of correlation.

CONCLUSION

Iris recognition has been increasing its popularity during the recent years. The various methodologies used for the feature extraction in an iris recognition system proposed by several researches are reviewed in this paper. Iris biometry has been gaining its popularity due to its stability and uniqueness in the life time. All the methodologies reviewed in this paper have its own importance depending on the area of application of these methods. Researches are still going on to increase the accuracy and to reduce the time required for recognition.

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