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Biometric Identification Based on Conjuctival Vasculature Pattern using Contourlet Transform

Authors

Nutan S. Jadhav[1], Prof S. N. Dharwadkar[2]

Electronics and Telecommunication Department, M. E. S. College of Engg. Savitribai Phule Pune University Pune, India

Email: *nutansjadhav@gmail.com, sndharwadkar@mescoepune.org*

Abstract

The performance of any biometric system depends on the reliable and robust feature extraction. Biometric recognition refers to the use of distinctive anatomical (e.g., fingerprints, face, iris, palm) and behavioral (e.g., speech) characteristics for automatically recognizing individuals. Iris recognition was found to be most accurate bio-metrics technology. Apart from the red, green, and blue (RGB) format, we analyze significance of using HSV, Otsu's multi thresholding is applied on V channel, K-means clustering is applied to merge over segmented region to get sclera mask. Pyramidal directional filtering approach (Contourlets) for feature extraction for ocular biometrics are proposed. In this paper, we pursue a "true" two-dimensional transform that can capture the intrinsic geometrical structure that is key in visual information. Our approach starts with a discrete domain construction. For Classification, linear discriminant analysis (LDA) is used.

Keywords- *LDA (Linear discriminant analysis); Contourlet transform; K-means clustering, Conjuctival vasculation pattern*

I. INTRODUCTION

Present time demands very high level of security which can be provided through biometrics. Biometrics is becoming an essential component of effective person identification solutions because biometric identifiers cannot be shared or misplaced, and they represent the individual's bodily identity [1,2]. From all characteristics of biometrics, iris recognition has attracted growing more attention from academia, government and industry due to its highly desirable properties for person identification [3]. The success of ocular biometrics is based on its inherent advantages and recent progress in related supporting technologies and processing algorithms [4]. Retina imaging techniques require specialized devices, very close proximity, and user cooperation [5-10]. Recently, personal recognition using ocular imaging in the visible spectrum has received increased attention. However, the iris modality which requires near infrared imaging for the majority of dark, pigment-rich eyes. The conjunctival and its underlying episclera are anterior segment structures of the human eye, exposed to the naked eye and easy to capture with regular RGB cameras). The conjunctival vasculature can be used to complement the iris modality to compensate for iris images with off-angle gaze (especially images captured at an extreme gaze in the left or right direction) [7] also, used as a separate modality. Previous work on textural classification of conjunctival vasculature has demonstrated high accuracies that support the practical use of conjunctival vasculature as a biometric modality [10,11].

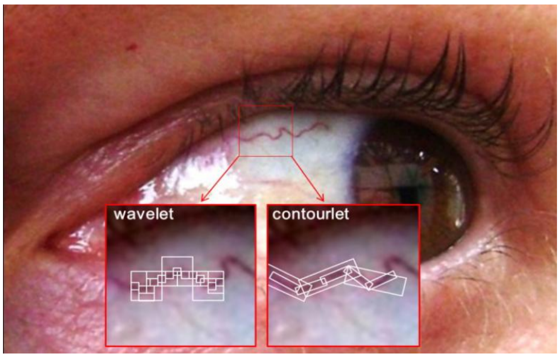

Figure 1. Wavelet vs Contourlet approach across vascular patterns

In general, biometrics is a pattern recognition problem, and thus is heavily dependent on the following stages: segmentation and preprocessing, feature extraction and classification (matching). The performance of any biometric system depends on the reliable and robust feature extraction. Previous work on conjunctival vasculature recognition shows the importance of various feature extraction methods for obtaining higher accuracies [11-13]. So, we have present iris recognition system using pyramidal directional filtering approach (Contourlets) for feature extraction [17] shown in figure 2. Contourlets overcome the limitations of traditional wavelets [15,17]. As an extension of wavelets with an added property of multi-directionality, the Contourlet transform has the ability to extract edge information as well as smooth contour information. Contourlets are the discrete version of the Curvelets with added benefits of multi-resolution and multi-directional functionality. Similar to 2D-Curvelets, the Contourlets have advantages to process edges as curves and derive reliable information from image patterns. And the favorable verification results are attained with the linear discriminant analysis (LDA).

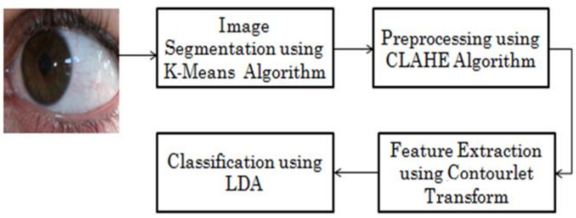

Figure 2. Main Block Diagram

II. SAGMENTATION AND PREPROCESSING

A. Segmentation of Sclera

Segmentation of scleral regions of RGB ocular images was performed using k-means clustering with Euclidean distance metric and k=3 [10, 14]. In this method, foreground objects are distinguished clearly from the background. As the HSV color space is same to the way human eyes perceive color, hence, RGB image is converted to HSV (Hue, Saturation, Value) color model and V (Value) channel is extracted, as Value corresponds to intensity/brightness. Next an Otsu'thresholding is applied on V(Value) channel to get the best thresholds from the image. The result of Otsu's multi-thresholding may consist of over segmented regions, hence to merge the over segmented regions, K-means clustering is applied. The pixels pertaining to the scleral region were determined as the cluster with the largest Euclidean distance from the origin of the coordinate system to its centroid. The pixels belonging to the iris mask were determined as the cluster with the smallest Euclidean distance from the origin of the coordinate system to its centroid. See Figure 4. The largest connected region was selected for scleral and iridial masks. Finally background subtraction is done along with morphological processing.

B. Preprocessing

A Contrast Limited Adaptive Histogram Enhancement algorithm (CLAHE) was used to enhance vascular patterns of the ROI. The effects of histogram equalization and contrast limited adaptive histogram equalization are investigated and the one which gives good enhancement results is extended to the suitable color space.. Uniqueness of this work is that contrast limited adaptive histogram equalization technique is applied to the chrominance channels of the cardiac nuclear image. In contrast limited histogram equalization (CLAHE), the histogram is cut at some threshold and then equalization is applied. Contrast limited adaptive histogram equalization

(CLAHE) is an adaptive contrast histogram equalization method , where the contrast of an image is enhanced by applying CLAHE on small data regions called tiles rather than the entire image. The resulting neigh-boring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be limited so that noise amplification can be avoided. The CLAHE algorithm is performed on non-overlapping partitions (tiles) of an image (8 x 8 tiles per ROI in this study).

An exponential power density function applies an exponential distribution to an intensity image, and is described as

$$f\left({}^{x}/_{\mu}\right) = \frac{1}{\mu} e^{-x/\mu} \quad ...(1)$$

The above formula, in which μ is the mean parameter, was applied to each pixel of the ROI. As a result, higher intensities are attenuated, accentuating the lower intensities of the ROI vascular patterns (Figure 5).

III. FEATURE EXTRACTION AND CLASSIFICATION

Feature extraction is performed using the Contourlet transform.. Preprocessed ROIs is used as an input to the Contourlet transform with the level of decomposition l = 4. For each sub-band of the decomposed image, a feature vector was formed using the calculated mean, median, variance, and entropy. Contourlets apply a two-step filter bank to extract information from contour-rich patterns of an image. Contourlets were developed for extracting reliable information from the contour pattern segments of an image and overcoming the limitations of traditional wavelets in this regard [15]. The Laplacian pyramid, in conjunction with directional filter bank, are used as a two-step filter bank.

A. *Laplacian pyramids*

The Laplacian pyramid decomposes an image into low-pass and band-pass images. The process generates a Down sampled low-pass (LPout) version of the original image. And band-pass filtered image (BPout) difference between original image and synthesis filtered image (SF).

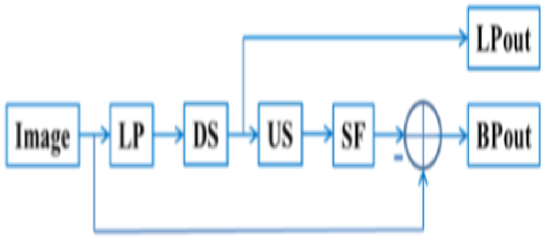

Figure 3. Laplacian pyramid

B. *Directional filtering*

A directional filter bank was efficiently implemented using an l-level binary tree. It decomposes in 2^l sub- bands that use a wedge shaped filter. Decomposition tree expansion includes two building blocks. The first block involves a two channel Quincunx filter bank for dividing the 2D-spectrum into horizontal and vertical directions. The second block is a shear operator . Laplacian pyramid and directional filter banks, the Contourlet transform is given as

$$C_{j,k,n}^{(l)} = \sum_{m \in Z^2} g_k^{(l)}\left[m - S_k^{(l)} n\right] * \mu_{j-1,m}(t) \quad ...(2)$$

Where, $g_k^{(l)}\left[m - S_k^{(l)} n\right]$ is the directional filter bank basis

$\mu_{j-1,m}(t)$ is the Laplacian pyramid

l is the level of decomposition

$S_k^{(l)}$ is the sampling matrix

$g_k^{(l)}$ is the synthesis filter

C. *Classification*

Linear Discriminant Analysis (LDA) is a supervised linear classification and dimensionality reduction method for casting multi-dimensional features into a single dimension in a way that the projected data points, of the original classes, are maximally separable. Fisher's LDA is used. LDAs were trained with Contourlet features. It try to optimize class separability. In the so-called high dimensional, low sample size (HDLSS) settings, LDA maps all points from the same class in the training data to a common point, and so when viewed along the LDA projection directions, the data are piled up [20].

IV. EXPERIMENTAL PROCEDURE AND RESULTS

a. *Data Collection*

The database utilized in the experiment for sclera extraction is the UBIRIS v2 database [21]. Database contain off angle images having maximum sclera region. This was a major motivation for the development of a new version of the database (UBIRIS.v2) in this database the images were captured on non constrained conditions (at-a-distance, on-the-move and on the visible wavelength), with corresponding more realistic noise factors. The major purpose of the UBIRIS.v2 database is to constitute a new tool to evaluate the feasibility of visible wavelength iris recognition under far from ideal imaging conditions.

b. *Segmentation of sclera and preprocessing*

To verify proper segmentation, result were visually inspected and corrected when necessary. Otsu's multi thresholding is done , but we may get over segmented region, to merge that over segmented region K-means clustering is done [14]. After K means clustering, ROIs are extracted, images are closed to 128×128 pixels.

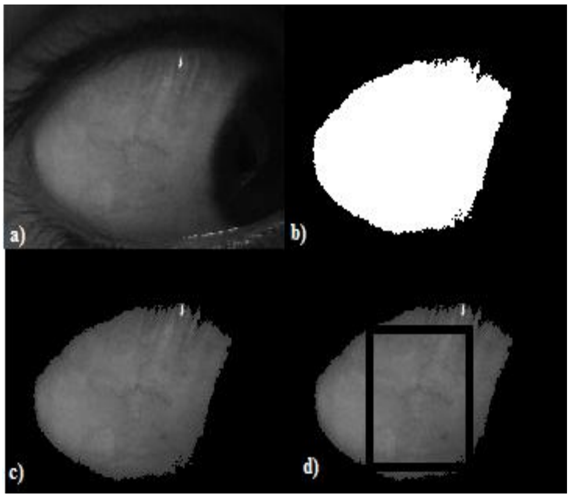

Figure 4.Segmentation of sclera using Otsu's multi thresholding and K-means clustering.

a)V channel of original image b) Resultant sclera mask c) Sclera mask imposed on v channel d) Inscribed max area rectangle on segmented area.

c. *Preprocessing*

To enhance vascular pattern, CLAHE is applied to ROIs with parameters: contrast enhancement limit of 0.01, uniform histogram. Image is further processed using exponential power density function with mean value of 0.25

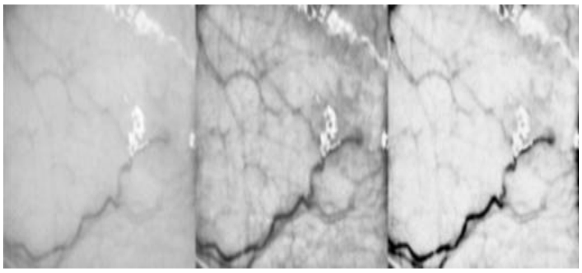

Figure 5. ROI is extracted, CLAHE is used, and after enhancement with exponential power density function.

d. *Feature Extraction*

Feature extraction is performed using Contourlet transform[15]. Preprocessed ROIs are used as input to contourlet transform with laplacian pyramid decomposition level I=4.

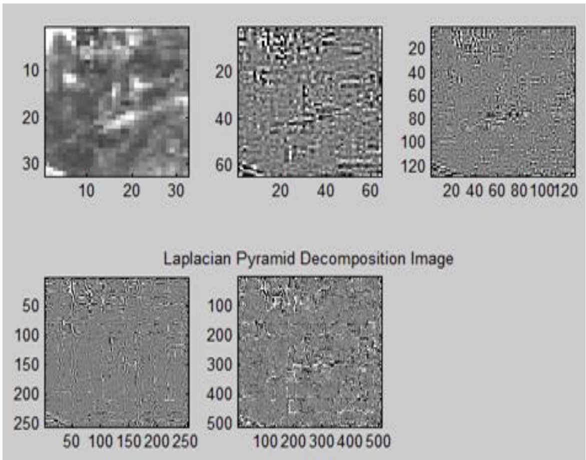

Figure 6. Laplacian pyramid decomposition

After laplacian decomposition we get point discontinuities and to link point discontinuities directional filter is used . Hence we get contourlet transform coefficients.

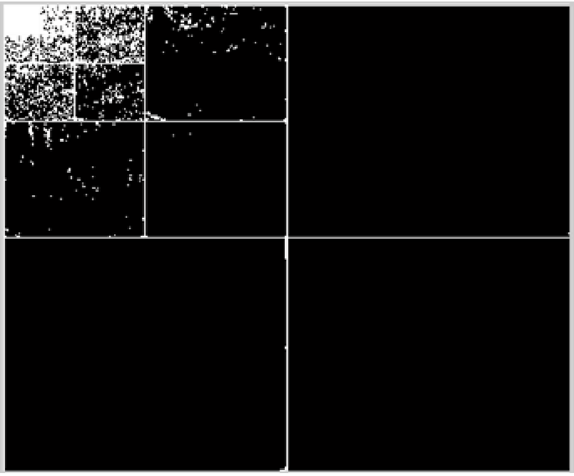

Figure 7. Contourlet Transform Coefficients

e. Classification

LDAs were trained with Contourlet features. It try to optimize class separability. It try to reduce dimension of feature vectors without loss of information**.** In the so-called high dimensional, LDA possesses the data pilin" property, Which is used to maps all points from the same class in the training data to a common point, and so when viewed along the LDA projection directions, the data are piled up. Matching is done using Euclidian distance.

f. Experimental results

This work has been tested on 400 images (3:1 group), 225 images(3:2, 4:1 group) of group 11, 12, 14, 15,. We have tested database in three manner, In 3:1 group each identity contain 4 samples, in which 3 samples are trained and 1 sample is tested. This comprises of 100 identities of database. In 3:2 group each identity contain 5 samples, in which 3 samples are trained and 2 samples are tested. This comprises of 45 identities of database. In 4:1 group each identity contain 5 samples, in which 4 samples are trained and 1 sample is tested. This comprises of 45 identities of database. The performed experiment has shown accuracy shown in table

Table 1. Accuracy

Database	3:1	3:2	4:1
Accuracy	96	95.56	97.78

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