Indian Journal of Science and Technology, *Vol 7(9), 1289–1296, September 2014*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Retinal Identification System using Fourier-Mellin Transform and Fuzzy Clustering

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Abstract

The uniqueness of the retina blood vessels pattern is the most accurate pattern among other biometric systems. In this paper, we present a new approach for human identification using retina recognition and fuzzy C-means clustering algorithm. This method is insensitive to rotation, rescaling and transformation. The Fourier-Mellin transform coefficients and moments of the retinal image have been used as features extracted in our system. To compensate the rotational effects of the retinal scanner, a rotation compensator was designed. For optic disc localization, the Haar wavelet and snakes model have been used. The experimental results show an error rate close to zero for the propose method.

Keywords: Fourier-Mellin Transform, Fuzzy Clustering, Haar Wavelet, Identification Systems, Retinal Identification

1. Introduction

Nowadays with the growth of information technology and the need for high security, applying different identification methods has received special attention. It is important for an identification system is to be accurate, low cost, fast, and safe. Some current identification methods are based on the recognition of fingerprint, face, hand palm, iris. However, these methods are all vulnerable considering plastic surgeries and similar changes, while this is not the case for the retina. Human retina would never change during one's life. This characteristic and the uniqueness of the retina blood vessels pattern increases identification accuracy and thus is the most accurate method among other biometric systems[1,2]. Retina based identification systems are mostly used in sensitive places such as military service centers, biological laboratory, and power reactors which demands high amount of security.

According to[3], a majority of biometric studies fall into the categories of fingerprint, facial and symbol analysis and recognition, about 74%. It can be shown in the Figure 1.

In this paper we proposed a new precise approach to human identification. Also by applying some preprocessing stages on retina image, arises the performance and neediness of accurate and valid retina recognition system.

2. Retinal Anatomy

The retina is a 40 mm thin layer of cell at the back of the eyeball which converts the received light to electrical nervous signals and sends it to the brain. Retina is surfaced by blood vessels which branch from a part called *Optic disc* and spread through the retina surface. The optic disc is the region on the retina at which optic nerve axons enter and leave the eye. Due to lack of photoreceptors this area has more brightness than other areas of the retina and has a diameter of almost 1.5 mm.

The optical disc position is a very important matter and can be used as an origin to determine the position of other parts such as *Fovea*[4]. Fovea or the "yellow spot" is a very small area at the center of retinal that is most sensitive to light and is responsible for our sharp central vision[5]. Figure 2 shows the surface anatomy of retina.

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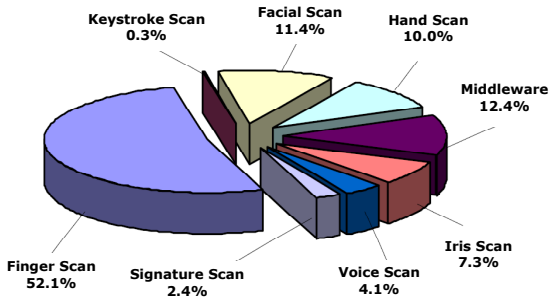

Figure 1. Percentage of biometric applications in real life (Int. biometric group (2003)).

Figure 3. Retina scanners.

3. Retina based Identification Systems

One of the most accurate techniques for human identification is based on the uniqueness of the retina blood vessels pattern. The unique structure of the blood vessels in the retina pattern was first introduced in 1936 by Simon and Goldestein[6].

Retina scanners are used to take image of retina pattern. These scanners take pictures of retina vessels pattern by analyzing absorption and reflection of scattered light and thus darker areas are detected as vessels. The first identification system using commercial retina scanner called Eye Dentification 7.5 was proposed by Eye Dentify Co. in 1976. Figure 3 shows two current commercial retina scanners.

Research on biometrics based on retinal vascular patterns has been limited for the most part to applications on image registration and subsequent detection of vascular patterns. The registration process can be feature-based or area-based. In the area-based, pixel intensities of the retinal image are used in objective functions based on statistical properties such as cross-correlation, phase correlation, or error values[25,27]. For feature-based registration, the process done by matching characteristic high-contrast or point entities using a similarity measure and may also

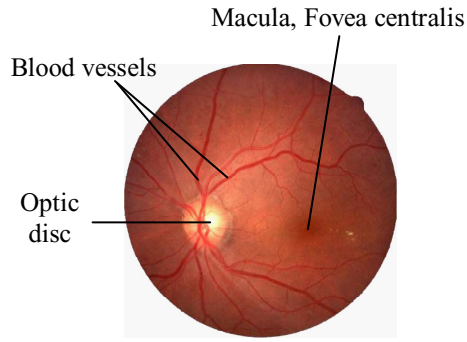

Figure 2. Retina Surface anatomy.

use geometric features such as bifurcations and angles in vascular patterns to achieve matching[19,22–24,26].

One of the common methods for retina recognition with the most attention in research papers, is retinal image superposition based on index points. These index points can be the end points and bifurcation points. Different techniques are used to find these points. In[19, 26, 24 and 22] cross number techniques have been used to extract these points. In[23] from the Harris detector has been used for this purpose. Another method that has been used in some papers, is applying Fourier or Wavelet Transform on retinal images to feature extraction based on the level of energy in different part of the image. In[20], particular sectors as concentric half-circles are considered. In[18], the image is partitioned into radial and angular forms to create the feature vector, the number of edge points is defined as a feature element.

Early method was proposed by Hill[7], on retina recognition. He immediately utilized scanned retina image as feature vector. A feature was intersection angle of scattered blood vessel with two concentric circles. First circle was divided in 0 to 120 degree and second circle was divided in 120 to 360 degree. Radius of larger circle almost was equal to retina diameter and other was half of first circle. In fact numbers in range 0 to 360 were feature vectors constituent that should be compared with stored feature vectors. It's obvious that main drawback of Hill's method is high sensivity to imaging variation such as unwanted rotation. In addition to didn't apply any preprocessing on original retina image.

4. Block Diagram Presentation of Proposed Identification System

Proposed system consists of three main blocks predicted on Figure 4; 1- preprocessing main block, 2- feature

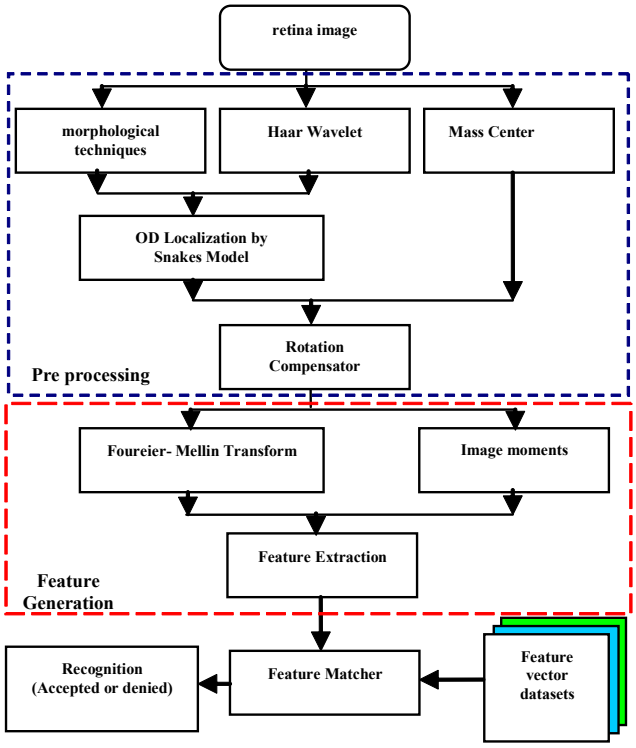

Figure 4. Block diagram presentation of proposed recognition system.

generation main block, 3- Feature matcher main block**.** Elementary block itself comprises three blocks:

a) Mass center finding block
b) Haar wavelet transform (third level) block for detecting primitive optic disk candidate
c) Applying morphological operators (dilation and erosion) block

In elementary block we want to find two fixed points in retina images: mass center of image and optic disk center, by using two fixed point we construct a rotation compensator which eliminate unwanted rotation in retina imaging. The highest bright point of third level output from retina image's wavelet transform is primitive candidate for Optic Disk (OD) center; reason for utilizing two dimensional wavelet transform is related to wavelet's multi resolution analysis theorem. To obtain correct convergence onto the boundary of the optic disk, we need to preprocess the image to remove pixels corresponding to thickness vascular structures, and replace them by pixels representative of the optic disk background behind. This action is performed by morphological techniques: dilation and erosion with same 5 × 5 structuring element. In OD localization block we use of snakes model.

In secondary main block we apply Fourier-Mellin transform on preprocessed image to extracting features, although central section of output plus image moments are defined as feature vector. Finally in feature matcher main block we can classify output features with respect to enrollment retina images which are feature vector dataset.

5. Optic Disc Localization

Since the optical disc position is a very important matter and can be used in analytical matters, different methods have been proposed to determine this position[8]. In this paper we used an effective approach with some modifications to Mendels work[9] which uses active contours or snake model. Snakes model were first presented by Kass, Witkin, and Terzopoulos[10], for image segmentation.

Active contours, also know as snakes, are generated curves that move within images to find object boundaries and are often used in image analysis to detect and locate objects. These closed curves move by internal and external forces. Internal forces are determined from curve specification and external ones from image information. These forces were defined in such a way that the initial curve moves through object borders in the image. The active contour model is defined as an energy minimizing spline and the snake's energy depends on its shape and location within the image.

One of the problems of snake model is its dependency to the initial contour[11]. If the initial contour is not enough close to the aimed object, it may cause error and thus selecting initial contour is very important for error reduction. In this paper we used Haar wavelet to estimate the initial contour to find optic disc position. By applying Haar wavelet in three levels on retina image and using third level image, we find the position with maximum luminance. This is the initial point corresponding to optic disc position which is shown by P_{ODC}. Now by selecting appropriate threshold $I_t \in [0.9,1]$ the optic disc center is calculated as in (1)

$$R_{OD}(x,y)=\left\{P(x,y)\,|\,I_P(x,y)\geq\left(I_t.I_{P_{ODC}}\right)\right\}$$
$$0.90\leq I_t\leq 1.0 \qquad (1)$$
$$P_{OD}=mean\{P(x,y)\in R_{OD}(x,y)\}$$

where, $R_D(x, y)$ is the candidate optic disc area and P_{OD} is the center of optic disc. $P(x, y)$, indicates the pixel position and $I_p(x, y)$ shows its gray level. This approach avoids optic disk center localization algorithm error.

After we found the position of the optic disc, being aware of the fact that it has a circular shape, the initial contour would be a circle with the center of the optic disc and a specific radius by the center of P_{OD}.

Since active contour approach is based on image gradient and spread through the homogeneous area surrounded by high gradient, applying this method to retina image for finding optic disc that is divided into parts by thick blood vessels, is a difficult matter. Therefore we used Mendels approach[9], to overcome this problem.

Using morphological operators, in this method we remove blood vessels from optic disc area in order to provide a homogenous area before applying snake model. Figure 5 shows each time we apply the snake's model, snakes shape modifies and spread through the optic disc boundary. In each step we calculate snakes center of gravity and add it to optic disc center candidate set. This process continues iteratively for some steps. Finally we find the exact optic disc center by averaging the candidate set. The final position is shown in Figure 6.

6. Rotation Compensation

The identification approach should not be sensitive to rotation which might occur during scanning process. To do so rotation compensation was implemented using two fixed point: center of optic disc, and mass center of image. The mass center of a 2D object is calculated as the following:

$$\bar{x} = \frac{\iint x f(x, y)dxdy}{\iint f(x, y)dxdy} \quad \bar{y} = \frac{\iint y f(x, y)dxdy}{\iint f(x, y)dxdy} \tag{2}$$

where, $f(x, y)$ is the density distribution function. We define luminance intensity of a pixel $I(x, y)$, as $f(x, y)$ for our gray scale images and as a result, the center of mass for a M × N image would be defined as Equations 3.

$$\bar{x} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} xI(x, y)}{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x, y)} \quad \bar{y} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} yI(x, y)}{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x, y)} \tag{3}$$

The importance of mass center of image is the fact it is independence from scale and rotation. Considering this fact, images in this pre-processing step would be rotated in such a way that the line through optic disc center and mass center, lies on the horizon.

7. Feature extraction

To extract features of retina image, we used analytic *Fourier-Mellin Transform* (FMT) and *Image Moments* (IM).

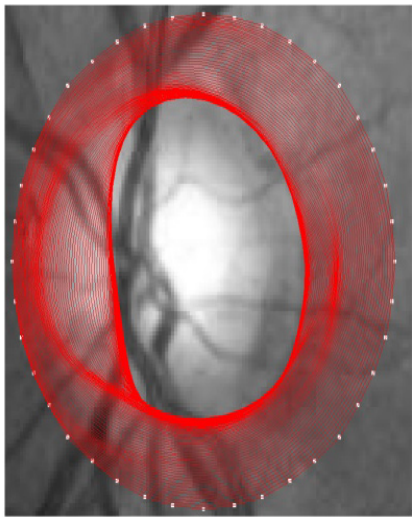

Figure 5. Snake shape modification process.

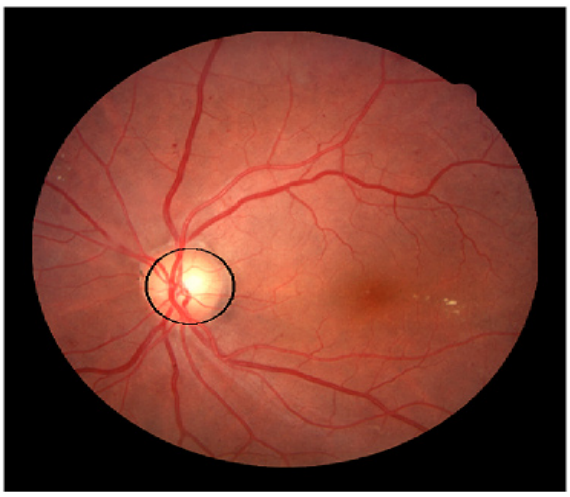

Figure 6. Optic disc final position.

7.1 Standard Fourier-Mellin Transform

Fourier-Mellin transform was proposed in the late 70's for pattern recognition[12] which was used later for signal and image processing. For image retrieval, rotation and scaling invariant features based on FMT can be used. This transform investigates the image similarity. Consider that f indicates the gray scale level of a 2D image. Standard Fourier-Mellin transform of function f is defined as Equation 4:

$$\forall(k,v)\in Z\times\Re$$
$$M_f(k,v)=\frac{1}{2\pi}\int_0^{\infty}\int_0^{2\pi} f(r,\theta)r^{-iv}e^{-ik\theta}d\theta\frac{dr}{r} \qquad (4)$$

in which the positive function f is additive on $\Re_+^*\times S^1$ which means:

$$\int_0^{\infty}\int_0^{2\pi}|f(r,\theta)r^{-iv}e^{-ik\theta}|d\theta\frac{dr}{r}=\int_0^{\infty}\int_0^{2\pi}\frac{1}{r}f(r,\theta)d\theta dr<\infty \quad (5)$$

where, $\Re_+^*$ is a productive group and S^1 indicates unit circle on R^2. Also $\Re_+^*\times S^1$ makes a commutative group with rule $(\alpha, \theta)\circ(\rho, \psi)=(\alpha\rho, \theta+\psi)$.

Ghorbel in[13] suggested that $f_\sigma(r,\theta)=r^\sigma f(r,\theta)$ can be used instead of standard FMT $f(r,\theta)$, in which σ is a positive real constant. Thus Considering Equation 4 in the origin, we would have analytic Fourier-Mellin transform which is a unique transform of an image.

$$\forall(k,v)\in Z\times\Re$$
$$M_{f\sigma}(k,v)=\frac{1}{2\pi}\int_0^{\infty}\int_0^{2\pi} f(r,\theta)r^{\sigma-iv}e^{-ik\theta}d\theta\frac{dr}{r} \qquad (6)$$

$f(r,\theta)$ can be retrieved using inverse analytic Fourier-Mellin transform as in Equation 7, where $M_{f\sigma}$ is additive on $Z\times\Re$.

$$\forall(r,\theta)\in\Re_+^*\times S^1$$
$$f(r,\theta)=\int_{-\infty}^{+\infty}\sum_{k\in Z}M_{f\sigma}(k,v)r^{-\sigma+iv}e^{ik\theta}dv \qquad (7)$$

Figure 7 shows analytical FMT of a retina image.

7.2 Image Moments

Moments based features are widely used as invariant identifiers for pattern recognition. In[21] the feature vector is computed using Zernike moments on the binary preprocessed version of the retinal fundus image. Two different feature vectors based on moment and independent of transform, scaling, rotation, and contrast are *Hu* moment invariants[14], and Complex Moments Magnitudes (CMM). Since computing CMM is much simpler than Hu moment invariants, we used CMM for density distribution function f (x,y) as the followings:

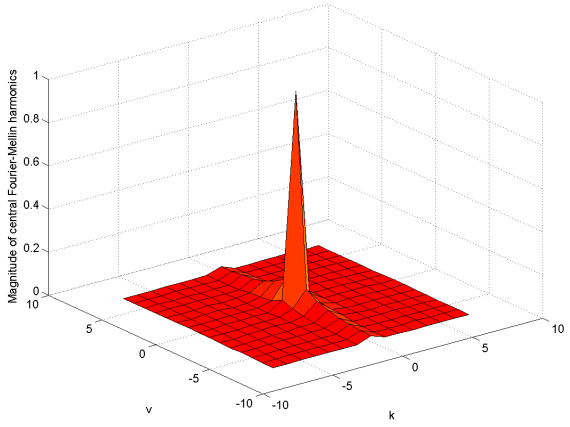

Figure 7. Retina (Figure1) image FMT.

$$C_{pq}=\sum_{x=0}^{M}\sum_{y=0}^{N}(x+iy)^p(x-iy)^q f(x,y) \qquad (8)$$

where, C_{pq} is the $(p+q)^{th}$ order moment. Complex moments are not invariants in their place, however by applying Equation 9 and considering amplitude, rotation, transformation, rescaling and contrast, will become independent.

$$\forall(p+q)\geq 2 \quad C_{pq}=\frac{C_{pq}}{C_{00}^{\gamma}} \quad \gamma=\frac{p+q}{2}+1 \qquad (9)$$

8. Classifier Designing

In order to create the retina "feature vector", we used a combination of FMT and IM in such a way that feature vector, consists of central FMT harmonics length which contain valuable information about the image and are moments up to (2 + 2) order i.e. moment C_{22}.

The next step was to design a classifier for input vectors and we applied Fuzzy C-means for this task.

8.1 Fuzzy C-Means

Fuzzy C-Means Clustering (FCM) is a method which employs fuzzy partitioning in such a way that a point can belong to all groups with different membership grades between 0 and 1 and tries is to find cluster centers (centroids) which minimize a dissimilarity function. The algorithm of FCM is as follows[15,16].

1. Randomly initialize the membership matrix (U) with respect to Equation 10.

$$\sum_{i=1}^{c} u_{ij} = 1, \ \forall j = 1, \ldots, n \tag{10}$$

2. Calculate centroids(c_i) by using Equation 11.

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{11}$$

3. Compute dissimilarity between centroids and data points using Equation 12 where u_{ij} is between 0 and 1, c_i is the centroid of cluster i, d_{ij} is the Euclidian distance between i_{th} centroid (c_i) and j_{th} data point; and m $\in [1, \infty]$ is a weighting exponent. Stop if its improvement over previous iteration is below a threshold.

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \tag{12}$$

4. To reach a minimum of dissimilarity function compute a new U using Equation 13 and Go to Step 2.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \tag{13}$$

Due to randomly initialization of membership matrix, FCM might not converge to an optimal solution however in our work since centroids are database vectors, there would be no such problem.

9. Results

The proposed system was implemented in Matlab 6.5 Software and tested on a database of 37 different images of 512x512 pixels as shown in Figure 8. To show that our method is not sensitive to rotation and rescaling, we increased the test data to 148 images by rotation and rescaling modifications. Experimental results show high accuracy classification capability among similar images. Plots of both FAR and FRR against a supposed threshold value are a commonly used method for ratings of biometric systems. Figure 9 shows False Rejection Rate and False Acceptance Rate to determine system reliability.

To comparing error rates between our method and other biometric recognition methods Table 1 is showed in our method error rates closes to zero with large range in threshold's amount.

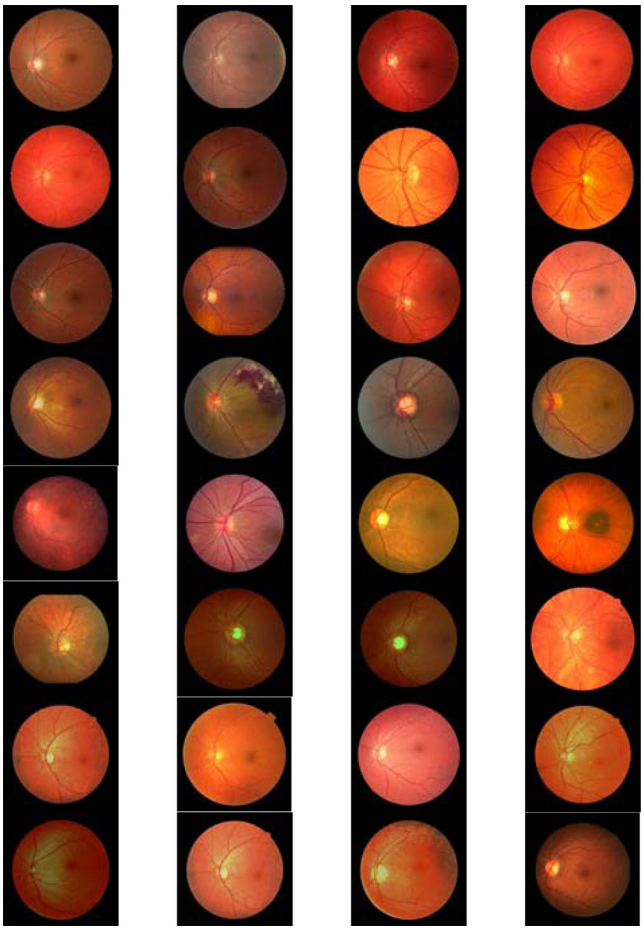

Figure 8. Some of our main retina image database.

Table 1. The false accept and false reject error rates associated with the fingerprint, face, voice and iris modalities[17].

Biometric Trait	Test	Test Conditions	FRR	FAR
Fingerprint	FVC 2004 (Maio et al.)	Exaggerated skin distortion, rotation	2%	2%
Fingerprint	FpVTE 2003 (Wilson et al.)	US Government operational data	0.1%	1%
Face	FRVT 2002 (Phillips et al.)	Varied lighting, outdoor/indoor, time	10%	1%
Voice	NIST 2004 (Przybocki and Martin)	Text independent, multi-lingual	5–10%	2–5%
Iris	ITIRT 2005 (International Biometric Group)	Indoor environment, multiple visits	0.99%	0.94%

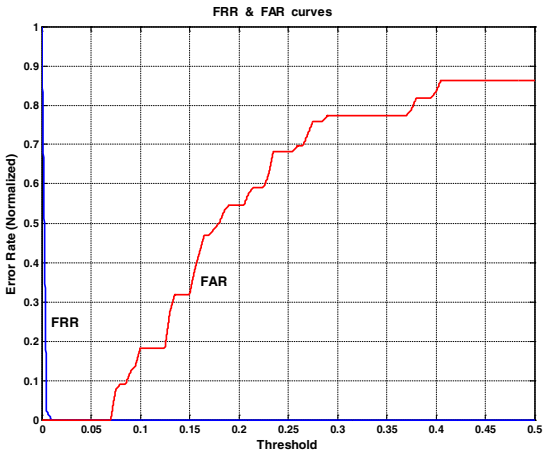

Figure 9. FRR and FAR diagrams.

10. Conclusion

In this work a new approach for human identification using retina recognition and fuzzy clustering algorithm was proposed which is insensitive to rotation, rescaling and transformation. For feature extraction, the Fourier-Mellin transform coefficients and moments of the retinal image have been used. Implementation results indicate an error rate close to zero for the propose method.

11. References

1. Jafariani H. Human identification based on retina image. Biomedical Engineering [M. Sc Thesis]. KNT University of Technology, 2003.
2. Jafariani H, Moghaddam HA, Moein MS. A New Approach for Human Identification Based on Retina Image, 11th Conference of Iran Biomedical Engineering; 2003 Feb; Amir Kabir University of Technology.
3. Yanushkevich SN, Gavrilova ML, Wang SPS, Srihari SN. Image pattern recognition synthesis and analysis in biometrics. World Scientific Publishing Co. Pvt. Ltd; 2007.
4. Lalonde M, Beaulieu M, Gagnon L. Fast and robust optic disc detection using pyramidal decomposition and hausdorff based template matching. IEEE Trans Med Ima. 2001; 20:1193–200.
5. Guyton AC, Hall JE. Textbook of Medical Physiology. 10th ed. Saunders WB; 2000.
6. Simon C, Goldstein I. Retinal Method of Identification. New York State J Med. 1936 Sep; 15.
7. Hill RB. Apparatus and method for identifying individuals through their retinal vasculature patterns. United States Patent 4109237; 1978.
8. Lowell J, Hunter A, Steel D, Basu A, Ryder R, Fletcher E, Kennedy L. Optic Nerve Head Segmentation. University of Durham, UK: 2002. Technical Report no. 7 (tech-report0702).

9. Mendels F, Heneghan C, Thiran JP. Identification of the Optic Disk Boundary in Retinal Images Using Active Contours. Proc. IMVIP; 1999. p. 103–15.
10. Kass M, Witkin A, Terzopoulos D. Snakes:Active contour models. Int J Computer Vision. 1987; 1(4):321–31.
11. Samadini RC. Adaptive Snakes:Control of Damping and Material Parameters. Proc. SPIE. 1991; 1570:202–13.
12. Yatagay T, Choji K, Saito H. Pattern classification using optical Mellin transform and circular photodiode array. Optical Communication. 1981 Aug; 38(3):162–65.
13. Ghorbel F. A complete invariant description for gray-level images by the harmonic analysis approach. Pattern Recogn Lett. 1994 Oct; 15:1043–51.
14. Hu MK. Visual pattern recognition by moment invariant. IRE Transactions on Information Theory. 1962; 8(2): 179–187.
15. Jang JSR, Sun CT, Mizutani E. Neuro-Fuzzy and Soft Computing. Prentice Hall; 1997.
16. Bezdek JC. Fuzzy Mathemathics in Pattern Classification [PhD thesis]. Ithaca: Cornell University; 1973.
17. Ross AA, Nandakumar K, Jain AK. Handbook of Multibiometrics. Springer Science+Business Media, LLC; 2006.
18 Barkhoda W, Akhlaqian F, Amiri MD, Nouroozzadeh MS. Retina identification based on the pattern of blood vessels using fuzzy logic. EURASIP Journal on Advances in Signal Processing. 2011 Nov 23:113.
19. Qamber S, Waheed Z, Akram MU. Personal identification system based on vascular pattern of human retina. 6th Cairo International Biomedical Engineering Conference; 2012 Dec 20–21; Cairo, Egypt.
20. Sabaghi M, Hadianamrei SR, Fattahi M, Kouchaki MR, Zahedi A. Retinal identification system based on the combination of fourier and wavelet transform. J Signal Inform Process. 2012; 3:35–8.
21. Aich S, Mamun GMA. An efficient supervised approach for retinal person identification using zernike moments. Int J Comput Appl. 2013 Nov; 81(7)38–45.
22. Hajek J, Drahansky M, Drozd R. Extraction of Retina Features Based on Position of the Blood Vessel Bifurcation. JMRD. 2013; 2(3):55–8.
23. Dehghani A, Ghassabi Z, Moghddam HA, Moin MS. Human recognition based on retinal images and using new similarity function. EURASIP Journal on Image and Video Processing. 2013; 58.
24. Islam MN, Siddiqui MA, Paul S. An Efficient Retina Pattern Recognition Algorithm (RPRA) towards Human Identification. 2nd International Conference on Computer, Control and Communication, IC4 2009; 2009 Feb 17–18; Karachi. IEEE. p. 1–6.
25. Kakarwal SN, Deshmukh RR. Analysis of Retina Recognition by Correlation and Covariance Matrix. Third International Conference on Emerging Trends in Engineering and Technology; 2010 Nov 19–21; Goa India. IEEE; 2010. p. 496–9.
27. Chora RS. Retina Recognition for Biometrics. 2012 Seventh International Conference on Digital Information Management (ICDIM); 2012 Aug 22–24; Macau. IEEE; 2012. p. 177–80.
28. Fukuta K, Nakagawa T, Hayashi Y, Hatanaka Y, Hara T, Fujita H. Personal Identification Based on Blood Vessels of Retinal Fundus Images. Proc. of SPIE. 2008 Mar 11; 6914.