A New Approach for Non-Ideal Iris Segmentation Using Fuzzy C-Means Clustering Based on Particle Swarm Optimization

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Abstract-Segmentation is an important step in iris recognition system because the accuracy of the iris recognition system is affected by the segmentation of the iris. In this paper, an efficient method has been proposed for the segmentation of non-ideal iris images captured under uncooperative conditions. A fuzzy c-means clustering algorithm based on Particle Swarm Optimization (PSO) technique has been employed as a presegmentation step in the iris recognition framework. The fuzzy c-means clustering method delimits the iris and eliminates the unwanted portions of an image. The particle swarm optimization technique is incorporated to avoid FCM fall into local minimum. The segmentation accuracy of the proposed method is implemented by considering CASIA v3 Interval and UBIRIS databases. The proposed method is compared with the classical segmentation methods and has an encouraging performance.

Keywords: Geodesic Active Contours (GACs), Fuzzy C-Means, Particle Swarm Optimization (PSO), Iris Recognition System

I. INTRODUCTION

The iris function is to control the diameter of the pupil and thus the amount of light entering the retina. The unique and stable complex patterns (crypts and furrows) of an iris make the iris recognition system popular now a day. Hence, the Iris recognition is based on the fact that the human iris contains unique features and even genetically identical individuals have completely independent iris textures[1][2].

Iris recognition system has modules, namely, segmentation/localization, normalization, feature extraction and iris code matching. The segmentation step is a crucial in iris recognition system because the recognition accuracy solely depends on segmentation. Thus, it is logical that the first step in an iris recognition system is extracting the iris region from the other parts of the eye image.

A very popular iris segmentation technique, has been proposed by Daugman[3], which is based on the assumption that the iris is circular and introduced an integro-differential operator(IDO) to localize the iris. IDO acts as a circular boundary detector. It is a conventional method and almost all international companies for iris recognition are using this method. Another classical method is proposed by the Wildes[4], circular Hough transform(CHT) is applied on a gradient based edge detected image to accomplish iris detection. This method is computationally cost. Masek and Kovesi[5], proposed an improved variant of CHT, which is a combination of Canny edge detection and a circular Hough transform. Eyelids and eyelashes are localized by a simple thresholding technique. The authors in[6], introduced a 2D Fourier Phase Code (FPC) for representing an iris image. Gravity based method is proposed for iris segmentation. Li Ma *et al*[7], used a combination of an edge detection and a circular Hough transform to segment the iris image. An elliptical Hough transform is employed to detect the eyelids.

Optimization based segmentation methods are becoming popular in recent years. The authors in [8], proposed a multilevel thresholding accomplished by Artificial Bee Colony(ABC) and G-best guided ABC as a presegmentation step in the recognition system pipeline.

The methods discussed above do not segment accurately the iris images that are captured under non-ideal conditions. Variations of Level set based segmentation methods have been proposed by many authors to address the above problem[9][10][11]. For instance, a method proposed by Shah&Ross[12],Employ Geodesic Active Contours (GAC) inspired by level sets to segment iris images captured under non-ideal conditions.



Fig. 1 Block Diagram of the Proposed Method

In this paper, we propose a fuzzy c-means based on particle swarm optimization technique has been proposed as presegmentation step for the efficient segmentation of nonideal iris images. GACs are then employed to segment the iris from an eye image. Fig. 1 illustrates the proposed methodology. The later sections of the paper are organized as follows: The basic segmentation methods are discussed in Section II. Section III provides the proposed method. The results and discussions are furnished in Section IV. Finally, Section V concludes the paper.

II. BASIC SEGMENTATION METHODS

A. Geodesic Active Contours

Geodesic active contour model [12][13], is based on the relation between energy minimization in snakes[14] and curve evolution approach in geometric active contours[15].Both inward and outward boundaries of an object can be detected simultaneously due to its split and merge curve evolution capability.

A signed distance function, Eq. 1, is initialized near the pupil and is updated in every iteration until stopping criterion(Eq. 2) is satisfied.

$$\begin{split} \phi_{i,j}^{t+1} &= \phi_{i,j}^t + \Delta t (-cK_{i,j}' \| \nabla \varphi^t \| - K_{i,j}' \big(\varepsilon \phi_{i,j}^t \| \nabla \varphi^t \| \big) \\ &+ \nabla \phi_{i,j}^t \cdot \nabla K_{i,j}'^t \end{split}$$
(1)

Where, Δt is the time step. For implementation $\Delta t = 0.05, c = 0.65$ and $\varepsilon = 1$ values are assigned for all images in the database. K is the stopping function, and ϕ is the Euclidean curvature of the level set. Curvature is computed by considering the values of current level set and is given by $\varphi_{xx}\varphi_y^2 - 2\varphi_x\varphi_y\varphi_{xy} + \varphi_{yy}\varphi_x^2$

$$\phi = -\frac{\varphi_{xx}\varphi_y^2 - 2\varphi_x\varphi_y\varphi_{xy} + \varphi_{yy}\varphi_{xy}}{\left(\varphi_x^2 + \varphi_y^2\right)^{3/2}}$$

Where φ_x and φ_y are the gradients of the image in x and ydirection respectively; φ_{xx} and φ_{yy} are the second-order gradients in the x and y-direction respectively; φ_{xy} is the second-order gradient, first in the x-direction then in the ydirection.

In the case of real images, the selection of stopping criterion is a very important step because, real images do not have ideal edges. GACs are independent of stopping function if the image to be segmented contains ideal edges. The stopping function used for evolution is

$$K(x,y) = \frac{1}{1 + \left(\frac{\|\nabla(G(x,y) \times I(x,y))\|}{\beta}\right)^{\alpha}}$$
(2)

Where, I(x, y) is the input image, α and β are positive real constants.

B. Fuzzy C-means Clustering Algorithm

The objective function of FCM[16] is given below

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^{q} \|x_{k} - v_{i}\|^{2}$$
(3)

Where q is real number, $1 \le q < \infty$, u_{ik} is the membership degree of x_k in the *i*th cluster, $u_{ik} \in \{0,1\}, C$ is number of clusters ($2 \le C < n$), Euclidean distance is used to measure the distance between data points and cluster center. The objective function in Eq 3. is iteratively optimized by updating cluster centers c_i and membership matrix u_{ik} where

$$v_{i} = \frac{\sum_{k=1}^{n} u_{ik}^{q} \cdot x_{k}}{\sum_{k=1}^{n} u_{ik}^{q}}$$
(4)

 $u_{ik} = \frac{1}{\sum_{j=1}^{C} \left[\frac{\|x_k - v_j\|}{\|x_k - v_j\|} \right]^{\frac{2}{q-1}}}$ (5)

A membership value is assigned to a data sample based on how it differs with the cluster center. Iteration process will terminate if $||u_{ik}^{b+1} - u_{ik}^{b}|| < \epsilon$, where *b* is the number of iterations.

III. THE PROPOSED METHOD

A. Particle Swarm Optimization (PSO)

PSO is a heuristic global optimization technique developed by [17], based on swarm intelligence. The PSO algorithm implementation steps are as follows:

Step 1: Read the data and initialize algorithm parameters and generate the initial solution randomly.

$$\begin{aligned} x_{i,j} &= (x_{1,1}, x_{1,2}, x_{1,3}, \dots \dots x_{pop,n}), \\ i &= 1 \ topopandj = 1 \ ton \\ v_{i,i} &= (v_{1,1}, v_{1,2}, v_{1,3}, \dots \dots v_{pop,n}). \end{aligned}$$
(6)

$$i = 1 \text{ topopandj} = 1 \text{ ton}$$
(7)

Where, pop is population size and n is dimension of the problem

Step 2: Calculation of fitness value of the objective function from Eq. 3

Step 3: Calculate p_{best} i.e. the higher objective function value of each particle in the population when compared with the previous iteration is recorded as the current best position of the particle.

$$p_{\text{best}_{i}}^{t+1} = \begin{cases} p_{\text{best}_{i}}^{t} & \text{if } f_{i}^{t+1} \ge f_{i}^{t} \\ p_{i}^{t+1} & \text{if } f_{i}^{t+1} \le f_{i}^{t} \end{cases}$$
(8)

Where, f is the objective function evaluated for the particle.

Step 4: Calculate g_{best} i.e. the higher objective function value associated with the p_{best} among all particles when compared with that in the previous iteration is recorded as the current overallg_{best}.

$$\mathbf{g}_{\text{best}_{i}}^{t+1} = \begin{cases} \mathbf{g}_{\text{best}_{i}}^{t} & \text{if } \mathbf{f}_{i}^{t+1} \ge \mathbf{f}_{i}^{t} \\ \mathbf{p}_{\text{best}_{i}}^{t+1} & \text{if } \mathbf{f}_{i}^{t+1} \le \mathbf{f}_{i}^{t} \end{cases}$$
(9)

Step 5: Update the velocity of the particles for the next iteration using the following equation

$$v_{i}(t+1) = v_{i}(t) + c_{1}rand_{1}(t) \left(p_{best_{i}} - x_{i}(t)\right) + c_{2}rand_{2}(t) \left(g_{best} - x_{i}(t)\right)$$
(10)

Step 6: Particle velocities should be clamped to the limits by verifying the following conditions

If $v_{id} > v_{max}$, then $v_{id} = v_{max}$

(or) If $v_{id} < -v_{max}$ then $v_{id} = -v_{max}$ Step 7: Position of each particle should be updated according to Eq 11 for the next iteration (t+1).

$$x_i(t+1) = x_i(t) + v_i(t+1)$$
 (11)
Step 8: Check for the stopping criterion i.e. if *iter* =

itermax, then go to step 9. Otherwise, go to step 2. Step 9: The individual that generates the latest *gbest* is the

Step 9: The individual that generates the latest *gbest* is the optimal thresholds at maximum objective function. The problem specific implementation block diagram of the proposed method has been illustrated in Fig 2. The assigned values for PSO algorithm has been given in Table I.

and



Fig. 2 Implementation Steps of the Proposed Method

Parameter description	Assigned values
Population size	50
Dimension	Number of cluster centers
Number of iterations	1000
Cognitive parameter($c_1 \& c_2$)	2

TABLE I THE ASSIGNED VALUES FOR PSO TECHNIQUE

B.Pupil Segmentation

The image is smoothed using Gaussian filter before segmenting the pupil. The binarized image is obtained by setting a proper threshold value. The accuracy of the pupil segmentation depends on the choice of threshold[6]. If many nonpupil regions like eyelashes, specular reflections etc. are present, that have pixel values '1' in the binarized image, leads to a false detection of the pupil. Therefore, pixels belong to nonpupil regions should be eliminated. Morphological filtering operations such as "Opening by reconstruction" and "Closing by reconstruction" are performed to eliminate nonpupilregions[18].

C. Pre-Segmentation

The iris image is over segmented when the stopping function have weak edge details. In this work, a presegmentation step is proposed to overcome the above stated problem. A Fuzzy c-means based on particle swarm optimization technique has been implemented as presegmentation. The iris image can be categorized into three regions. The first, pupil and eyelashes, have low intensity values. The second, sclera and specular reflections, have high intensity values. The third, iris region, has intensity values between the former two. Thus, the number of cluster centers suitable for iris databases is three. However, captured images in the database may not adequate due to various reasons i.e. occlusions, defocus blur, illumination degradation, etc. In such cases, the number of cluster centers 'three' may not be enough. Therefore, the input image is pre-segmented by considering 'three', 'four' and 'five' cluster centers simultaneously. The corresponding stopping functions are determined using Eq2. The stopping function that has strong edge details is chosen as stopping criterion for segmentation of the iris outer boundary. The GACs are then employed to detect the outer boundary. The segmentation results of some sample iris images from CASIA and UBIRIS datasets using the proposed method has been illustrated inFig. 3 to 4.



Fig. 3 Pre-Segmentation of some sample images from CASIA v3 interval dataset using the proposed PSO-FCM, corresponding stopping functions and segmentation using GACs

Segmentation accuracy =	
Number of images segmented correctly	(12)
Total input images	(12)

IV. RESULTS AND DISCUSSION

The iris recognition system performance of the method proposed has been evaluated on the CASIA v3 Interval and UBIRIS session1 database. The CASIA v3 Interval iris left and right eye database contains 2,655 images from 249 individuals. There are 0-15 classes of left and right iris images of each individual. To simplify the implementation, in this work, 1885 iris images are considered. Out of which 895 images are from left eye and 990 images are from the right eye. The iris image size is 320×280 pixels. The details of the databases considered for evaluation has been furnished in Table II.

The UBIRIS session1 database contains 1205 iris images. The images are captured from 241 individuals, 5 images from each individual. The size of each iris image is 200×150 pixels. The effectiveness of the method proposed was exhibited by comparing with the existing methods Masek's[5] segmentation method and Daugman's[3]Integro Differential Operator. F ig 3, Illustrates the segmentation results of some sample images from CASIA v3 Interval using the proposed method. Fig. 4 illustrates the segmentation results of same samples from UBIRIS database using the proposed method.

TABLE II DATABASES CONSIDERED FOR THE EVALUATION

Database	Subject	Sample/ subject	Total Images
CASIA v3 interval(L&R)	341	5 each	1705
UBIRIS(s1&s2)	372	5 each	1860
MMU1(L&R)	90	5 each	450



Fig. 4 Pre-Segmentation of some sample images from UBIRIS dataset using the proposed PSO-FCM, corresponding stopping functions and segmentation using GACs

Method	CASIA v3 Interval	UBIRIS	MMU1
Proposed	95.89	92.83	99.11
Masek's	92	89.97	84.4
Daugman's	75.33	59.41	52.72

The segmentation accuracy of the proposed method has been determined from Eq. 12 and the obtained results are furnished in Table III. It can be observed from the obtained results that the proposed method yields good results for nonideal iris database.

V. CONCLUSION

The iris recognition system performance highly depends on how effectively the iris is segmented. In this paper, a Fuzzy c-means based on particle swarm optimization technique for a robust segmentation of non-ideal iris images. The novelty of the proposed method mainly includes 1) A presegmentation step using optimization based fuzzy c-means method. 2) The iris image is pre-segmented by considering multiple cluster centers i.e. for individual images three, four and five clusters are considered. 3) Geodesic active contours are then employed to segment the pupil and iris boundaries. The proposed method is validated on the CASIA v3 Interval, UBIRIS, and MMU1 database. The proposed method is robust for non-ideal iris images and achieves high segmentation accuracy.

REFERENCES

- [1] F. G. Adler, "Physiology of the eye", *Mosby*, Chapter VI, pp. 143, 1953.
- [2] J.H. Doggart, "Ocular Signs in Slit-Lamp Microscopy", *Kimpton*, pp. 27, 1949.
- [3] J. Daugman, "How Iris Recognition Works", Essent. Guid. to Image Process., Vol. 14, No. 1, pp. 715-739, 2009.
- [4] R. P. Wildes, "Iris recognition, an emerging biometric technology'*Proc. IEEE*, 1997, Vol. 85, No. 9, pp. 1348-1363.
- [5] L. Masek and P. Kovesi, "A Biometric Identification System Based on Iris Patterns' the school of Computer Science and Software Engineering, The University of Western Australia, 2003.
- [6] K. Miyazawa, K. Ito, T. Aoki, K. Kobayashi andH. Nakajima, "An effective approach for Iris recognition using phase-based image matching", *IEEE Trans. Pattern Anal. Mach. Intell.*, Vol. 30, No. 10, pp. 1741-1756, 2008.
- [7] L. Ma, Y. Wang, T. Tan, "Iris recognition using circular symmetric filters", *Object Recognit. Support. by user Interact. Serv. Robot.*, Vol. 2, pp. 414-417, 2002.
- [8] A. Bouaziz, A. Draa and S. Chikhi, "Artificial bees for multilevel thresholding of iris images", *Swarm Evol. Comput.*, Vol. 21, pp. 32-40, 2015.
- [9] J. Daugman, "New methods in iris recognition.", *IEEE Trans. Syst. Man. Cybern. B. Cybern.*, Vol. 37, No. 5, pp. 1167-1175, 2007.
- [10] K. Roy, P. Bhattacharya and C. Y. Suen, "Towards nonideal iris recognition based on level set method, genetic algorithms and adaptive asymmetrical SVMs", *Eng. Appl. Artif. Intell.*, Vol. 24, No. 3, pp. 458-475, 2011.
- [11] D. S. Jeong and J. W. Hwang and B. J. Kang, et al., "A new iris segmentation method for non-ideal iris images", *Image Vis. Comput.*, Vol. 28, No. 2, pp. 254-260, 2010.
- [12] S. Shah and A. Ross, "Iris segmentation using geodesic active contours", *Inf. Forensics Secur. IEEE Trans.*, Vol. 4, No. 4, pp. 824-836, 2009.
- [13] V. Caselles, R. Kimmel and G. Sapiro, "Geodesic Active Contours", IEEE Int", l Conf. Comput. Vis., Vol. 22, No. 1, pp. 694-699, 1995.
- [14] M. Kass, A. Witkin and D. Terzopoulos, "Snakes, Active contour model", Int. Journ. of Comput. Vision, pp. 321-331, 1998.
- [15] S. Kichenassamy, A. Kumar, P. Olver, A. Tannenbaum and A. Yezzi, "Gradient flows and geometric active contour models", *Proc. IEEE Int. Conf. Comput. Vis.*, pp. 4-9, 1995.
- [16] Cannon, R.L., Dave, J. V, Bezdek, J.C., "Efficient Implementation of the Fuzzy c-Means Clustering Algorithms", *IEEE Trans. Pattern Anal. Mach. Intell.*, Vol. 8, No. 2, pp. 248-255, 1986.
- [17] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory", Proc. Sixth Int. Symp. Micro Mach. Hum. Sci., pp. 39-43, 1995.
- [18] S. Rapaka andP. R. Kumar, "Efficient approach for non-ideal iris segmentation using improved particle swarm Q1 optimisation-based multilevel thresholding and geodesic active contours", pp. 1-9, 2018. [Online] Available: https://doi.org/10.1049/iet-ipr.2016.0917.