Proceedings of the 17th Iranian Conference of Biomedical Engineering (ICBME2010), 3-4 November 2010

A Novel Iris Recognition System Based on Active Contour

Seyyed Mohammad Sadegh Moosavi
Department of Electrical Engineering
Iran University of Science & Technology
Tehran, Iran
s.moosavi1363@gmail.com

Seyed Mohammad Seyedzade
Department of Electrical Engineering
Iran University of Science & Technology
Tehran, Iran
sm.seyedzade@ieee.org

Ahmad Ayatollahi
Department of Electrical Engineering
Iran University of Science & Technology
Tehran, Iran
Ayatollahi@iust.ac.ir

Abstract—**Image segmentation is a method which is widely used in image processing application, and it is one of the most difficult steps of the process. This matter becomes more significant when we try to use the algorithms presented in complicated systems, such as the biometric systems. Different methods of iris segmentation have been presented so far. In this article, a new algorithm has been proposed for iris segmentation. We tried to use the greedy snake algorithm for the iris segmentation process. The proposed algorithm was tested on the CASIA Iris Image Database 1.0 and the obtained results showed that the proposed method has an acceptable accuracy.**

Keywords-** **iris recognition; biometric; active contour; segmentation; snake

I. INTRODUCTION

Using the biometric systems is a method which is widely applied for personal identification. These systems use the features unique to each human. These unique features can be fingerprint, palm print, the face, images of the retina and iris, shape of the ear, and the lips' movement.

Iris recognition is one of the most active research topics for the last few decades in biometric technology because iris pattem has stable and distinctive features for personal identification. In addition every iris has fine and unique pattems and does not change over time since two or three years after the birth.Therefore, in recent years, the iris is used more frequently in biometrics. The iris forms a ring between the sclera (white part of the eye) and the pupil (dark part of the eye). The iris contains complex tissues which vary in different people. The region of the iris close to the pupil is called the zigzag collarette. This region, relative to other parts of the iris, has a richer tissue.

An iris recognition system includes the following steps: 1- segmentation, 2- normalization, 3- feature extraction, and 4- matching. Segmentation is the act of separating the intended portion from the overall image. In an iris recognition system, one should be able to precisely separate the iris from the whole image of the eye. If the image of iris is not accurately cut out from the eye image, incorrect information will be fed into the system, and as a result, the other processing steps will not yield the correct results and the final identity recognition will be erroneous. Therefore, the segmentation is the most important step in the iris recognition system. For the iris segmentation, two boundaries should be detected; one between the iris and pupil, and the other between the iris and sclera. These boundaries can be modeled roughly by two non-concentric circles. Different methods have been presented for iris segmentation. Daugman used the integro-differential operator to define these circles [1]. He considered various circles in the eye image and by calculating image gradient on these circles, selected the highest value as the iris boundary. References [2], [3], and [4] have used the Hogh transform method to carry out the iris segmentation. The Hogh transform is an algorithm for identifying geometrical shapes in images. These methods have problems, since the iris boundaries cannot be modeled by two approximate circles, and thus, the two boundaries cannot be defied exactly. On the other hand, the Hogh transform algorithm uses a long processing time.

The active contour is one of the methods, which has been used extensively in recent years for segmentation of images, especially, medical images. Recent reviews have shown that using the active contour method has yielded acceptable results from both standpoints of accuracy and process speed. The probabilistic active contour [5], the geodesic active contour [6], and the active contour based on the Fourier coefficients [7] are among the methods used for iris segmentation. The idea of using an active contour was first brought up by Mr. Kass in 1988, which became known as the snake model [8]. One of the problems of the Kass model is that the snake control points in the Kass active contour model are not always evenly spaced. Sometimes the snake control points bunch together in regions of the contour where the image energy has high negative values. This behavior negatively affects curvature calculations, since the assumption that the active contour parameter is an arc segment will not remain true if the snake points are not equally spaced. So, D. J. Williams and M. Shah developed an active contour algorithm named the greedy snake to improve and correct some of the problems associated with the Kass snake model [9]. In this article, for the purpose of iris segmentation, the greedy snake model [9] is used. In the second section of this article, the traditional contour model is briefly introduced. In the third section, the proposed algorithm (the greedy snake algorithm) is reviewed, in the fourth section, our iris recognition system is introduced, and in the fifth section, the results of our iris recognition system are presented.

II. ACTIVE CONTOURS

A. Introducing the Active Contour

Active contour is a two-dimensional curve in the image space whose deformation is based on energy minimization. In this method, first, a primary contour is defined close to the edge of the object in mind and then, in order to detect the edge, an energy function is specified for contour deformation. Finally, by minimizing the specified energy through various arithmetic techniques, the edge detection and segmentation process is completed. If x and y are the position coordinates of the 2-D image I(x, y), then, for parametric representation of the contour on the image, one can use the curve v(s) = (x(s), y(s)), in which, In general, the energy function of the active contour is expressed as:

$$E_{total} = \int_0^1 E(v(s))ds = \int_0^1 [E_{\text{int}}(v(s)) + E_{ext}(v(s))]ds. \tag{1}$$

The defined energy function for the contour consists of two components which, respectively, are:

- Internal energy component $E_{\text{int}}(v(s))$: this component is used to control the rate of stretch and to prevent discontinuity in the contour.
- External energy component $E_{ext}(v(s))$: this component is generated by using the image characteristic features or the limitations imposed on the contour by the user, and it is used for contour displacement.

In order to control the contour deformation and displacement, these energy components, are converted into two internal and external force components. During the process of contour evolvement, the force resulting from internal energy, keeps the contour smooth and prevents breaking and discontinuity of the contour which are caused mainly by the presence of irregularities and noise in the image. Also, the external force has the task of displacing the contour from its initial position and guiding it towards the subject's edge.

B. The Kass Snake Model

Mr, Kass defined The internal energy component as follows:

$$E_{\text{int}}(v(s)) = [\frac{1}{2}\alpha(s)|v_s(s)|^2 + \frac{1}{2}\beta(s)|v_{ss}(s)|^2] \tag{2}$$

The first term of the internal energy is related to the contour's bending ability, and to control and adjust it, the weight factor α(s) is used. Also, the second term in this relation specifies the contour's strength and resistance against sudden changes, and for controlling it, the weight factor β(s) is used. Relation (3) represents the external energy defined by Kass for the contour.

$$E_{ext}(v(s)) = -\lambda|\nabla[G_\sigma(x, y) * I(x, y)]|. \tag{3}$$

In this relation, γ is the external energy weight factor, G_σ (x, y) is a two-dimensional Gaussian function with the standard deviation σ, ∇ is the gradient operator, and * specifies the convolution operator for the 2-D image I(x,y).

When the energy function attains its minimum value, or in other words, when external and internal forces balance out (relation 4), contour evolvement stops and the edge detection process comes to an end. This indicates that the contour has coincided with the edge.

$$F_{\text{int}} + F_{ext} = 0\ . \tag{4}$$

III. THE GREEDY SNAKE ALGORITHM

Before The greedy snake algorithm sums up the energy terms to get the total energy:

$$E_{total}(x, y) = \alpha(s_i)E_{cont}(x, y) + \beta(s_i)E_{curv}(x, y) + \gamma(s_i)E_{img}(x, y)\ . \tag{5}$$

where $E_{cont}(x, y)$ is the continuity energy, $E_{curv}(x, y)$ is the curvature energy, $E_{img}(x, y)$ is the image energy, and (x, y) are the indices to the points in the neighborhood.

A. Calculating the Image Energy

The image energy of the greedy snake is calculated as

$$E_{img} = |\nabla[G_\sigma(x, y) * I(x, y)|^2\ . \tag{6}$$

The greedy snake algorithm works by examining the neighborhood surrounding each snake point and then moving to a new position which has the lowest energy. Therefore, the image energy in the neighborhood of the snake control point $v(s_i)$ has to be normalized in a manner which assigns large negative values to pixels with high energy values, while assigning smaller negative values to pixels with lower energy values. The energies are all in the interval [0, 255]. The normalization sets the lowest energy in the neighborhood to 0 and the highest energy to -1.

B. The Curvature Term of the Greedy Snake

To compute the curvature for each point in the neighborhood of the snake point, in ref. [9], D. J. Williams and M. Shah used the following expression:

$$|v(s_{i+1}) - 2v(s_i) + v(s_{i-1})|^2\ . \tag{7}$$

After calculating the curvature for each control point in the neighborhood of the current snake control point, the values are normalized by dividing them by the largest value.

C. The Continuity Term of the Greedy Snake

The greedy snake calculates the continuity term in a way that reduces the shrinking effect of the curve and also makes certain that the snake control points do not cluster together in places with high image energy. The continuity term in the greedy snake is calculated for the neighborhood of each snake control point as:

$$\bar{d} - \left|v(s_i) - v(s_{i-1})\right| = \bar{d} - \sqrt{(y(s_i) - y(s_{i-1}))^2 + (x(s_i) - x(s_{i-1}))^2} \ . \quad (8)$$

Where $\bar{d}$ is the average distance between all the points in the contour. Once the above term has been calculated for each pixel in the neighborhood of a snake control point, all the obtained values are divided by the largest value, thereby, normalizing the neighborhood. The minimum energy will be achieved when the continuity term is equal to zero. So, the distance between the current and the previous points on the snake equals the average distance. This new continuity term will therefore make the snake control points be equally spaced along the curve.

D. Algorithm

Once the total energy has been calculated for each point in the neighborhood of the snake control points, the algorithm makes a greedy choice and moves the snake control point to the location that has the lowest total energy. So, the name of the algorithm signifies its behavior. Once all the control points along the snake have been moved to new positions, the curvature is recalculated. This time, however, the curvature is only calculated once for each control point along the active contour and not for all the points in the neighborhood. The reason for calculating the curvature again is to locate the points where the curvature is high and then, to set the parameter β for those control points to zero. By doing this, a corner is allowed to form at each of these points of the active contour. The following expression is used when the curvature is computed for the second time:

$$\left| \frac{h_{i+1}}{\left|h_{i+1}\right|} - \frac{h_i}{\left|h_i\right|} \right| . \quad (9)$$

Where hi = $[x(s_i)-x(s_{i-1}), y(s_i)-y(s_{i-1})]$ and $h_{i+1} = [x(s_{i+1})-x(s_i), y(s_{i+1})-y(s_i)]$. This gives a more accurate estimation of the curvature since we normalize by the magnitudes of the vectors. We, thus, avoid the problem of the points having to be equally spaced to get a reliable curvature measure. Due to high computational expenses, the equation (9) is not used initially to calculate the curvature for all the points in the vicinity of each snake control point. Once the new and exact curvature has been calculated for all the snake control points the β parameter is set to zero for control points in the active contour where the following conditions are satisfied:

- the curvature for the control point $v(s_i)$ has to be larger than the curvature for its two neighbors $v(s_{i-1})$ and $v(s_{i+1})$.
- the curvature has to be larger than a specific threshold value.
- the magnitude of the gradient at the control point also has to be above a specific threshold.

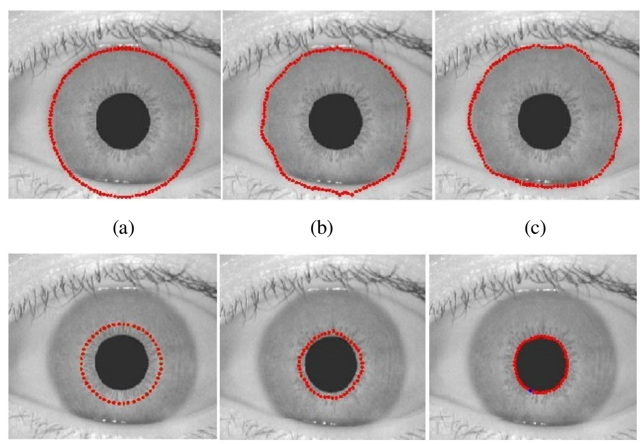
If all the above conditions are true, then the control point's β value will be set to zero. When the β value is zero, the curvature at the corresponding snake control point no longer influences the total energy of the snake and therefore, a sharp corner develops.

The final step in the iteration of the greedy snake algorithm consists of checking whether the number of points moved in the iteration is below a specific threshold. This is used as a stopping criterion, as the snake is presumed to have reached minimum energy when most of the control points have stopped moving.

IV. IRIS RECOGNITION SYSTEM

A. Iris Localization

We used the greedy snake algorithm for our iris localization. The results of localization for the outer and inner boundaries are shown in Fig. 1. The steps for detecting the outer boundary, for example, are illustrated in Figs. 1(a), 1(b), and 1(c). In Fig. 1(a), a contour close to the outer boundary is defined. Fig. 1(b) shows the contour after 17 iterations, and Fig. 1(c) depicts the final contour as the outer iris boundary.



(a) (b) (c)

(d) (e) (f)

Figure 1. iris segmentation process. (a) Initial contour for outer iris boundary. (b) Contour after 17 iteration. (c) Outer iris boundry. (d) Initial contour for inner iris boundry. (e) Contour after 8 iteration. (f) Inner iris boundry.

B. Normalizaton

Once the iris region is successfully extracted from an eye image, the next process is to convert the iris region so that it has fixed dimensions in order to allow comparisons. Therefore, in our investigation, the iris ring was normalized into a rectangular block with a fixed size of 64×360 pixels (Fig. 2(a)). Only two regions between 180° - 245° and 314° - 359° on the iris ring (Fig. 2(b)) were used for our system, because it was found that these two regions are almost free of noises such as eyelashes and eyelids.

(a)

(b)

Figure 2. (a) Normalized iris. (b) Region of interest.

C. Feature Extraction

In order to provide accurate iris recognition, the most important information present in an iris pattern must be extracted so that comparisons can be made between templates. Most iris recognition systems make use of a band pass decomposition of the iris image to create a biometric template. We used a log-gabor filter for feature extraction. The frequency response of a Log-Gabor filter is given as:

$$L(f) = \exp\left(\frac{-(\log f / f_0)^2}{2(\log \sigma / f_0)^2}\right). \tag{10}$$

where f_0 is the center frequency, and σ is the bandwidth of the filter.

D. Matching

The template which is created in the feature extraction process will also need a corresponding criterion to provide a measure of likeness between two iris templates, so that a decision can be made with high confidence as to whether the two templates are from the same iris, or from two different irises. We used the Hamming distance for our matching process[1]. The Hamming distance gives a measure of how many bits are the same between two bit patterns. Using the Hamming distance of two bit patterns, a decision can be made as to whether the two patterns were generated from different irises or from a same iris. In comparing the bit patterns X and Y, the Hamming distance, HD, is defined as the ratio of the sum of disagreeing bits (sum of the exclusive -OR- between X and Y) over N, the total number of bits in the bit pattern.

$$HD = \frac{1}{N}\sum_{j=1}^{N} X_j (XOR) Y_j. \tag{11}$$

V. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed algorithm, we used the CASIA Iris Image Database 1.0 [10] which includes 756 iris images from 108 eyes; each iris has seven images of 320×280 pixels each in 256 gray levels. The results of different iris recognition systems (the differences arising from different segmentation methods) is shown in TABLE I. The results demonstrate that our method has the highest accuracy.

TABLE I. THE RESULTS OF DIFFERENT IRIS RECOGNITION SYSTEMS BASED ON DIFFERENT SEGMENTATION METHODS

methods	***Accuracy(%)***
Hough transform (Wildes' method)	87.3
Kass model	95.6
Our method	99.1

VI. CONCLUSION

In this article, an attempt was made to use the greedy snake algorithm for the iris segmentation process. The obtained results showed that this method has a relatively good accuracy and can be used for iris segmentation.

REFERENCES

[1] J. Daugman, "High Confidence Visual Recognition of Persons by a Test of Statistical Independence," IEEE Transactions on Pattern Analysis Machine Intelligence, vol. 15, no. 11, pp. 1148–1161, 1993.

[2] R. Wildes. "Iris recognition: an emerging biometric technology," Proceedings of the IEEE, vol. 85, no. 9, pp. 1348-1363, 1997.

[3] C. Tisse, L. Martin, L. Torres, M. Robert. "Person identification technique using human iris recognition," proc. International Conference on Vision Interface, Canada, pp. 294-299, 2002.

[4] W. Kong, D. Zhang. "Accurate iris segmentation based on novel reflection and eyelash detection model," Proceedings of 2001 International Symposium on Intelligent Multimedia, Video and Speech Processing, Hong Kong, pp. 261-266, 2001.

[5] R. Chen, X. Lin, T. Ding, J. Ma. "Accurate iris segmentation Applied to Portable Image Capture Device," International Workshop on Imaging Systems and TechniquesShenzhen, China, pp. 80-84, 2009.

[6] S. Shah, A. Ross. "Iris Segmentation Using Geodesic Active Contour," IEEE Transactions on Information Forensics and Security, vol. 4, no. 4, pp. 824-836, 2009.

[7] J. Daugman, "New method in iris recognition," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 37, no. 5, pp. 1168-1176, 2007.

[8] M. Kass, A. Witkin, D. Terzopoulos, "snakes: active contour models," International Journal Of Computer Vision, vol. 1, no. 4, pp. 321-331, 1988.

[9] D. J. Williams, M. Shah. "A fast algorithm for active contours and curvature estimation ," CVGIP: Image Underst., vol. 55, no. 1, pp. 14-26, 1992.

[10] CASIA database, http://www.sinobiometrics.com.