Iris Recognition Method for Non Ideal Images

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Abstract. The issue of counterfeiting is one of the most pressing threats to people's security because of the many complex security problems. Many systems used in the field of verification and identification but the basic criterion for choosing is the degree of safety identification. Identification and verification systems use biometric characteristics of individuals. The system of iris recognition is one of the most important biometric recognition systems. The system used iris images for 100 persons belonging to the UBIRIS V1 database. Each person has 5 captures; the total number is 500 images. A hybrid iris segmentation method combined two algorithms ChanVese (CV) and grabcut to obtain high verification rate and to detect the outer boundary and localize the iris region. The system includes several steps starting with acquiring the image of the iris, enhancing the image quality, segment iris region, determining the coordinates of iris center and radius of the pupil, convert the iris coordinates of the cutting segments from Cartesian coordinates to the polar coordinates to reduce the processing time and to avoid the noise image problems due to eyelids and eyelashes, then utilize Gabor wavelets to extract the features of iris, and finally perform the matching process using Euclidian distance. The performance indicators, which include the recognition rate, false rejection rate(FRR), False Acceptance Rate(FAR), Correct identification rate(CIR), are as follows(97.5%, 39%, 0.025%, 0.0975). The proposed system has many advantages includes high processing capability of low-quality images and low storage capacity.

Keyword: Iris Segmentation; Chan-Vese Algorithm; GraphCut

1. INTRODUCTION

Iris recognition biometric systems have several advantages over other biometric systems, for instance, most iris patterns have not been altered over the life span, cannot be easily falsified or modified, and each individual possesses individual iris pattern with a high grade of fluency (Kazakov, 2011). Biometric research used iris recognition to determine high dependability and this led to overall studies in the development of iris techniques in an unrestricted environment, off-angles, noise, vagueness and obstruction by eyelashes, eyelid, glasses, and hair. These causes lead to the likelihood of gaining a non-ideal iris image is very high (Zainal, et al., 2015) (Suvarchala, et al., 2013). Most of the preceding research on iris segmentation is concentrate on exact detection of iris images which are captured in closely controlled condition compared to the new trend of research that applies different approaches to
reduce the error percentage even in the presence of types of noise include iris obstructions and specular reflection.

In this paper proposed iris recognition system using hybrid method active contour and grabcut are used to accurately localize the structure of the iris in image of eye. While many fragmentation methods rely mainly on edge detection, Chan and Vese's "Active Contours without Edges" method completely ignores edges. Chan Ves active contour is a powerful and flexible method which is able to segment many Types of image and Used extensively in medical fields. The structure of the paper as follows: in the next section, related work is presented. Section 3 presents the proposed iris recognition system. Section 4 the technical details of the system are described. Section 5 shows the experimental results and finally, Section 6 gives the most important conclusion of the proposed system.

2. RELATED WORK

The concept of the iris is defined as a specific area bounded from the inside by the pupil and from the outside by the hard part and the eyelids. Most studies detect these two areas and remove the eyelid, lashes and light reflection.

- Daugman was the first one who exhibits a total iris recognition system (Daugman, 1993). To divide the iris he defined the so-called Daugman Integro-differential factor. This factor seeking for the circle with the topmost alteration in values by changing both positions, radius and center (x,y) of the outline curve. The two top value congruous to the both gained circles that locate the iris. Daugman does not employ any threshold on the image gradient, which applies the information of each image. However, the factor is significant to the outrageous value that might progress to misconception discovery in the iris. Daugman uses a duplicate agent for the eyelids, then the factor searches the parabola curvature shapes the eyelid. Finally, eyelashes reflexion results from isolation of severing threshold.

- Wilds established the circular Hough transform to locate the iris (Wildes, 1997). The tendency of the images is calculated by this algorithm and makes a brink-maps to transform it to Hough. The voting is then calculated to recognize both the given circles which are represented the potential radius. The external iris boundaries are discovered prior to the internal boundaries; the outcome is agreeable for the image of the particular gradient and the predetermined domain of the radius of the potential circle.

- Iris localizing is done by the use of Morphological factor such as density thresholds opening and closing (Ghodrati, et al., 2010)(De Mira & Mayer, 2003). More specifically speaking in (Ghodrati, et al., 2010) a square region that's fully besetment the pupil it discovered by using the intensity information. The region is thereafter binaries to educator a brink-maps out of it. It using a reiterated morphological factors algorithm locating the iris internal boundaries. The mechanism for determining external tires is going along with the outer boundary.is separated into left and right sides in which they are detected by arched Hough transform and finally consolidated together. Attractive results obtained which show development on the accuracy of the iris localization. In any case, it must be taken into an account that the database used to experience the system (CASIAV4) is considered as a simple unchallenging database.

- Chan and Vese (T. Chan & Vese, 1999) (T. F. Chan, et al., 2000), suggested a new level set model. This model has large properties for global optimization because it employs all the information in the full image area. The usefulness of this proposal is that this method optimally fits the given image which it it Consist of a two-phase piecewise constant model. The border segmentation is working implicitly with a level set function the levelset effects on handle segmentation, it make easier than snake Classic model

- Jahangiri and Heesch (Göring, et al., 2012), prepare an unattended GrabCut algorithm configured with a rough segmentation acquired by active argument. However, they are solitary fit to segment the front-end objects from a clear background and not use any category-specific information.
3. THE PROPOSED SYSTEM
This section reviews the proposed iris recognition system using hybrid method which integrates two techniques used in cutting the picture which is the active contour (Chan-Vese) and GrabCut, Figure 1 shows the steps for the proposed system. Thus we get more accurate and efficient results in cutting the iris.

![Figure 1. Show the proposed system](image)

4. IMAGE PREPROCESSING
This section presents the iris image quality enhancement through reflection removal steps.

4.1. Remove Reflection from Pupil Region
The interpolation method (bicubic method) is used to deal with this problem. Bicubic interpolation, also known as crossover curing interpolation, (4×4) adjacent pixels are considered. It is different from linear double interpolation which is only (2x2) pixels into account, using this equation (Rajarapoli & Mankar, 2017):

\[ v(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^{i} y^{j} \]  

Where:
- \( v(x, y) \): the coordinates of the resulting point.
- \( a_{ij} \): the coordinates of the adjacent

For more illustration of the above equation, the chromatic value of the coordinate is the sum of the color values of sixteen contiguous [12]:

\[ \text{Chromatic Value} = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^{i} y^{j} \]
\[ v(x,y) = \begin{bmatrix} f(i-1,j-2) & f(i,j-2) & f(i+1,j-2) & f(i+2,j_2) \\ f(i-1,j-1) & f(i,j-1) & f(i+1,j-1) & f(i+2,j-1) \\ f(i-1,j) & f(i,j) & f(i+1,j) & f(i+2,j) \\ f(i-1,j+1) & f(i,j+1) & f(i+1,j+1) & f(i+2,j+2) \end{bmatrix} \] (2)

Where:
\( F(i,j) \): the coordinates of the sixteen contiguous.

Figure 2 display the result of removing reflection from the pupil region using interpolation method.

4.2. Iris Reflection Removal

Morphological filter operation is used to iris reflection removal, region fill algorithm, and complement image. The region fill of the image can be selected in two ways: (i) inner region and (ii) boundary region. The inner region is characterized by specifying an identical value to all the pixels inside that region. The algorithms exercised to change the values of all pixels in the interior regions to new values are FLOOD-FILL algorithms (ANBALAGAN, 1989). The boundary regions are characterized by the similar incentive to each pixel on the regions. The pixels of the regional boundary and the inner ones should not have identical values. BOUNDARY-FILL algorithms are used to change the value of all pixels in boundary regions to new value (ANBALAGAN, 1989).

The algorithm used for region filling depend on set of intersections, complementation, and dilations this algorithm working as filling the entire region interest with ‘black’ starting from a point “p” inside the boundary. The first step of the convention is that all the non-boundary (background) points are Refers ‘white’ and then assigned a value of black to point “p”. Filling the region with ‘black’ executed by the following procedure (Raid, Khedr, El-Dosuky, & Aoud, 2014):

\[ x_k = (x_{k-1} \oplus B) \cap A^C \] (3)

Where:
\( k=1,2,3,... \)
\( B \): is the symmetric structure element
\( A^C \) : is the complement of the set.

When \( k=0 \) then \( x_0 \) will equal to the point “p” in Eq. 3. Figures 3 shows the results of the iris reflection removal steps.

Figure 3. The outcomes of pre-processing stage. (a) Authentic image, (b) RGB image to grey image, (c) complement image, (d) fill image, and (e) the resulting image without reflection.
5. IRIS SEGMENTATION

The iris segmentation is one of the most important stages in the recognition system of the iris. This stage includes the separation of iris from the rest of the other parts. Iris is a part that contains the unique characteristics of the eye in which the recognition rely on. Chan-Vese active contour and graph cut is a hybrid method that used for the segmentation in the proposed algorithm.

![Image 1](https://example.com/image1.png)

**Figure 4.** Illustrate the iris segmentation stage

6. CHAN VESE ACTIVE CONTOUR

Chan-Vese active-area model (Brown, et al., 2012) is a strong and soft method to segment many types of image, in particular some images which are complicated to segment suitably by "classic" segmentation technique using a gradient-based (Jamaludin, et al., 2016). This pattern is established on Mumford-Shah functional and is extremely used in medical imaging, particularly for brain, heart, and tracheal dissection. This model is firstly based on the power decrease problem, which can be reformulated in the form of the level groups, resulting in problem-solving.

Let \( f \) mark the given eye grey image in a domain \( \Omega \) to be segmented. The Chan–Vese strategy is enlivened by the Mumford–Shah Model (Tai, et al., 2009). Mumford and Shah functional approaches the image \( f \) by a soft segment function \( u \), as a result for the minimizing case (Getreuer, 2012):

\[
\underset{u,c}{\arg \min} \mu \text{length}(C) + \lambda \int_{\Omega} (f(x) - u(x))^2 \, dx + \int_{\Omega \setminus C} |\nabla u(x)| \, dx \tag{4}
\]

While C is the edge range curved, \( u \) is permitted to be sporadic. The first term secure regularity of \( C \), the second term support \( u \) to be near to \( f \), and the third term ensure that \( u \) is be differentiable from \( \Omega \setminus C \). The Mumford–Shah approximation suggested selecting this edge set \( C \) as the segment action limit.

To simplify the equation (4), Mumford and Shah also looked at a fixed intermittent model (Getreuer, 2012):

\[
\underset{u,c}{\arg \min} \mu \text{length}(C) + \lambda \int_{\Omega} (f(x) - u(x))^2 \, dx \tag{5}
\]

Where \( u \) desired be fixed on each linked element of \( \Omega \setminus C \). At this time, \( C \) is refer to the limit of a closed set necessarily, i.e. \( C \) is collected from closed curves. Contrast to the Mumford Shah's model, the
main variation with the Chan-Vese model is an extra item that penalizes a closed area and furthermore simplification that \( u \) is permitted to have two values only (Getreuer, 2012):

\[
u(x) = \begin{cases} c_1 & \text{where } x \text{ inside } C \\ c_2 & \text{where } x \text{ outside } C \end{cases}
\]

(6)

Where \( C \) represents the boundary of a closed set, while \( c_1, c_2 \) represents both inside and outside the values of \( C \) respectively. Chan–Vese model finds through all \( u \) of this formula the one that best convergent \( f \) (Getreuer, 2012):

\[
\begin{align*}
\arg_{c_1,c_2} & \mu \text{ length}(C) + \nu \text{Area}(\text{inside}(C)) + \lambda_1 \int_{\text{inside}(C)} |f(x) - c_1|^2 \, dx + \\
& \lambda_2 \int_{\text{outside}(C)} |f(x) - c_2|^2 \, dx
\end{align*}
\]

(7)

The first term monitoring minuteness by correction the length. The second term correct enclosed \( C \) area to dominate its size. The third and the fourth terms complete the contradiction “piece-wise constant model” \( u \) and the input image \( f \). Figure 5 display the application results of the Active Contour method (Chan Vese) on the iris image. The implementation started with the initialization of mask curve (initial contour location close to the object that is to be segmented), then segment the image using the method with 150 iterations and finally boundary determination of the segmented image.

![Initial Image](image1)
![Initialization of Mask Curve](image2)
![150 Iterations](image3)
![Global Region-Based Segmentation](image4)

**Figure 5.** Show the results of Chan Vese algorithm, (a) input image, (b) initialization of mask curve, (c) segmentation with 150 iterations and (d) boundary of the segmented image.

7. **GRAB CUT METHOD**

Boykov and Jolly 2001 (Boykov & Jolly, 2001), proposed a technique of repeated image segmentation established on the GraphCut algorithm. There are algorithms for returns the cut with minimum cost in a graph. It is beneficial for segmentation if the energy can be expressed as a cost of a cut in a special graph builds from the image. This is the situation of the Chan-Vese model.

GrabCut expansion images can be coloured by Graph cutting and more over the deficient developments are extremely raise the advantage of graph cut. This process of user interaction can be simplified by drawing a rectangle around the desirable foregrounding, followed by a small amount of modifying editing. The color information module in the algorithm of graph cut and the refined learning process raises its hardness. Consequently, GrabCut is a modifying tool of a hopeful image for foreground extraction (Basavaprasad & Hegadi, 2014). Figure 6 shows the selection of nodes according the segmented region for foreground and background (Pundlik, et al., 2008). The results of GrabCut algorithm and segmentation are fully illustrated in Figure 7.

![Node Selection](image5)

**Figure 6.** shows t-links between terminals and nodes and n-links between two nodes (Pundlik et al., 2008).
The algorithm of GrabCut uses Gaussian Mixture Models (GMM) to lump the RGB pixel values from the image. There are two GMMs, one foreground and one for background pixels. Each GMM is defined to have 5 clusters (K = 5, set to be constant). There is an inflexible segmentation of the pixels between the foreground and background GMMs by n = 0 (background) or 1 (foreground). A Gaussian Mixture Model (GMM), the probability distribution used, is defined by sundry parameters (Boykov & Jolly, 2001).

\[ \Theta = \{\pi(\alpha, k), \mu(\alpha, k), \Sigma(\alpha, k)\} \]  

where:
- \( \alpha = (0, 1) \), \( k = 1 \)
- \( \mu \) mean RGB value
- \( \pi \) weighting coefficient
- \( \Sigma \) covariance matrix (3x3)

The algorithm of Grab Cut hard segmentation which is iterative image segmentation in Grab Cut Colour data modelling can be shown as below (Rother, et al., 2004):

**8. Initialisation**
- The user initialize trimap T by supply only TB. The foreground is set to TF = /0; T.U = T.B, complement of the background.
- Initialize \( \alpha_n = 0 \) for \( n \in TB \) and \( \alpha_n = 1 \) for \( n \in TU \).
- Foreground and background GMMs initialized from sets \( \alpha_n = 0 \) and \( \alpha_n = 1 \) respectively.

**9. Iterative minimization**
- Assigned GMM components to pixels: for each \( n \) in TU, \( k_n := \arg\min k_n D_n(\alpha_n, k_n, \theta, z_n) \).
- Learning GMM parameters from data \( z \): \( \theta := \arg\min \theta U(\alpha, k, \theta, z) \).
- Estimate segmentation: use min cut to solve: min \{\alpha_n: n \in TU\} min k E(\alpha, k, \theta, z).
- Repeated from step 1, until convergence.

**Figure 7.** illustrate the output of iris segmentation in ubiris v1. A: preprocessing image, b: selected boundary box, c: applying GrabCut, d: applying chan-vese active contour

**10. IRIS NORMALIZATION**

The Normalization process point to transformation the iris region from Polar coordinates to Cartesian coordinates. The parameters angle (\( \theta \)) and iris radius (\( r \)) are used in the normalization stae to selected the rectangular size of the iris image, and can significantly appear the iris recognition rate. This normalization is referring to use Daugman’s rubber sheet model. Figure (8) explain normalization from polar to Cartesian coordinate.
Figure 8. Polar to Cartesian Coordination

Equation (2.24) used for this transformation (Rathgeb, et al., 2012):

\[ I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \]  

(9)

Where:

\[ r = \sqrt{(x_n)^2 + (y_n)^2} \]

\[ x_n = x_c + r \sin(\theta) \]

\[ y_n = y_c - r \cos(\theta) \]

the iris normalized image \((i, j)\) describes as \((I(x_n, y_n))\),

\((x_c, y_c)\): refer to the center of the image, and

\(I(x_n, y_n)\): refer to the value for iris region and the value angle \((0^\circ, 360^\circ)\).

Correct normalization is necessary to satisfy the three main differences. These three advantages of normalization were in the following:

- Adjustments in external lighting cause variations in pupil size, which in turn affects the size of the iris.
- It ensures that the irises of different individuals are mapped onto a common image domain in spite of the variations in pupil size across subjects.
- Through the matching, the degree iris in a simple translation process. Depending on the eye-head plan, the rotation can perform this operations.

Figure (9) illustrate the outcomes of the iris normalization steps. Algorithm (3): illustrates in detail of the iris normalization.

**Figure 9.** the outcomes of the iris normalization, a: iris segmented, b: apply Canny edge detection, c: localized pupil and iris region, d: normalized iris

11. FEATURE EXTRACTION

It is the procedure by which key features of the sample chosen or enhanced. Frequently, the procedure of feature extraction depends on set of algorithm; the strategy changes relying upon the sort of biometric identification utilized.

Many schemes and methods utilized to find the iris features. One of the important reasons to use the iris feature than original iris image is the small memory size, especially for the system dealing with a huge database. There is much research in the literature that has been explained and studied. Some of these methods like the following (Hu, et al., 2014):

- Linear Discriminate Analysis (LDA), which is also known as Fisher Linear Discriminate (FLD) Analysis.
- Grey Level Co-occurrence Matrix.
Fourier transforms
- Gabor Filters.
- Zernike moment.

In this present paper, Gabor filters method will explained in details.

11.1. Gabor Wavelet

Gabor functions were first proposed by Dennis Gabor 1946 as a tool for signal detection. But there is a trade-off between time resolution and frequency resolution. Gabor discovered that Gaussian modulated complex exponentials provide the best trade-off (Tai Sing, 1996). Gabor wavelet kernel function has similar characteristics as the reflection area of the human cerebral cortex (Yu & Xie, 2015). So Gabor wavelet is one of the most successful local feature extraction methods due to their biological relevance (Gomathi & Baskaran, n.d.). Gabor wavelets are usually called Gabor filters in the scope application. Gabor filters have been used in many applications, such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, image coding, and image representation Human, Md. & Mst. (2017). The 2D Gabor filters optimally achieve joint resolution-localization in space and spatial frequency domains (Acharya, 2007). Therefore, it extend two dimensions frame criterion developed by Daubechies to one-dimensional wavelets (Tai Sing, 1996).

In the spatial domain, the 2D Gabor filter is contained from a Gaussian kernel function modulated by a sinusoidal plane wave, where the goal of using Gaussians window is to describe signals goes to Gabor (1946) (Ajao, 2014). A quadrature couple of Gabor filters used to the signal analysis. The real portion determined by cosine (cos) and the imaginary portion by sine (sin) and the modulation is by a Gaussian. Odd and Even symmetric components are real and imaginary definition to these filters, respectively. The frequency of the sine/cosine wave determines the filter centre frequency, and the width of the Gaussian determines the bandwidth of the filter. The optimal resolution in both time & Frequency domains can be obtained by Gabor function and extract domestic features. Texture analysis used in Gabor wavelet to obtain the extraction feature for both global and local details in the iris. The value of the feature is local

Power and the average capacity of each filtered image constitutes the feature vector components. These features are arranged to form a feature vector (Iris Codes). Gabor wavelet defined in equation (2.25) (Meyer, 2001):

$$Gabor\ (x, y) = e^{-\pi\left(\frac{(x-x_1)^2}{\alpha^2} + \frac{(y-y_1)^2}{\beta^2}\right)} \ast e^{-2\pi i(u(x-x_1) + v(y-y_1))}$$

Where:
- $x_1$ and $y_1$ are the position in the iris image?
- $u$, and $v$: specify the modulation which has spatial and frequency, $\omega = \sqrt{u v}$, respectively.
- $\alpha$ and $\beta$ specify effective width, and length.

Gabor filters can be applied on a multi-channel basis in some ways. In this method, the filters will be applied locally to multiple parts of the image instead of the entire image. The entire image of the iris is represented by global information formed by local information calculated from the iris. The number of Gabor filters that used is the first issue to deal with extracted features from images, it's depends on the application requirements, Normally 40 filters that result from 5 scales and 8 orientations for iris recognition. As shown in Figure (10).

![Figure 10. Gabor filter for 5 scales and 8 orientation](image-url)
Matching is a measure of the degree of similarity between two templates. This is always required for pattern recognition tasks. Generally, there are two biometric matching schemes: verification, identification (Porter, 1997).

Verification matching mode is where an individual displays the characteristics of the biometrics and the type of identifier, for example, a keen card., an approach to the biometric charts in the database.

- Identification matching mode is where the customer’s biometrics information is viewed against different schemas, to check if they are present within the specified data set.

There many matching approaches most of them depend on measuring the distance in feature space, in this paper present Euclidean distance.

12. Euclidean Distance
Euclidean Distance (ED ) or (Sum of Squared Difference SSD) A separate measure used as part of a biometric system. Distinguish the convergence of the degree of coordination between the two iris highlight templates (Schalkoff, 1989). Euclidean separation characterized as:

\[ ED = \sum_{i=1}^{n} (a_i - b_i)^2 \]

Where

- \( N \): is the no. of digits in the templates,
- \( a_i \): is the tested iris template,
- \( b_i \): is the stored iris template in the database.

13. EXPERIMENT RESULT

Image pre-processing in this step the eye image will enhance by remove the noise that is found in loaded image. This process is done by morphology operation and histogram equalization to deals with noise in iris image. Figure (11) explain five samples of pre-processing eye images in two database ubiris v1.

*Figure 11. Results of preprocessing Stage in ubiris v1 data base*
From figures(11) Note that there is no change in the values of the pixels of the whole image, but only in areas where there is a reflection and eyelashes is founded, where the pixels at these region are replaced by values of morphology operation.

The differences between the original image and the preprocessing image is large, comparison with the similarity index, mean-squared error, and peak signal-to-noise ratio between the original image and preprocessing image is large as the value showing in table(1)

| Person no. | Difference | SSIM    | MSE         | PSNR         |
|------------|------------|---------|-------------|--------------|
| The first person | 35.257    | 0.5453359 | 1809.997222 | 15.554024 |
| The second person  | 39.584    | 0.6297340 | 1961.984397 | 15.203848 |
| The third person    | 46.339    | 0.6356150 | 3470.728568 | 12.726597 |
| The fourth person   | 54.609    | 0.4069318 | 4150.435066 | 11.949867 |

**Table 1.** Image quality measure

Iris segmentation The second stage aims to determine outer boundaries of iris. In this stage, three major steps will performed on image enhancement, the results of the iris boundary determination for four persons are shown in Figure (12).

![Figure 12. Steps of Iris segmentation for five Eyes in UBIRIS v1](image)

From figures(12) and the grabcut model working perfectly for the most samples, if it failed to segment iris can the change the value of label matrix from( 500) to (700) or vice versa . the Chan Vese model working well in image has medium sharp edges , in sharp edges does not work well, so in here shows the usefulness of the first stage(preprocessing image) to unify the color intensity of all iris images

The accuracy of iris segmentation calculated in equation (12).
Accuracy = \frac{\text{no. of image localized correctly}}{\text{total no. of image in database}} \times 100 \quad \text{(12)}

The accuracy of iris localization of the proposed system is (99.3).

**Iris normalization** In iris normalization step, the iris image normalized from circle shape to rectangle shape, three steps will performed in ubiris v1 shown in Figure (13)

![Segment iris 1st](image1)
![Segment iris 2nd](image2)
![Segment iris 3rd](image3)
![Segment iris 4th](image4)

**Figure 13.** Steps of Iris Normalization for eight Eyes

Iris Recognition In this stage, the feature extracted for each person of database as the Recognition Stage is divided to training stage and testing stage. In the training stage, the template feature vector is determine for all persons used in the database. The gained feature

Template vector stored as array in devoted file. Each person corresponds to the feature vector by the name of image. In testing stage, the image-tested sample that belong to specific person is done all phases on the system down to specifying feature its own. His feature vector comparing with all template vectors, which stored in the devoted file mentioned above. The result of comparing will gained the distance between the specific person, which tested iris image, and all persons in templates vectors. The minimum distance achieved by Euclidean distance is used to give recognize status.

In the following, two studies will perform to measure the best efficiency of the proposed system. The system applied on the database UBIRIS V1. Different number of persons utilized is (100 persons and 200 person) a different number of training image vs. with testing image.

**The first study**

In this case study, the first trial of database is used (i.e. 100 persons, 3 images for training with 2 images testing, and 3 images for training with 2 images for testing, and 5 training with 1 testing).

**Table 2.** Measurement performance for first study-first case

| Number of person | 100 |
|------------------|-----|
| Number of training image | 300 |
| Number of testing image | 200 |
| Recognition rate(%) | 97.5% |
| FAR | 39 |
| FRR | 0.025 |
| CIR | 0.0975 |
Table 3. Measurement performance for first study-second case

| Number of person | 100 |
|------------------|-----|
| Number of training image | 200 |
| Number of testing image | 300 |
| Recognition rate(%) | 87.3% |
| FAR | 6.1428 |
| FRR | 0.14 |
| CIR | 0.86 |

Table 4. Measurement performance for first study-third case

| Number of person | 100 |
|------------------|-----|
| Number of training image | 400 |
| Number of testing image | 100 |
| Recognition rate(%) | 100% |
| FAR | 0 |
| FRR | - |
| CIR | 1 |

Figure 14. The measurement performance of All Cases in first study

Figure 15. The Relationship between No. Training Images and Recognition Rate in first study

The second study:
In this case study, the first trial of database is used (i.e. 200 persons, 3 images for training with 2 images for testing, and 3 images for training with 2 images for testing, and 5 training with 1 testing).

Table 5. Measurement performance for second study-first case

| Number of person | 200 |
|------------------|-----|
| Number of training image | 600 |
| Number of testing image | 400 |
| Recognition rate(%) | 87.5 |
| FAR | 7 |
| FRR | 0.125 |
| CIR | 0.875 |
Table 6. Measurement performance for second study-second case

|                           |       |
|---------------------------|-------|
| Number of person          | 200   |
| Number of training image  | 400   |
| Number of testing image   | 600   |
| Recognition rate(%)       | 76.66 |
| FAR                       | 3.28  |
| FRR                       | 0.233 |
| CIR                       | 0.767 |

Table 7. Measurement performance for second study-third case

|                           |       |
|---------------------------|-------|
| Number of person          | 200   |
| Number of training image  | 800   |
| Number of testing image   | 200   |
| Recognition rate(%)       | 95%   |
| FAR                       | 19    |
| FRR                       | 0.05  |
| CIR                       | 0.95  |

Figure 16. The measurement performance of All Cases in second study

Figure 17. The Relationship Between No. Training Images and Recognition Rate in second study

14. CONCLUSIONS

The present paper offered a new algorithm that proceeds a hybrid method that combines Chan-Vese and GrabCut methods in case of minimal forced situations, consisting variety in the average of closure, lighting and different positions of the iris. The reasons that made robustly are the validity of the proposed algorithm is due to for reasons: dealing with non-ideal iris, spectral reflection, the pupil is not center, remove eyelid and eyelashes. The accuracy of the algorithm range between 99% for the normal cases and 97% for the critical cases. A possible continuation of this work may be to think of a good automated initialization of the generalized Chan-Vese model. The original method with constant regions can be initialized with a well-chosen threshold. For the polynomial regions, the problem is more complicated. For example, using the Otsu thresholding as an initial segmentation.
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