ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

IJARMATE

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 2,Special Issue 6, March 2016

Fast and Accurate Iris Segmentation Using Hough Transform

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1. ABSTRACT

Iris segmentation is one of the decisive operations involved in iris recognition. Accurate iris segmentation is fundamental for the success and precision of the subsequent feature extraction and recognition, and consequently the high performance level of the iris recognition system. Most iris segmentation approaches proposed in the literature require highly complex-exhaustive search and learning of many modeling parameters and characteristics, which prevents their effective real-time applications and makes the system highly sensitive to noise. This paper presents a fast and efficient iris segmentation methodology to address relatively simple solutions to these problems. Three major procedures involved in the proposed iris segmentation approach, namely pupil detection, limbic boundary localization, and eyelid and eyelash detection, were carefully designed in order to avoid unnecessary and redundant image processing, and most importantly, to preserve the integrity of iris texture information. The proposed iris segmentation algorithm has the following particular properties and advantages: (a) avoidance of complex geometric and mathematical modeling; (b) no need of a training phase for algorithm design and implementation; (c) guaranteeing real-time iris segmentation even for iris images with severe occlusions; (d) high accuracy in iris segmentation and therefore low segmentation error rate. Experimental results, reported in this paper, demonstrate that the proposed iris segmentation algorithm outperforms some well-known methods in both accuracy and processing speed. As a consequence, the iris recognition system that incorporates the proposed iris segmentation algorithm is capable of offering recognition performances comparable with those reported by other state-of-the-art methods.

Keywords:Iris segmentation, Iris recognition system, Biometrics, image processing.

2. Introduction

The term biometrics, in the context of this paper, refers to the identification of an individual based on his/her physical or behavioralcharacteristics.The keys to the growth of biometric technology are manifold, including (a) the consequence of positive proofs of physical presence and the elimination of the need of remembering passwords or carrying identifiers that could be easily forgotten, borrowed or stolen, and (b) the increasing demands of security in quotidian environments, especially in personal identification. Iris recognition has rapidly become one of the most researched biometric topics due to its high potentiality in practical applications and is probably one of the most reliable biometric identification methods. Iris biometrics makes use of the highly rich and discriminative texture information contained in the annular region between the dark pupil and white sclera.

Iris segmentation is one of several major processing steps in an iris recognition task. The main goal of this iris segmentation step is to determine the valid region of the iris for recognition purposes. Basically this region is delimited bythe pupil and sclera. However, frequently iris texture regions are occluded by upper and lower eyelids, eyelashes, light reflections, shadows, etc. Therefore, iris segmentation also includes localizing the eyelids and eliminating the effect of occlusions caused by the eyelashes, shadows and light reflections. The quality of the adopted iris segmentation method affects directly the overall iris recognition performance. On one hand, it is crucial for high quality of extracted iris features used for recognition, while, on the other hand, it is a determinant of biometrically real-time response due to fact that it is the most time-consuming module in an iris recognition system.Among many research works focusing on iris segmentation approaches, there are two well-known algorithms, reported, respectively, by Daugman and Wilders.Daugman,applied an integrodifferential operator to delimitate the circular boundaries of irises, while Wilders, in used Hough transforms to locate iris boundaries. Both algorithms grant goodperformances but computationally are highly

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Available online at www.ijarmate.com
IJARMATE
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 2,Special Issue 6, March 2016

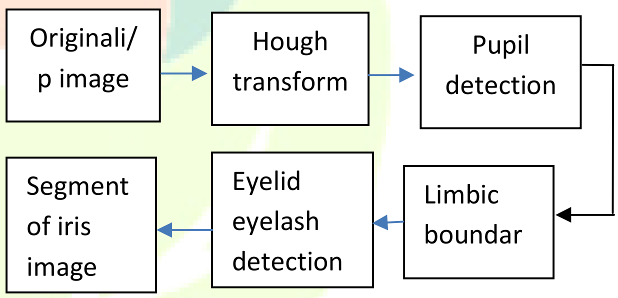
time-consuming. In addition, the two segmentation methods do not take into account the obstructions caused by eyelids, reflections, eyelashes and shadows. In order to overcome these challenging drawbacks, initially many subsequent research works attempted to improve or to optimize the methods based on circular modeling.Sooner after, deeper investigations focusing on occlusion detection, such as eyelid, eyelash and specular reflection detection, were reported. Most approaches for occlusion detection were based on the obstruction objects' edge detection. More recently, some scientific groups have concentrated their research studies on so-called nonideal iris images, for instance, non-circular and non-concentric iris images.

Based on the above descriptions, there are three important and challenging problems in iris image segmentation: (a) precise determination of pupillary and limbic boundaries, especially for nonideal iris and noisy images; (b) adequate treatment for occlusions caused by reflections, eyelids, eyelashes, etc.; (c) real-time iris recognition in practical applications. Among many tentative approaches for solving these challenging problems, recently Heetalhave proposed a novel algorithm dealing with great parts of these problems with the intention of achieving accurate and fast iris segmentation performance. More precisely, the algorithm intends to solve most occlusion problems, especially on highly noisy images: reflection removal and iris detection, pupillary and limbic boundaries determination, eyelid localization, and eyelash and shadow detection.

With rapid advance of electronic technologies and popularization of biometric applications, the production cost of much specialized biometric equipment, including eye/iris image cameras, has become lower and lower. Simultaneously, the quality of captured eye/iris images has become higher and higher. No doubt better iris image quality can contribute to even higher performance of iris recognition systems, and also simplification of iris segmentation algorithms without compromising the recognition performance. Also, it is worth mentioning that occluded iris areas invariantly have their iris texture information lost. Fortunately redundant information provided by the extracted iris features is able to minimize, if not to completely eliminate, the bad effect of iris area occlusion. Therefore, aiming at efficient and real-time iris segmentation, in this paper, we describe a new heuristic approach-based iris segmentation algorithm. The proposed method should attend simultaneously real-time application requirements and high iris image segmentation accuracies, without impacting the desired final iris recognition performance.

3. Materials and methods

As mentioned above, many different iris segmentation methods have been proposed in the literature. Unfortunately, many of them are unsuitable for real time applications, or present relatively high or unacceptable segmentation error rates. Here, error in iris segmentation means failure in correctly localizing and/or isolating iris texture regions for posterior iris feature extraction and recognition. In other words, being unsuccessful in correct iris image segmentation will compromise the overall iris recognition rate. The iris image segmentation algorithm proposed in this paper consists of three major modules, namely pupil detection, limbic boundary localization, and eyelid/eyelash detection. The image processing procedures implemented in these modules were designed in order to be executed sequentially without repetition and redundancy, and consequently minimize the overall processing time. More precisely, the implemented algorithms avoid unnecessary processing over image regions that do not contain relevant information for iris image segmentation, and consequently iris recognition.



Figure(a). Flow chart of the proposed system

Original input eye image Hough Transform Pupil detection Limbic boundary localization Eyelid eyelash detection Segmented iris image pupil detection (the determination of the centerand radius executed. Therefore, a specular reflection removal procedure also Figure 1. Flowchart of the proposed iris image segmentation algorithm.

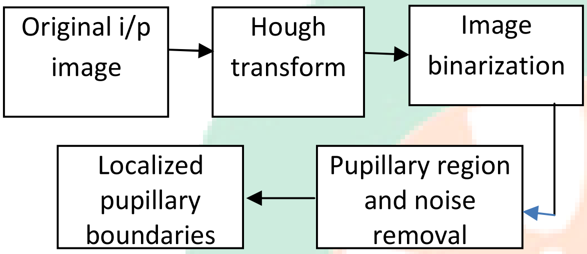
3.1 Pupil detection

The module of pupil detection was designed to localize pupillary boundaries. More specifically, the module is responsible for performing the following four processing steps, namely: (1) Hough Transform, (2) binary image generation (binarization), (3) pupil region detection and spectral removal and (4) pupil center and boundary localization.

A detailed description of the signal processing procedures involved in each step is given below. For the illustration purpose, Fig. 2 shows some major involved processing procedures and the obtained results through their respective sample iris image representations.

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 2,Special Issue 6, March 2016

In this work, we assume that a pupil has circular shape. Thus, under this circular modeling assumption, pupil detection consists of localization of the center of the pupil circle and estimation of the radius of the circular pupillary boundaries. However, due to specular reflections on the pupillary region, the is needed and pre-performed. The sub-regions in the pupil area where specular reflections occur should be isolated in advance; then, the specular reflections can be eliminated.



Figure(b).Flow chart of the pupillary detection algorithm.

Hough Transform

Hough transform is a standard image analysistool for finding that can be defined in aparametrical form such as lines, polynomials and circles. The recognition curve of a global pattern isachieved using the local patterns. For instance,recognition of a circle can be achieved byconsidering the strong edges in an image as thelocal patterns and searching for the maximumvalue of a circular Hough transform.Wildes et al.Kong and Zhang , Tisseet al. and Ma et al. use Hough transformto localize irises. The localization method, similartoDaugman's method, is also based on the firstderivative of the image. In the proposed methodbyWildes, an edge map of the image is firstobtained by thresholding the magnitude of theimage intensity gradient:(x, y) is a Gaussiansmoothing function with scaling parameter toselect the proper scale of edge analysis.The edge map is then used in a voting process tomaximize the defined Hough transform for the desired contour. Considering the obtained edgepoints Hough transform. The limbus and pupil are both modeled as circlesand the parametric function g is definedas:Assuming a circle with the center (x,y) andradius r, the edge points that are located over thecircle result in a zero value of the function. Thevalue of g is then transformed to 1 by the function, which represents the local pattern ofthe contour. The local patterns are then used in avoting procedure using the Hough transform, H,in order to locate the proper pupil and limbusboundaries. In order to detect limbus, onlyvertical edge information is used. The upper andlower parts, which have the horizontal edgeinformation, are usually covered by the twoyelids. The horizontal edge information is usedfor detecting the upper and lower eyelids, whicharemodeled as parabolic arcs.We implemented this method in MATLAB®by first employing Canny edge detection togenerate an edge map. Gradients were biased inthe vertical direction for the outer iris/scleraboundary, as suggested by Wildesetal.vertical and horizontal gradients were weightedequally for the inner iris/pupil boundary.The range of radius values to search for wasset manually, depending on the database used.For the CASIA database, values of the iris radiusrange from 90 to 150 pixels, while the pupilradius ranges from 28 to 75 pixels. In order tomake the circle detection process more efficientandaccurate, the Hough transform fortheiris/sclera boundary was performed first, thenthe Hough transform for the iris/pupil boundarywas performed within the iris region, instead ofthe whole eye region, since the pupil is alwayswithin the iris region.

3.1.2 Binary image generation (binarization)

This processing step has the following major objective: to learn the grey level distribution of the improved filtered image in order to be able to enhance the whole pupil area, as well as the sub-regions inside the pupillary regions where specular reflections appear. Most importantly, this learning procedure allows us to obtain an optimal threshold value for binary image generation. The result of this investigation reveals that invariantly all improved images present their gray level histograms similar to that shown in Fig. 3. There are three local maximum peaks localized in the following grey level intervals: [0, 100], [100, 250], and [250, 255]. The first, second and third peaks are mainly due to the contribution of pixels localized in the pupil, iris, and sclera regions, respectively. A natural question is how to choose a good threshold value so that the generated binary image is able to retain most pupil area for good segmentation purposes. The binarization operation here mentioned aims at identifying and isolating some regions of interest in the raw input image from its background. The threshold value used for generating the desirable binary image is automatically estimated in advance from the gray level histogram of the improved image. Under the 256 gray level (0-255) standard, we define parameter S as the total amount of pixels in the improved image with their gray levels ranging from 0 to 150. The chosen threshold for binarization has its numerical value corresponding to the upper bound of gray levels that covers exactly the 70% of the total number of the lower gray level pixels determined by S.Notice that this 70% numerical value was determined empirically after an extensive experimental investigation by varying the threshold value in the range of 50-100%. We judge that this 70% threshold is able to preserve as

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ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 2,Special Issue 6, March 2016

much as possible the integrity of the pupil region. The gray level interval (0 to 150) for calculating S was chosen due to the fact that seldom pupil has its brightness superior to 150. Notice that the 70% threshold is not a particular characteristic of an iris image data base. On the contrary, it is common feature for any eye image under its gray level representation. Therefore, the 70% threshold was chosen for our image binarization operation. Particularly, for one of our iris image database used in our experimental investigation, called CASIA-IrisV3-Lamp, this 70% threshold has its numerical value equal to the gray level of 100.

3.1.3 Pupil region detection and spectral removal

Although the binary images obtained in the previous step (image binarization) are capable of enhancing most pupil area, they also, however, preserve many irregular and non-connected stains having varying sizes and formats, both inside and outside of the true pupil region . Many elements can contribute to this result, including light reflections and shadows. One of two major goals of this step is to identify a unique, valid, and connected pupil region candidate even with the presence of these reflections. In principle, one expects that, once a valid pupil candidate has been identified, the whole pupil and its boundaries can be easily and accurately localized in the next processing steps. Unfortunately, many pupillary boundary detection methods are not indeed efficient if the amount of noise present in eye images is significant, especially due to specular reflections inside the pupil area. Thus, the second goal of the current image processing step is the spectral reflection removal, inside the pupil candidate area.Pupil region detection is carried out relying on the following premise: the valid pupillary region is the one having the largest connected area. This premise is the consequence of the application of the accurate threshold value, which is also optimal in the sense of the unique, largest, and connected pupillary area, after intensively and recursively being tested and analyzed. For measuring the size of a connected area in a binary image, here we apply the area growing technique proposed in.For reflection noise removal, we apply the following filtering criterion: A point (pixel) is considered as a noise point if (a) it has the background grey level and is removed (changed to grey level 0), and (b) any one of the four neighbor pixels, horizontally and vertically, retains the zero grey level value. Notice that this spectral reflection removal procedure is executed only after the detection of the valid pupillary candidate area. shows the obtained pupillary area after with spectral reflection removal, which is ready for pupil localization (pupillary boundary detection) to be executed in the next step.

3.1.4 Pupil center and boundary localization

As mentioned before, in this work, we assume that pupillary boundaries are circularly modeled. Therefore, boundary detection consists of estimating the pupil center(Xp, Yp) and radius (Rp) of the circle based on the binary image obtained in the previous step, i.e., after applying the reflection noise removal procedure. Technically speaking, the boundary detection is composed of two operations; (1) pupil edge detection (the delimitated pupil region may not be perfectly circular) and (2) center localization and radius estimation (under circular modeling).

The pupil edge detection has the goal of delimiting edge points of the region of interest obtained in the previous step. For this end, we apply a gradient technique, i.e., filtering through two Sobel operators. Equation 2 depicts the matrix representation of two Sobel operators. Figure 4 shows all detected edge pixels (in white color) obtained from processing the binary image. The detected edge basically corresponds to a contour of the valid pupil candidate area. Here, for simplicity, the gradient vector at each edge point is expressed in its polar representation in order to facilitate the operation of boundary.The estimation of the center and radius of the obtained circle is carried out based on the detected edge points. First, these edge points are grouped into one of four quadrant sets according to their corresponding gradient angles: Quadrant I (the [0º, 90º] sector), Quadrant II (the [90º, 180º] sector), Quadrant III (the [180º, 270º] sector), and Quadrant IV (the [270º, 360º] sector). Therefore, the determination of the circle parameters, the pupil center (Xp, Yp) and radius Rp, consists of searching for two points on the edge belonging to two opposite quadrants (Quadrant I and III or Quadrant II and IV) but separated by a distance approximately equal to the diameter of the circle. If this is the case, as a result, it is expected that the midpoint of these two detected points of the edge indicates the most probable position of the pupil center (Xp, Yp). For reliable detection, the search, in principle should be carried out through every pair of edge points of the circle. However, in practice, we only need to test the half of the total edge pixels and possibly much less to speed up the estimation process. In other words, the center (Xp, Yp) is determined by the mid-point with the highest occurrence frequency among all possible combined candidate pairs selected from the edge pixels localized on the two opposite quadrants as well as the radius (Rp), by the most probable candidate value.

Notice that for the center (Xp, Yp) estimation, we apply the concept of Hough accumulator cells, instead of employing any traditional mathematical circumference formula, what implies significant gains in terms of processing time. Also, the proposed method is attractive even when the pupil is altered by dilation or the detected contour is considerably irregular.

3.2 Limbic boundary localization

After pupil detection, the remaining segmentation operation of the iris area that covers the iris texture region consists of limbic boundary and eyelid localizations. This subsection is devoted to a detailed description of left-and-right-side limbic boundary detection. It is interesting to mention that we do not attempt to detect entire limbic boundaries. Instead, we simply estimate part of them: left and right hand side limbic boundaries. The proposed approach, to be described below, proves to be a simple, fast and efficient operation. Most importantly, we are able to preserve all readable iris areas as well as all extractable iris texture information even when limbic boundaries are only partially detected. Such quality and simplicity are consequences of the fact that (a) we assume that the whole limbic boundary can be modeled by a circle with the center (Xi, Yi) and radius (Ri), and (b) we know the exact localization of the pupil (obtained from the previous processing module). Thus, the limbic boundary localization here is nothing more that the estimation of these two parameters from partially detected iris outskirts. In detail, the procedure for limbic boundary detection can be divided into the following four steps, namely: (1) delimiting of the region of interest; (2) identification of the best median filter; (3) determination of the left and right borders of the iris; (4) verification of the detected iris boundaries.

Before we proceed with a detailed description of each processing step above mentioned, it is worth observing some facts and problems one may encounter in limbic boundary detection which justify our approach. In general, limbic boundaries are not clearly defined due to low contrast between iris texture and sclera. Also, pupillary and limbic boundaries are by no means concentric. Therefore, the estimation of the center (Xi, Yi) and radius (Ri) becomes imperative, and the use of pupillary boundary information helps greatly to maintain a good tradeoff among processing time, segmentation error and robustness offered by the proposed algorithm.

3.2.1 Delimitation of the region of interest

The region of interest here declared is the smallest strip area cropped from the improved image, which covers the whole pupil. The estimation of the center (Xi, Yi) and radius (Ri) of circular limbic boundaries is based on the iris edge points confined inside this rectangle strip region. We determine this delimited strip area using the parameters YpandRpestimated from the pupil detection procedure. In other words, we draw two horizontal lines through pixel points, (Xp, Yp+ Rp) and (Xp, Yp- Rp), to limit the rectangle in the binary image obtained previously. Only for better illustration purposes, positions of these two delimitation lines drawn in the original eye image and the delimited areas (1 and 2), respectively, to be limbic boundary detection.

3.2.2 Identification of the best median filter

This step can be viewed as a further but necessary image pre-processing step in iris detection before we are in fact performing the limbic boundary detection procedure, in order to minimize the interference of iris texture. Here, we show how to choose a suitable median filter used for this end. This median filter is determined through an interactive process involving iris edge detection and verification, recursively. In other words, we vary the dimension (size n × n) of a mask filter until the detection of iris edges is declared. Operationally, the filter dimension parameter n varies from 10 to 55 (pixels) in a 5-pixel step until edge points are detected. (See the next subsection for details). Note that this filtering operation is always performed over the original raw eye image.

show the original example image and the delimited/filtered image by a 15 × 15 median filter, respectively. Note that the iris texture details are completely erased while limbic boundaries are enhanced

3.2.3 Limbic boundary localization

The purpose of this processing step is to determine limbic boundaries based only on the information given by delimited regions and assumption of circular limbic boundary modeling. Unfortunately, the filtered image (e.g., is still not suitable for detection. Further image processing is necessary which consists of binarization of the filtered image. The threshold value to be used for binary image generation is exactly the average gradient value estimated from the median filtered image after it has been submitted to the same two Sobel operators used for pupil localization. shows the obtained binary image from the original eye image.

Having a suitable binary image in hand, in order to execute limbic boundary localization fast and efficiently, once again, we restrict our search inside of some limited areas of interest as depicted . In addition, in order to achieve high detection accuracy, once again, we make use of pupil localization information (the center and radius). That is, the limbic boundary search is restricted to the box areas, the regions 1 and 2 only. An advantage of this approach is the elimination or avoidance of interferences of eyelids and eyelashes in limbic localization for most real situations. .

It is possible that we could make our limbic boundary detection approach even faster by restricting further to be searched areas if the information of the pupillary center position is used, especially when we have low quality and noisy input eye images. Notice that we do not assume that the pupillary and limbic circle boundaries are concentric. However, it is perfectly plausible affirming the centers of these two distinct boundary circles are close enough. Next, we describe the proposed procedure for limbic localization (the center (Xi, Yi) and radius (Ri)) from the very restricted box areas, the regions 1 and 2 as indicated. First, we compose a set of all possible pairs of enhanced pixels, the first element of pairs selected from region 1, the other from region 2. In order to optimize our search and avoid unnecessary calculations, immediately we try to eliminate all improbable candidate pairs based on the Euclidean distance measures of two pixel points to the center of the pupil. If these two distance measures are not close enough (say, the difference is superior to 5% of the larger distance), the pair is removed from the set which means the pair elements do not belong to the limbic boundary. For each surviving pair, the midpoint localization is found and the Euclidean distance between its two pixel elements is computed. The midpoint position with the highest occurrence frequency will be the localization of the limbic boundary circle and the circular boundary diameter is given by the average value of all corresponding distance measures computed from all survived pairs.

3.2.4 Optimization of limbic boundary detection

This step aims at achieving reliable limbic boundary detection, i.e., to reliably determine the circle-model-based parameters, (Xi, Yi) and Ri. This detection procedure can be viewed as one of optimization, which consists of maximizing the total amount of overlaps between valid (survived) pair pixels in the restricted regions (1 and 2) and an artificially generated boundary circle. This circle is generated based on the circle center and diameter information estimated from using only the surviving pairs of pixels, as described in the last subsection, B3. The criterion of optimization is, therefore, in function of the size n of the median filter, which is responsible erated binary images, from which candidate boundary points are enhanced. However, in order to meet real-time response requirement, the optimization procedure was elaborated in the following manner. The detection of limbic boundary is declared when there are 30% or more overlapping pixels, for n varying from 10 to 55 in step of 5 pixels. In practice, a few numbers of n is needed to be tested. The experimental investigations indicated that, in general, no more than three different values of n needed to be tried for boundary detection. Notice that the 30% decision threshold value for the overlapped pixel amount was empirically determined and proved efficient.

4. Conclusion

Accurate iris segmentation is essential for the success and exactitude of the feature pulling out and dentification,and as a result of allowing the iris recognition system to achieve desired high act . Most iris recognition approaches proposed require in-depth search and learning of many modeling parameters and characteristics, which prevents their effective application in real time, and turns the system highly sensitive to noise. Very few iris segmentation algorithms reported in the literature have indeed been tested by or are capable of accurately segmenting iris images with very low quality, mainly due to severe occlusions, and also providing online responses. This report by using hough transform has presented a easy and proficient iris segmentation methodology to tackle a solution to these problems. Three major procedures involved in the proposed iris segmentation approach, namely pupillary detection, limbic boundary localization, and eyelids and eyelash detection, were carefully designed in order to avoid needless and superfluous image processing, and most importantly, to preserve the integrity of iris texture information. The proposed segmentation approach of usinghough transform is simple but tough in terms of being less sensitive to large variations of input iris images.

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ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
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International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE) Vol. 2,Special Issue 6, March 2016

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