A Brief Survey on Recent Progress in Iris Recognition

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Abstract. Great progress of iris recognition has been achieved in recent years driven by its wide applications in the world. This survey summaries the progress in iris image acquisition, segmentation, texture analysis, classification and cross-sensor recognition from 2008 to 2014. The core ideas of various methods and their intrinsic relationships are investigated to obtain an overview and insights in the development of iris recognition. The future research work to improve the usability, reliability and scalability of iris recognition systems is also suggested.

Keywords: Iris recognition, iris image acquisition, iris image segmentation, iris texture analysis, iris classification, cross-sensor.

1 Introduction

Iris is one of the most reliable biometric traits due to its uniqueness and stability. The uniqueness of iris texture comes from the random and complex structures such as furrows, ridges, crypts, rings, corona, freckles etc. which are formed during gestation. The epigenetic iris texture remains stable after 1.5 years old or so. Iris recognition has been widely applied in large-scale identity management systems, such as the border control systems in United Arab Emirates and the UID project of the Unique Identification Authority of India (UIDAI). The research of iris recognition has achieved great progress driven by its real world applications. And some new problems of iris recognition are arisen from practical requirements such as cross-sensor iris recognition and iris indexing for efficient large-scale identification.

Bowyer et al. [1,2] have given a review of iris recognition in 2010. This paper is intended to mainly investigate the progress of iris recognition from 2008 to 2014. The purpose of this survey is not to list all research papers in details, but try to summarize the core ideas of various methods and their intrinsic relationships. This paper focuses on the main modules in iris recognition, such as iris image acquisition, iris segmentation, iris texture analysis and some new topics such as iris image classification and cross-sensor iris recognition. The following sections will introduce the research ideas of these problems one by one.

Z. Sun et al. (Eds.): CCBR 2014, LNCS 8833, pp. 288–300, 2014.

2 Iris Image Acquisition

Accurate iris recognition depends on high resolution iris images. However, it is difficult to capture iris images because human iris is a small imaging target with only 11 mm in diameter [3]. And near infrared (NIR, 700-900 nm) illumination is needed to illustrate clear texture details of Asian subjects.

An iris imaging system's capture volume and standoff distance are closely related to its ease of use. The early iris imaging devices such as Panasonic's BM-ET300 and IrisGuard's IG-H100 have limited capture volume in close-up range so that they require significant user cooperation. In order to enlarge the capture volume, auto-focus lens and pan-tilt-zoom (PTZ) units are employed, such as Panasonic's BM-ET500, OKI's IRISPASS-M and the prototype systems proposed in [4,5,6,7,8,9]. These systems usually contain a wide field of view (FOV) camera for scene imaging and a narrow FOV camera which is mounted on a PTZ unit for iris imaging. Typically, the 2D position of a detected face in the wide FOV camera is combined with the face's depth information to adjust the narrow FOV camera towards iris. Yoon et al. [4] adopt light stripe projection and face detection to obtain the 3D location of a user. An optical rangefinder is integrated in Eagle-Eyes [6] for depth estimation. Wheeler et al. [5] use a stereo pair of fixed wide FOV surveillance cameras to locate the 3D position of a face. Boehnen et al. [9] employ a stereo camera and reconstruct the stereo information on the field-programmable gate array (FPGA). Dong et al. [7] use linear regression to coarsely estimate the geometric relationship between the wide FOV camera and the narrow FOV camera, which avoids 3D estimation and speeds up the PTZ adjustment.

Even though auto-focus lens and PTZ units extend the capture volume significantly, the mechanical adjustment of narrow FOV cameras is still too slow to track the human movement. Matey et al. [10] develop an iris on the move system which can identify subjects while they walk through a portal at a normal pace. Two narrow FOV and fixed focal length cameras are vertically stacked to provide a larger capture volume. Unlike the aforementioned systems, some iris imaging systems based on computational photography consider iris imaging and image processing simultaneously. The depth of field of an iris imaging system can be extended by wavefront coded lens [11] and light field cameras [12]. McCloskey et al. [13] utilize flutter shutter technique to avoid motion blur.

In addition to a large capture volume, a long standoff distance is also a desirable feature for an iris imaging system. Fancourt et al. [14] present the first study of iris recognition at a distance. They capture iris images with a telescope and infrared camera at up to 10 m standoff distance. Their experiments report no performance degradation with distance. But this system requires the subject's head to be positioned in a chin rest. The iris on the move system [10] can capture iris images at 3 m standoff distance with the benefits of high resolution cameras and high power NIR strobed illumination. Eagle-Eyes [6] demonstrates iris recognition at 3-6 m standoff distance using a well-designed laser illuminator. The systems presented by Dong et al. [7] and Boehnen et al. [9] are capable of

acquiring iris images of sufficient quality for iris recognition at a distance 3 m and 7 m respectively.

Iris image acquisition is still a bottleneck for iris recognition. Great efforts are needed to develop innovative iris imaging systems that can safely and quickly acquire high quality iris images in a large capture volume and at a long distance.

3 Iris Segmentation

Human iris is small in size and always in motion, so it is difficult to capture an image only containing the iris region. Iris cameras usually capture a large area around the human eyes, which means that an iris image may contain not only the iris texture regions but also some neighborhood background regions such as pupil, sclera, eyelids, eyebrow, nose, forehead and eyeglasses. To define valid iris image regions for feature extraction and classification, it is necessary to segment the iris texture regions from others in iris images and represent the boundaries of these ROIs (region of interest) with proper models.

The early work on iris segmentation mainly focuses on locating circular or elliptical iris boundaries. The approaches proposed by Daugman and Wildes motivated most segmentation methods in the past two decades. Daugman's integro-differential operators [3,15] exhaustively search over the parameter space of curves for the maximum in the blurred partial derivative. Camus and Wildes [16] define a component-goodness-of-fit metric, which plays a similar role as integro-differential operators, to find the parameters that maximize gradient strengths and uniformities measured across rays radiating from a candidate central point. The estimated center location is updated in a gradient descend way to reduce the search space. Tan et al. [17] further extend the idea of gradient descent and design an integro-differential constellation which significantly accelerates the original exhaustive search nearly without reduction of accuracy.

Different from integro-differential operators, Wildes [18] creates a binary edge-map via edge detectors at first and then localizes iris boundaries by Hough transforms. Much attention has been paid on edge detection because Hough transforms can be misled by noisy edge points caused by non-iris boundaries. Liu et al. [19] use intensity thresholds to select candidate edge points. Proença and Alexandre [20] detect edges not in original but in clustered images to create more accurate edge maps. Tang and Weng [21] train a SVM classifier for limbic boundary detection using gradient and shape features. Li et al. [22] employ Adaboost to learn class-specific boundary detectors for left/right pupillary boundary and left/right limbic boundary detection. In order to speed up traditional Hough transforms, Uhl and Wild [23] use weighted adaptive Hough transforms to find the center of concentric circles considering both gradient magnitude and orientation. On the other hand, other techniques rather than Hough transforms are adopted to determine the parameters of iris boundaries after well-designed edge detection. Ryan et al. [24] detect edge points on rays and then estimate the parameters in a RANSAC-like manner. He et al. [25] find edge points in polar coordinates and fit the points by a pulling and pushing model. Edges are

detected in polar or ellipsopolar coordinates by Gabor filters in the fine localization stage of [23]. Li et al. [26] take advantage of shape information and learned iris boundary detectors to extract genuine pupillary contour segments.

Because the iris texture regions are often partly occluded by eyelids and eyelashes, it is necessary to detect upper and lower eyelid boundaries and eyelashes after iris boundary localization. Even though integro-differential operators and Hough transforms can be straightforwardly generalized for eyelid boundary localization by adopting suitable curves, such as spline [15] and parabolic curves [18], accurate and robust eyelid localization remains unsolved due to eyelids and other occlusions. He et al. [25] use horizontal rank filtering and histogram filtering successively for noise removal. Liu et al. [27] combine an integro-differential parabolic arc operator and a RANSAC-like algorithm for eyelid detection. Li et al. [22] detect eyelid edge points using learned boundary detectors. Eyelashes are hard to be modeled by any parametric shapes because of their random appearance. Daugman [28] excludes eyelashes by statistical inference according to the difference between the intensity histograms of the upper and lower parts of an iris. He et al. [25] detect eyelashes and shadows via a learned prediction model which indicates the amount of occlusions according to the intensity histogram dissimilarity of two iris regions. Zuo and Schmid [29] estimate eyelashes by smearing the horizontal edge. In addition to eyelids and eyelashes detection on original iris images, these occlusions can be detected in normalized images. Huang et al. [30] fuse the edge information obtained through phase congruency and region information to localize the occlusions. Li and Savvides [31] use Gaussian mixture models to model the probabilistic distributions of the Gabor features extracted from both valid and invalid iris regions.

Iris boundaries can be approximated by circles or ellipses in many cases, but sometimes they present irregular shapes and need to be fitted by flexible curves. A popular way to solve this problem is to evolve active contours towards iris boundaries. There are mainly two kinds of representations of active contours, i.e. snakes and level sets. Daugman [28] describes iris boundaries in terms of snakes based on Fourier series expansions of the contour data, while some researchers use level sets to represent iris boundaries [32,33,34]. The major concern in applying active contours to iris segmentation is to design suitable energy functions for curve evolution. Different energy functions are proposed in [32,33]. Nevertheless, active contours tend to be trapped by highly textured regions. Hence Zhang et al. [34] create semantic iris contour maps to remove most iris textures before adopting active contours.

Apart from localizing iris boundaries to isolate valid iris regions, some work directly classifies each pixel in iris images into iris or non-iris regions. Pundlik et al. [35] model an iris image as a Markov random field and use a graph cut based energy minimization algorithm to separate eyelash pupil, iris and background regions. Proença [36] classifies pixels into sclera, iris and background by neural networks using location and color information in the neighborhood of pixels. Tan and Kumar [37] extract Zernike moments around pixels and then use SVM classifiers to identify the iris and non-iris regions. After pixel classification,

these methods will fit iris boundaries using parametric curves for segmentation refinement or iris normalization.

4 Iris Texture Analysis

The uniqueness of iris pattern comes from the discriminative information of iris texture. Iris texture analysis plays a core role in the whole recognition system, and remains unsolved for iris images captured in less constrained environments.

Daugman [3] proposes the first effective algorithm for iris recognition, in which Gabor filters are applied to extract the phase information, and then the phase value is quantized into binary codes. At the matching stage, the dissimilarity of two iris codes is measured by Hamming distance. Wildes et al. [38] use Laplacian pyramids to describe iris texture, and employ correlation filters to match two iris feature patterns. Considering iris texture as one dimensional signals, zero-crossing points [39,40] or local sharp variations [41] are detected over the signals. Then, the Euclidean distance of feature points position or the Hamming distance of encoded features are used for matching.

Great progress has been made on iris texture analysis in the past decades. Ma et al. [42] represent iris features using a bank of spatial filters. Noh et al. [43] adopt Haar wavelet decomposition to obtain iris features. In [44], discrete cosine transform (DCT) is employed to extract features from iris texture. These methods obtain similar performance compared to Gabor filters. Sun and Tan [45] propose a general framework for iris texture analysis based on ordinal measures (OMs) which encode the ordinal intensity relationship between several image patches using binary codes. Their experiments show that OMs achieve state-of-the-art performance both in accuracy and efficiency.

In order to deal with the low-quality iris images captured in uncontrolled conditions, more robust iris texture representation methods are introduced. OMs encoded covariance matrices [46] are proposed to capture the correlation of spatial coordinates, intensities, 1st and 2nd-order partial derivatives. Rahulkar and Holambe [47] present a shift, scale and rotation-invariant technique for iris feature-representation and fuse post-classification to improve the accuracy and efficiency of the iris-recognition system. Dynamic features in [48] can capture the properties of iris images under NIR and visible-light illuminations. Advanced image-based correlation [49,50,51] is also a popular approach which can take advantage of the global features. The band-pass geometric features and low-pass ordinal features are fused in [52] to handle the pupillary deformation problem. Zhang et al. [53,54] introduce Daisy features and key-point selection for matching the deformed iris texture.

The recognition performance is closely related to the parameters of filters. Traditionally, the parameters are determined manually, which is often time-consuming and sub-optimal. It is desirable to design an algorithm that can find the optimized parameters driven by training data. He et al. [55] propose an Adaboost based algorithm, namely SOBoost, to select the most effective OMs features. Wang et al. [56,57] formulate the feature selection problem in a

linear programming model, which can select a compact and discriminative feature subset by using sparsity regularization.

Sparse representation based iris recognition is first proposed by Pillai et al. [58]. Later, Kumar and Chan [59] model iris representation problem as quaternionic sparse coding problem. However, spare representation has a basic assumption that a test image can be linearly represented by the training samples from the same class. Then, one possible limitation is the acquisition and storage of adequate training samples for each class.

The original Hamming distance of binary iris code treats every bit equally [3]. However, some bits are more stable and some bits tend to be more easily effected by deformation or occlusions. Various strategies are proposed to adaptively set each bit a weight according to different considerations. Daugman [15] proposes a mask to ignore bits occluded by eyelids and eyelashes, where occluded bits are masked by zeroes and the visible bits are reserved by ones. Chen et al. [60] consider that local iris image regions with better quality have better classification capability and vice versa. They incorporated the local quality measures (or local energy) as weights to compute the matching score. Hollingsworth et al. [61] mask the real (imaginary) bits from complex numbers too close to the imaginary (real) axis as fragile bits. Dong et al. [62] present a personalized iris matching strategy by using a class-specific weight map learned from the training images of the same iris class. The importance of each bit in an iris feature is determined by its performance in the training dataset. In [63], Liu et al. focus on recognition of motion blurred iris images and propose a blur mask to adaptively weight each bit in an iris code based on its blur situation. Depending on whether there are available training samples, two mask generation methods are proposed. Extensive experiments are conducted to find the iris regions which are robust to motion blur. Afterwards, penalty coefficients are adaptively assigned based on the robustness.

5 Iris Image Classification

In contrast to iris recognition, iris image classification does not concern the identity label of an iris image. It aims to classify an iris image to an application specific category (genuine vs. fake, Asian vs. non-Asian, etc.). Recently, Sun et al. [64] discuss iris image classification systematically and propose a general framework for iris image classification based on hierarchical visual codebook which encodes the texture primitives. A comprehensive literature review of iris image classification for three kinds of typical applications, i.e. iris liveness detection, race classification and coarse iris classification, has been presented in [64]. The core content of the review is abstracted as follows.

1) Iris liveness detection. In highly secure applications of iris recognition, iris liveness detection is extremely important to prevent attacks of forged iris. Daugman [3] and Wildes [18] suggest pupillary athetosis as the evidence of liveness. The properties of iris imaging have been exploited for liveness detection, such as Purkinje images [65] and the relationship of reflectance ratio between

iris and sclera [65]. Most of liveness detection approaches are based on iris texture analysis. He et al. [66] propose to detect printed iris images via frequency analysis. Many well-designed texture features, including gray level co-occurrence matrix [67], statistical distribution of iris texture primitive [68], local binary patterns (LBP) [69] and weighted-LBP [70], are used to describe the discriminative appearance between the genuine and fake iris images. Recently, Galbally et al. [71] detect liveness using quality related measures.

2) Race classification. Race information of a subject is useful for many applications, such as advertising and human computer interface. Although iris texture is significantly different for subjects at micro scale, it presents some similarities at macro scale for the same race. Qiu et al. [72] propose the first texture analysis based racial iris image classification method. A bank of multichannel 2-D Gabor filters is used to extract the global texture information and Adaboost is used to train the classifier. In their later work [73], Iris-Textons are trained to represent the visual primitives of iris texture to classify Asian and no-Asian iris images. Zhang et al. [74] take advantages of supervised codebook and locality-constrained linear coding for race classification. Lyle et al. [75] encode the periocular regions by LBP for gender and race classification.

3) Coarse iris classification. Coarse iris classification divides a large enrolled iris image database into a number of sub-datasets to speed up personal identification. Yu et al. [76] calculate the fractal dimension value in iris blocks for coarse iris classification. Fu et al. [77] use artificial color filter to detect the color information of iris images, and employ margin setting to classify iris images into proper categories. In [78], iris images are grouped into five categories based on statistical description of learned Iris-Textons. Mehrotra et al. [79] use energy based histogram of multi-resolution DCT to group iris images. Sunder et al. [80] extract scale-invariant feature transform (SIFT) features to represent iris macro-features (structures such as moles, freckles, nevi, and melanoma) for iris retrieval and matching.

6 Cross-Sensor Iris Recognition

Various iris imaging devices have been developed with the large scale deployments of iris recognition. Different illuminators, lens and sensors of different imaging devices result in cross-sensor variations in iris images. These variations tend to increase the intra-class distance between samples that are captured by different devices. Therefore, the interoperability of different iris imaging devices becomes increasingly important. Bowyer et al. [81] investigate cross-sensor comparisons of two LG iris recognition systems. The experiments demonstrate that performance degradation of cross-sensor iris recognition is mainly caused by the shift of intra-class distribution. Connaughton et al. [82,83] conduct more experiments for interoperability of iris sensors on three commercially available sensors and three matching algorithms. They conclude that the relationship between sensors, algorithms and acquisition environment should be considered to develop a robust iris recognition system.

In order to alleviate performance degradation in cross-sensor iris recognition, several algorithms have been proposed. Arora et al. [84] first predict the source camera and then enhance images accordingly to minimize the appearance difference between images acquired by different cameras. Xiao et al. [85,86] propose feature selection solutions to represent the intrinsic features of iris images from different sensors. A coupled feature selection method is proposed in [86] to select coupled features simultaneously. They utilize $l_{2,1}$ regularization to model the problem and solve the formulation by an efficient algorithm based on a half-quadratic optimization. In [85], the coupled feature weighting factors is learned by a margin based feature selection method. The problem is formulated and solved by linear programming. Pillai et al. [87] propose a kernel learning method for sensor adaption. The learnt transformations on binary iris code can reduce the intra-class distance and increase inter-class distance of cross-sensor comparisons. On the other hand, Xiao et al. [88] fuse the iris and periocular biometrics to improve the performance of cross-sensor identification, where multi-directions ordinal measures are used for feature extraction.

7 Future Research Directions

Several promising research directions can be observed as follows.

1) Iris image acquisition. Currently, commercial iris recognition systems still require high user cooperation to capture iris images of sufficient quality. Although some prototype systems can work at a distance or on the move, their capture volume and imaging speed are unsatisfactory for practical applications, e.g. surveillance. Therefore, iris image acquisition is still a bottleneck for the wide deployment of iris recognition. One solution is to develop better NIR cameras and optical design, or to improve the accuracy and speed of the control units for PZT cameras. Another solution is to consider iris imaging and image processing simultaneously as in computational photography.

2) Iris recognition algorithms. It is inevitable to capture many iris images of low quality in less constrained environments, which brings many difficulties to recognition algorithms. Large occlusions, off-axis gaze and blur will mislead iris segmentation and increase the intra-class variations. Traditional knowledge based iris recognition algorithms are hard to model these large variations and will suffer from large performance degradation. Machine learning methods, such as Adaboost, SVM and neural networks, are powerful tools to automatically learn the optimal parameters for representation and classification. They have successfully improved the robustness and accuracy of iris recognition and will continue demonstrating their capacity at all levels.

3) Large-scale iris recognition Large-scale applications of iris recognition introduce many new challenges. Although the comparisons of binary iris codes are very fast, it is time-consuming for exhaustive search in national-scale databases, e.g. the UID project in India. Iris indexing or coarse classification can select a subset from the large database for comparison and will speed up the search. Another challenge is the interoperability of different iris imaging devices.

On one hand, we should develop more robust recognition algorithms that are insensitive to sensor variations. On the other hand, international standards are needed to reduce the differences among images captured by different sensors. These emerging problems have not been systematically investigated and remain far from solved.

4) Privacy and security The privacy and security issues become increasingly important nowadays, especially in wireless and mobile networks where personal data often faces malware attacks. Therefore, biometric templates should be protected by well-designed encryption algorithms which have negligible influence on the performance of recognition. Irreversibility and unlinkability are two major requirements of biometric template protection. However, the techniques to enhance the irreversibility and unlinkability may reduce the performance of iris recognition.

5) Multi-biometrics The major limitation of iris recognition is its usability. As it is convenient to capture iris and face images simultaneously, it is expected to develop a more accurate, secure and easy-to-use recognition system by combining iris and face biometrics. In addition, iris can be fused with other biometric traits, such as fingerprint and palmprint. However, it remains unsolved to efficiently and effectively unite the complementary advantages of different biometric modalities

8 Conclusions

In this paper, a brief review of some subareas of iris recognition, namely iris image acquisition, segmentation, texture analysis, classification and cross-sensor recognition, has been presented. Several trends of next-generation iris recognition have been concluded. Some important subareas, such as iris image quality assessment and multi-biometrics involving iris, are omitted in this survey due to limited space and will be included in our later survey.

Acknowledgements. This work is supported by the National Natural Science Foundation of China (Grant No. 61273272) and the Instrument Developing Project of the Chinese Academy of Sciences (Grant No. YZ201266).

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