Periocular Biometrics for IRIS Recognition

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Abstract - The periocular span embodies a trade-off amid the finished face and the iris alone. Encompassing the eye and its instant vicinity, it covers eyelids and eyelashes, adjacent skin span anda eyebrows. Its use as a biometric trait has appeared, including nowadays a forceful alternative for less constrained settings, after picture buy is not reliable, and to circumvent spoofing of the iris patterns. It is facile to buy lacking user cooperation and does not need a constrained close seizing, Also, this span is not so altered by the aging procedure as supplementary facial spans are, as for instance the mouth and cheek whose skin come to be loosened above time. This paper surveys Periocular Biometrics for Iris Credit. This chapter presents an overview of biometrics, a little of the growing biometric technologies and their limitations, and examines upcoming trials.

I. INTRODUCTION

Prevailing methods of human identification based on credentials (identification documents and PIN) are not able to meet the growing demands for stringent security in applications such as national ID cards, border crossings, government benefits, and access control. As a result, biometric recognition, or simply biometrics, which is based on physiological and behavioral characteristics of a person, is being increasingly adopted and mapped to rapidly growing person identification applications. Unlike credentials (documents and PIN), biometric traits (e.g., fingerprint, face, and iris) cannot be lost, stolen, or easily forged; they are also considered to be persistent and unique.

Use of biometrics is not new; fingerprints have been successfully used for over one hundred years in law enforcement and forensics to identify and apprehend criminals. But, as biometrics permeates our society, this recognition technology faces new challenges. The design and suitability of biometric technology for person identification depends on the application requirements.

These requirements are typically specified in terms of identification accuracy, throughput, user acceptance, system security, robustness, and return on investment. The next generation biometric technology must overcome many hurdles and challenges to improve the recognition accuracy. These include ability to handle poor quality and incomplete data, achieve scalability to accommodate hundreds of millions of users, ensure interoperability, and protect user privacy while reducing system cost and enhancing system integrity.

II. LITERATURE SURVEY

Jameson Merkow et al.2010 [1] In this paper,the periocular region, the region of the face surrounding the eyes, has gained increasing attention in biometrics in recent years. This region of the face is of particular interest when trying to identify a person whose face is partially occluded. They proposed the novel idea of applying the information obtained from the periocular region to identify the gender of a person, which is a type of soft biometric recognition.

III. PROPOSED METHOD

Matching and evaluation methods are processed in the following steps. First, iris images are segmented and irises are located. Secondly, we use SIFT algorithm to find key points and compute numbers of matched keypoints. Finally, whether two eye images are captured from the same eye is determined by a threshold.

A. Segmentation

Segmentation is the first step of recognition steps. Eyelashes, eyelid may cover iris in an eye image. Removing those interfere factors enhances recognition accuracy, because what should be compared are patterns of iris, and interfere factors are irrelevant to iris.

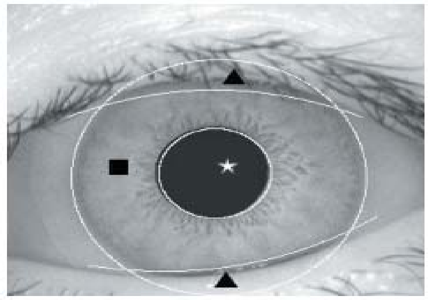


Fig. 2: A well-segmented image.

B. Matching

Matching process is implemented by using SIFT. SIFT algorithm works as follows. First, identify candidate key points and select key points from candidates. Difference-of-Gaussian (DoG) function, D (x; y;), is used to find candidate key points, which are invariant to scale changes of images.

$$L(x; y; \sigma) = G(x; y; \sigma) * I(x; y)$$

$$G(x; y; \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

$$D(x; y; \sigma) = (G(x; y; k\sigma) \quad G(x; y; \sigma)) * I(x; y)$$

$$= L(x; y; k\sigma) \quad L(x; y; \sigma)$$

Where G (x; y; σ) is the Gaussian function, the scale-space kernel. L (x; y; σ) is the convolution of a variable-scale Gaussian with I (x; y), an input image. D (x; y; σ) is computed from the difference of two scales separated by k, a constant multiplicative factor.

Sample points are selected as candidate keypoints only if they are local extrema of their neighbors

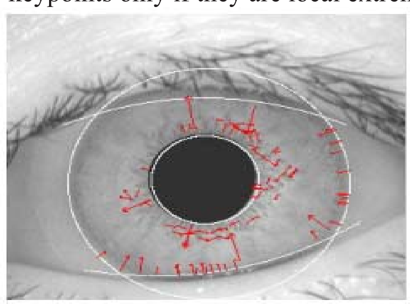


Fig. 3: Keypoints on iris after applying SIFT on Figure 2.

C. Evaluation

Evaluation of matching result is based on a threshold. When the number of matching result is less than the threshold, we considered the two images are captured from the same eye, vice versa.

IV. DATASETS

Only a few public datasets were designed for the development of periocular recognition methods. Instead, face and iris databases are generally used for that purpose. The most commonly used databases for the evaluation periocular methods are now introduced, and their specifications as table 1.

A. FERET

The Facial Recognition Technology (FERET) database was designed as a standard for developing face recognition methods, and acquired at George Mason University over 11 sessions and a three years period (1993 to 1996). Initially released as low resolution (256 $\times$ 384 pixels) grayscale data, years later a high-resolution color version was also disclosed. A total of 14051 images were gathered from 1199 different subjects. Image acquisition protocol contemplates a semicontrolled environment, with strict expression, pose and illumination changes.

B. FRGC

Collected at the University of Notre Dame, the Face Recognition Grand Challenge (FRGC) database consists of high resolution (≈1200 ×1400 pixels) color still images, captured on both controlled and uncontrolled environments. The controlled subset was captured on a studio under uniform illumination, where subjects were required to stand still while looking straight at the camera and essay neutral and smiling expressions. As for the uncontrolled acquisition, images were shoot in different scenarios, disregarding both background and illumination. Data is split into a training partition of 12776 images from 275 subjects, and a testing partition of 24042 images from 466 subjects, 6 images per session for each subject in both partitions. Illumination is not regular, as the illumination bursts for a short period of time, and main noise factors are observable (eye blink, motion blur, occlusions, reflections). Acquired data is stored on 2048×2048, 15 frames per second (fps) AVI files, where iris spatial extension is about 120 pixels'

(a) FERET (b) FRGC (c) MBGC (d) UBIRIS2 (e) FG-NET

Fig. 2. Sample images from the commonly used datasets on evaluating periocular algorithms. Except from (d), data has been cropped for illustration purposes.

Name	**Images**	**Subj.**	**Dimensions**	**Variations**
FERET	14051	1199	512 X 768	E, I, P.
FRGC	36818	741	≈1200 X 1400	E, I.
MBGC	149 AVI	114	2048 X 2048	D, E, I, O, P.
UBIRIS.v2	11102	261	800 X 600	D, O, I.
UBIPr	10950	261	Multiple	D, I, O, P.
FG-NET	1002	82	≈400 X 500	D, E, I, P.

TABLE I. OVERVIEW OF DATABASE SPECIFICATIONS. VARYING ELEMENTS ARE DISTANCE (D), EXPRESSION (E), ILLUMINATION (I), OCCLUSION (O) AND POSE (P).

C. UBIRIS.v2

The UBIRIS.v2 is a unconstrained iris database, captured on the VW from moving subjects, at different distances and challenging illumination conditions, simulating realistic acquisition issues with the associated noise factors. Data for both eyes is separately available, as well as the surrounding periocular data, thus being prone to stress not only robust iris related methods for the visible spectrum, but periocular ones and their fusion as well. The 11102 acquired images represent a total of 261 subjects, from different ages and ethnicities.

D. UBIPr

This newly created UBI Periocular Recognition (UBIPr) database, by Padole and Proenc¸a [14], represent a renewed effort to advance periocular biometric research, providing new means of evaluating robust methods, at "higher levels of heterogeneity".

V. RESULT

The toolboxes used for this thesis are image processing toolbox and wavlelet toolbox. These toolboxes provide engineers and scientists with an extensive suite of robust digital image processing and analysis functions. Image processing toolbox is designed to free technical professionals from the time consuming tasks of coding and debugging fundamental image processing and analysis operations from scratch. This translates into significant time saving and cost reduction benefits, enables to spend less time coding algorithms and more time exploring and discovering solutions to your problems. The toolbox supports a wide range of image processing operations, including the following:

a) Displaying and exploring images
b) Spatial transformations
c) Morphological operations
d) Analyzing and enhancing images
e) Linear filtering and filter design
f) Neighborhood and block operations
g) Image deblurring
h) Region based processing

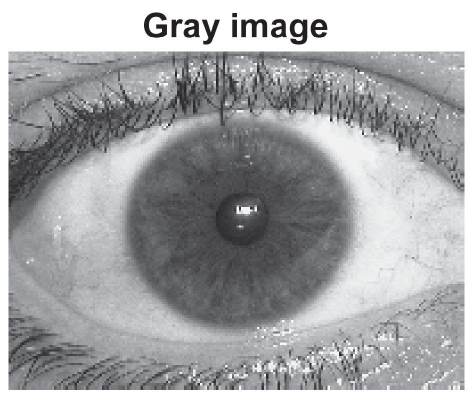


Fig 1: Image after grayscale conversion, conversion to grayscale is done to reduce complexity

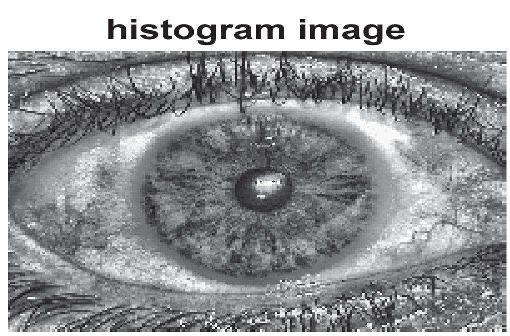


Fig: Image Histogram of the input image

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance.

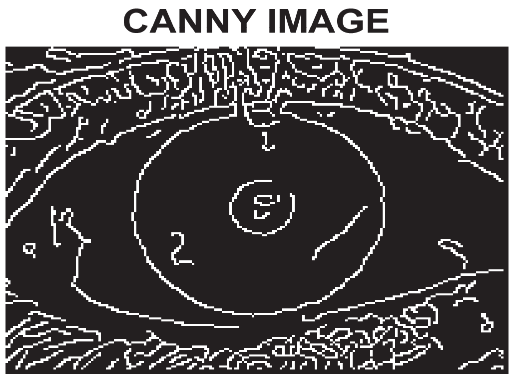


Fig: Canny Image

Edges characterize boundaries and are therefore a problem of fundamental importance in image processing. Edges in images are areas with strong intensity contrasts a jump in intensity from one pixel to the next. Edge detecting an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image.

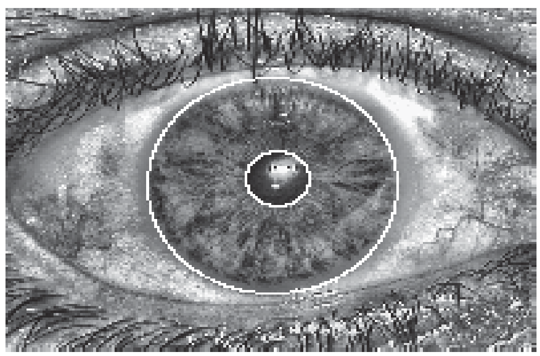


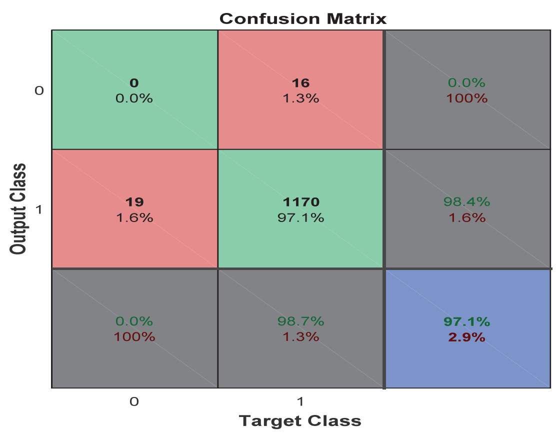
Fig: Iris Template of Person 1 in UBIRIS Dataset using Proposed Method

a template created by imaging an iris is compared to stored template(s) in a database. If the Hamming distance is below the decision threshold, a positive identification has effectively been made because of the statistical extreme improbability that two different persons could agree by chance ("collide") in so many bits, given the high entropy of iris templates.

Fig: Iris Mask of Person 1 in UBIRIS Dataset using Proposed Method

The goal of matching is to evaluate the similarity of two iris representations. Created templates are compared using the Hamming distance. The normalized Hamming distance used measures the fraction of bits for which two iris codes disagree. A low normalized Hamming distance implies strong similarity of the iris codes. If parts of the irises are occluded, the normalized Hamming distance is the fraction of bits that disagree in the areas that are not occluded on either image. To account for rotation, comparison between a pair of images involves computing the normalized Hamming distance for several different orientations that correspond to circular permutations of the code in the angular coordinate. The minimum computed normalized Hamming distance is assumed to correspond to the correct alignment of the two images.

confusion matrix usage to evaluate the quality of the output of a classifier on the iris data set. The diagonal elements represent the number of points for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of the confusion matrix the better, indicating many correct predictions. The figures below show the confusion matrix with and without normalization by class support size.



For Comparison database were used for the training and images for the testing purpose. The recognition accuracy was compared between the proposed method and previously reported work. The proposed method has an accuracy of 97.1% on this database.

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