Authentication Management for Information System Security Based on Iris Recognition

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***Abstract*—This paper presents an integrated security management for authentication of users based on weighted iris recognition technology. For the proposed system, a mobile device cooperating with a user calibration interface is used to capture the iris image. With large variation in the environment, there are two main improvements to develop the system. For calibration on line, we use a three-point localization scheme for extracting appropriate eye region according to the information of eye corners and the center of eyebrow. Furthermore, statistic based illumination normalization is used in preprocessing to decrease illumination influence under variant lighting conditions. The detection of the iris image is based on Adaboost algorithm and local binary pattern (LBP) histogram is then applied to texture classification. Experiment showed that the proposed system provided users a more flexible and feasible way to interact with the verification system through mobile device. The online authentication process for iris recognition can provide more protection for information system security.**

***Index Terms*—authentication, security control, iris recognition, adaboost, local binary pattern.**

I. Introduction

For information systems (IS) that are used to create, store, process or distribute information must be properly managed to protect against unauthorized access of classified information and to ensure the availability of the system. As the complexity of a specific IS increase, the need for authentication of users and process becomes more and more significant. Identification and authentication controls are required to ensure that users have the appropriate clearances and need-to-know for the information on a particular system [1].

Systems with biometric security technology are becoming preferable to traditional methods such as ID cards, passwords or PIN (personal identification numbers) that can be easily divulged to unauthorized users or stolen by impostors [2] and [3]. A reliable automatic recognition of users based on biometric features has long been an attractive goal. The biometrics can provide a natural and convenient means for individual identification by examining the physical or behavioral traits of human beings [4]. As in all pattern recognition problems, the key issue is the relation between interclass and intra-class variability: objects can be reliably classified only if the variability among different instances of a given class is less than the variability between different classes.

Among biometric systems, iris recognition is the most stable and reliable system since it uses the unique and immutable patterns of human iris such as arching ligaments, contraction furrows, ridges, crypts, coronas, freckles, colors, and rifts. Also, unlike fingerprint recognition, iris recognition has the advantage that image acquisition can be more easily achieved with noncontact data acquisition [5]. All these factors contribute to high effectiveness in the currently deployed iris-recognition systems. Their typical scenarios are: subjects stop and stare relatively close to the acquisition device while their eyes are illuminated by a near-infrared light source, enabling the acquisition of high-quality data. In the past years, great advances have been made in constrained environments where the users are closely cooperative. The state of the art iris recognition techniques are reviewed by [6]. However, constraints are a major obstacle for the mass implementation of iris-based biometric systems, especially in the handheld device like cell phone or pad.

Recent research interest in the field has focused on recognition in less constrained imaging conditions. Several factors make iris images non-ideal, such as at-a-distance imagery, on-the-move subjects, and high dynamic lighting variations. In such circumstances the iris images captured may be degraded due to off-axis imaging, image blurring, illumination variations, occlusion, specular highlights and noise [7]. Robust iris recognition in such degraded images pose a grand challenge. Daugman [8] reported some advances including accurate iris boundaries localization with active contour and image registration through Fourier-based trigonometry, among others. Sun and Tan [9] presented a general framework for iris feature representation based on ordinal measure. Li and Ma [10] introduced a robust algorithm based on the random sample consensus for localization of non-circular iris boundaries and an image registration method.

In this paper, an integrated security management for identification and authentication of users based on weighted iris recognition is presented. A mobile device is used as the user interface. The proposed system includes a three-point localization scheme for extracting

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appropriate eye region according to the information of eye corners and the center of eyebrow. Furthermore, statistic based illumination normalization is used in preprocessing to decrease illumination influence under variant lighting conditions. The detection of the iris image is based on Adaboost algorithm and weighted local binary pattern (LBP) histogram is then applied to iris recognition.

II. User Interface and Preprocessing

In this section, the user interface design is first described then some preprocessing steps are introduced. These preprocessing steps are all performed on the server including the iris detector, illumination normalization. After these preprocessing, more stable features are obtained and they are used to be the input of the iris verification step.

A. User Interface for Calibration Online and Eye Detection

The local rotations, affine transformations and distortions of the iris image are common phenomenon. Therefore, the calibration for the camera with the system is used to improve the invariability. In the scenario, the mobile device including the built-in camera is simply hold by the hand of the user. It is impossible to have calibration for the camera and the system in advance. There are three basic camera operations: camera pan, tilt, and roll that will influence the performance of iris verification heavily. To reduce the verification errors that usually caused by the basic camera operations, a three-points eye localization scheme is developed in the limit of the computing power of the mobile device. The corners of eye and eyebrow in the eye image are set to be the three points of the eye localization scheme. Three points must be fitted by user manually. The distance between each pair of two points solves the problems of camera pan and tilt. The position of points solves the problems of camera roll. In the design, user sees his eye on the screen of the handheld device and tries to fit each cross to its corresponding feature points as shown in Fig. 1. From the user interface developed on a cell phone, users should input user identification number and choose to verify or enroll. The rough iris image is then captured from the camera of the cell phone through the user interface for calibration online and eye detection.

Figure 1. The user interface for calibration online.

Three cross points are drawn on the screen of the handheld device by two different colors to represent fitting positions for eye corner pairs (red) and eyebrow (green). The user will first be asked to adjust his eye's position to fit with the two red crosses on the screen. After then, the user must centers his eyebrow to the green cross for tilt angle adjustment. Although the precision of the fitting process above may not be well controlled, it does provide a rough region of the eye image to be the input from the mobile device to the control server. It is noted that it does not need to transmit the whole image since the rough iris image is already obtained.

B. Illumination Normalization

It is well known that the image gray level (or image color) is very sensitive to the lighting variation. Considerably different images may be captured from the same object under different illuminations. Psychophysical experiments show that the human visual system is difficult to identify the images of the same object that are due to considerable changes in illumination [11]. For iris recognition system, it is also difficult to produce good classification accuracy if image samples in the training and testing sets are taken from different lighting conditions. The general purpose of illumination normalization is to decrease lighting effect when the observed images are captured in different environment. A common idea is trying to adjust observed images to approximate the one captured under a standard lighting condition. Most of the past works tried to define the standard lighting condition in statistically and modify the observed images to match these statistic properties. In the proposed system, we extract the statistical histogram feature of standard lighting condition from the training images in the database. Each testing image will be adjusted based on the extracted histogram information of the standard lighting condition. Fig. 2 shows the flow chart of the illumination normalization algorithm.

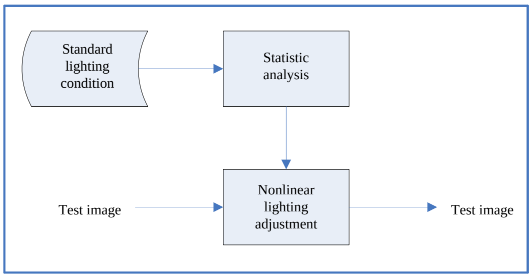


Figure 2. The flow chart of the illumination normalization.

For example, if R is the observed image and h is the histogram feature of standard lighting condition we get, the modification strategy [12] we used is to transform the statistic histogram of region R to the histogram h so that the transformed result has similar statistic histogram to h. The transform t is the one to one function T which can be expressed as follow equation.

$$T = G^{-1} \circ H, \tag{1}$$

where G is the empirical cdf of h and H is the empirical cdf of region R if we treat the intensity histogram at the region R as probability density function. Each pixel in the region R is normalized by using the transfer function T. Let R_t be the normalized region, then

$$R_t(x,y) = T(R(x.y)) = G^{-1} \circ H(R(x,y)), \qquad (2)$$

Ideally, R_t will have similar histogram distribution to the one under standard lighting condition has.

III. Iris Detection and Recognition

A. Iris Detection and Boundary Extraction

The AdaBoost was first proposed by Freund and Schapire [13]. It can automatically select some weak classifiers from the weak classifier space to construct a strong classifier through the weighted integration of selected weak classifiers. After that, authors proposed new AdaBoost just like Schapire and Singer [14], and J. Friedman, T. Hastie, and R. Tibshirani [15]. They was used extensively on face detection [16] and [17]. Iris has very fine textures compared with the other area of the eye image such that the AdaBoost has the ability to detect the iris and extract the exact boundary.

The proposed method is based on the Adaboost algorithm of Viola and Jones [16]. The method brings together new algorithms to construct a framework for robust and extremely rapid visual detection. This system achieves high frame rates working only with the information present in a single grey scale image. This is very useful to detect iris image on mobile device in the proposed system. First, an integral image that allows for very fast feature evaluation is used. The summed area table (SAT) is shown in Fig. 3. The formula is listed in the following.

$$\begin{aligned} SAT(x,y) &= \sum_{x' \le x, y' \le y} I(x', y'), \\ SAT(x,y) &= SAT(x, y-1) + SAT(x-1, y) \\ &+ I(x,y) - SAT(x-1, y-1), \\ SAT(-1, y) &= SAT(x, -1) = 0, \end{aligned} \qquad (3)$$

where x and y represent the coordinates in the input image.

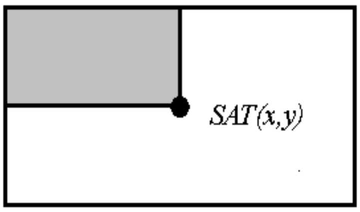


Figure 3. The summed area table

The second one is a simple and efficient classifier that is built by selecting a small number of important features from a huge library of potential features using AdaBoost. Within any image sub-window the total number of Haar-like features is very large, far larger than the number of pixels. In order to ensure fast classification, the learning process must exclude a large majority of the available features, and focus on a small set of critical features. As a result each stage of the boosting process, which selects a new weak classifier, can be viewed as a feature selection process. AdaBoost provides an effective learning algorithm and strong bounds on generalization performance. The algorithm is listed in the following.

Algorithm

Given the image features $(x_1, y_1), \ldots, (x_n, y_n)$, each $y_i = 0,1$ indicates the negative and positive pattern.

Initially the weighting is set by

$$w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$$

and the amounts of the negative and positive patterns are expressed by m and l.

for loop $t = 1, \ldots, T$:

Normalization the weighting, $w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=}^{n} w_{t,j}}$,

Calculate the weighting to select weak classifier $\in_t = \min_{f,p,\theta} \sum_i w_i \left| h(x_i, f, p, \theta) - y_i \right|$.

Defined $h_t(x) = h(x, f_t, p_t, \theta_t)$, when the f_t, p_t and θ_t are minimum of the $\in_t$.

The way to update the weighting is

$$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$

when the x_i is correct, $e_i = 0$, otherwise is $e_i = 1$, then $\beta_t = \frac{\in_t}{1 - \in_t}$.

At last, the decision of the strong classifier is obtained by $C(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \ge \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & otherwise \end{cases}$

where $\alpha_t = \log \frac{1}{\beta_t}$.

The detected results are shown in Fig. 4 and Fig. 5(a).

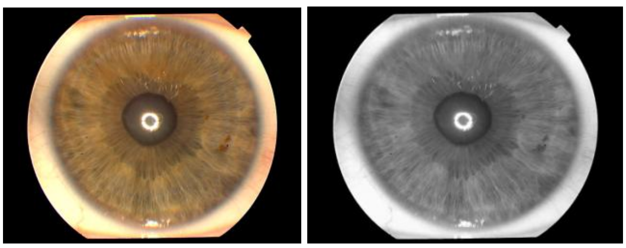


Figure 4. The input image and the transformed gray scale image.

Sharpening and morphological operations [18] are used to enhance the eyes on a face. A 3×3 mask is used here for image sharpening. Suppose (x, y) is the center of the mask, where x and y are coordinates. w_5 denotes the coefficient of the mask for position (x, y) and w_1, w_2, w_3, w_4, w_6, w_7, w_8, and w_9 are the corresponding neighboring coefficient in the mask. The result after morphological operations results are shown in Fig. 5(b).

$$\begin{aligned} T[x,y] = {} & w_1 f(x-1,y-1) + w_2 f(x-1,y) \\ & + w_3 f(x-1,y+1) + w_4 f(x,y-1) \\ & + w_5 f(x,y) + w_6 f(x,y+1) + w_7 f(x+1,y-1) \\ & + w_8 f(x+1,y) + w_9 f(x+1,y+1) \end{aligned}$$

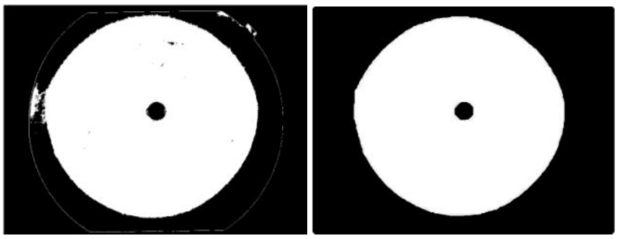
$T[x, y]$ is the pixel value after the operation of the mask. w_5 is set to 8 and the other coefficients are set to -1 in our experiment. After image sharpening, Closing operation by a structuring element with size 3×3 is performed to fill the intensity valley in image. Apply Different operation on the original image and the closing result and then the pixels of eye-analogue segments remain on the result image. Opening operation is used to remove noise.

$$\text{Dilation} = \max_{i,j} \arg\ f(x+i, y+j)$$

$$\text{Erosion} = \min_{i,j} \arg\ f(x+i, y+j)$$

$$\text{Opening} = \text{Erosion} + \text{Dilation}$$

$$\text{Closing} = \text{Dilation} + \text{Erosion}$$



(a) (b)

Figure 5. The image of iris region after iris detection

B. Weighted Iris Recognition

After the iris detection, the local binary patterns (LBP) are adopted to represent texture patterns of iris images. The LBP has emerged as a simple yet very efficient texture operator and become a popular approach in various applications of texture analysis [19, 20]. LBP is defined for each pixel by comparing its 3×3 neighborhood pixels with the center pixel value, and considering the result as a binary bit string.

Given a pixel $f(x,y)$ in the image, an LBP code is computed by comparing it with its neighbours:

$$LBP(x,y) = \sum_{p=0}^{P-1} s(f(x,y) - f_p(x,y)) 2^p, \tag{4}$$

where $s(z)$ is the thresholding function

$$s(z) = \begin{cases} 1, & \geq 0 \\ 0, & < 0 \end{cases}. \tag{5}$$

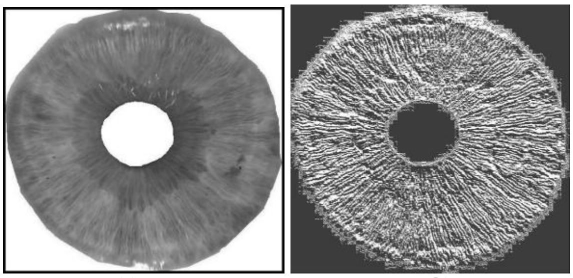
Here P represents the number of sampling points, i.e., 8 surrounding points. After the LBP pattern of each pixel is identified, a histogram of the image with size $I \times J$ is built to represent the texture image:

$$H(k) = \sum_{i=0}^{I} \sum_{j=0}^{J} w(i,j) g(LBP(i,j),k), k \in [0,K], \tag{6}$$

where $g(x,y)$ is the thresholding function:

$$g(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}. \tag{7}$$

The iris image and its corresponding LBP features are shown in Fig. 6.



(a) (b)

Figure 6. The iris image and its corresponding LBP features

After LBP, we followed the setup of [18] for nonparametric texture classification. The LL distance is suited for histogram type features. For histogram type features, we used the log-likelihood statistic, assigning a sample to the class of model minimizing the LL distance

$$LL(h^S, h^M) = -\sum_{b=1}^{B} h^S(b) \log h^M(b), \tag{8}$$

where $h^S(b)$ and $h^M(b)$ denote the bin b of sample and model histograms, respectively.

IV. EXPERIMENTATION RESULTS

For generating the iris image under variant environment, the first experiment applied different lighting conditions and transformations on the testing image in the database [21]. The average accuracy of verifications on the database is about 92.5%.

In second experiment, 10 individuals are enrolled in the training database and 20 images are used for each person in the testing process. The experimental results are shown in Table I, which is the confusion matrix of the experiment. Each row (column) represents the actual class (predicted class), respectively.

TABLE I. THE CONFUSION MATRIX OF THE EXPERIMENT

	A	B	C	D	E	F	G	H	I	J
A	10	0	0	0	0	0	0	0	0	0
B	0	10	0	0	0	0	0	0	0	0
C	0	0	10	0	0	0	0	0	0	0
D	0	0	0	10	0	0	0	0	0	0
E	0	0	0	0	10	0	0	0	0	0
F	0	0	0	0	1	9	0	0	0	0
G	0	0	0	0	0	0	10	0	0	0
H	0	0	0	0	0	0	0	10	0	0
I	0	0	0	0	0	0	0	0	10	0
J	0	0	0	0	0	1	0	0	0	9

V. Conclusions

This paper presents an integrated security management for identification and authentication of users based on weighted iris recognition technology. For calibration on line, we developed a three-point localization scheme for extracting appropriate eye region according to the information of eye corners and the center of eyebrow. Furthermore, statistic based illumination normalization is used in preprocessing to decrease illumination influence under variant lighting conditions. The Adaboost and LBP histogram are applied for iris detection and recognition. The proposed technology can provide information security system a more flexible and feasible way to do authentication through mobile device.

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