World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:8, No:1, 2014

A Weighted Approach to Unconstrained Iris Recognition

Yao-Hong Tsai

Open Science Index, Computer and Information Engineering Vol:8, No:1, 2014 publications.waset.org/9997132/pdf

***Abstract*—**This paper presents a weighted approach to unconstrained iris recognition. In nowadays, commercial systems are usually characterized by strong acquisition constraints based on the subject's cooperation. However, it is not always achievable for real scenarios in our daily life. Researchers have been focused on reducing these constraints and maintaining the performance of the system by new techniques at the same time. With large variation in the environment, there are two main improvements to develop the proposed iris recognition system. For solving extremely uneven lighting condition, statistic based illumination normalization is first used on eye region to increase the accuracy of iris feature. The detection of the iris image is based on Adaboost algorithm. Secondly, the weighted approach is designed by Gaussian functions according to the distance to the center of the iris. Furthermore, local binary pattern (LBP) histogram is then applied to texture classification with the weight. Experiment showed that the proposed system provided users a more flexible and feasible way to interact with the verification system through iris recognition.

***Keywords*—**Authentication, iris recognition, Adaboost, local binary pattern.

I. Introduction

BIOMETRIC identification systems are becoming preferable to traditional methods such as ID cards and passwords that can be easily divulged to unauthorized users or stolen by impostors [1], [2]. Among biometric systems, iris recognition is one of the most stable and reliable tool since it uses the unique and immutable patterns of human iris image. Also, iris recognition has the advantage that image acquisition can be more easily achieved without direct user contact [3].

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 [4]. However, constraints are a major obstacle for the real applications of iris-based biometric systems, especially under variant environments.

Recent research interest in the field has focused on iris 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 image captured may be degraded due to off-axis imaging, image blurring, illumination variations, occlusion, specular highlights and noise [5]. Robust iris recognition in such degraded images becomes a grand challenge. Daugman [6] reported some advances including accurate iris boundaries localization with active contour and image registration through Fourier-based trigonometry, among others. Sun and Tan [7] presented a general framework for iris feature representation based on ordinal measure. Li and Ma [8] introduce a robust algorithm based on the random sample consensus for localization of non-circular iris boundaries and an image registration method based on the Lucas–Kanade algorithm.

Recently, non-cooperative iris recognition has attracted much more attention since it greatly extends the iris recognition to real applications [9], [10]. For a non-cooperative iris recognition system, the iris images are often captured with more noisy artifacts. For example, they include blur, reflections, occlusions, oblique view-angles, etc., such that they are also called noise iris [11]. It makes non-cooperative iris recognition more challenge. The Noisy Iris Challenge Evaluation (NICE) competition [12] was concerned with methods that use the texture pattern of the Iris as a means to recognize a person under non-cooperative conditions. In other words, NICE focused on performing Iris biometrics on visible-light images. It attracted participation by many research groups from around the world. Several top-performing algorithms [13] from NICE are considered, and suggestions are made for lessons that can be drawn from the results.

In the proposed method, some improvements are considered to develop unconstrained iris recognition. For solving extremely uneven lighting condition, statistic based illumination normalization is first used in preprocessing to decrease illumination influence. Illumination correction focused just on irises not on eye images according to the coarse localizations. Normalization weights are assigned to spatial sub-region in the segmented iris especially on the boundary between the iris and non-iris regions. The weighting scheme developed by the Gaussian function is applied to the normalized rubber sheet to solve the problem whether segmentations are accurate or not. The fine detection of the iris image is based on Adaboost algorithm. Secondly, the weighted approach is designed by Gaussian functions according to the distance to the center of the iris. Combining with the generated weighting value, the local binary pattern (LBP) histogram is then applied to texture classification with the weight. Experiment showed that the proposed system provided users a more flexible and feasible way to interact with the verification system through iris recognition.

Y. H. Tsai is with Department of Information Management, Hsuan Chung University, Hsinchu City 300, Taiwan (phone: 886-3-5302255; fax: 886-3-5391252; e-mail: tyh@hcu.edu.tw).

Open Science Index, Computer and Information Engineering Vol:8, No:1, 2014 publications.waset.org/9997132/pdf

II. Preprocessing Step

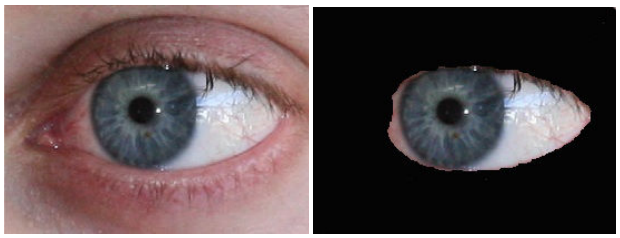
The most difficult problem for iris detection often occurs on classification between iris and non-iris regions due to the high local contrast. A coarse iris localization step may exclude the non-iris regions. In this section, the skin color classification is first described then illumination normalization steps are introduced. After these preprocessing, more stable features are obtained and they are used to be the input of the iris detection step.

A. Skin Color Classification

Detecting pixels with the skin color provides reliable information for coarse classifying iris and non-iris regions. Researchers have discovered that skin colors regardless of different races tend to cluster closely in a compact region in 2D chromatic color space [14]. The statistic distribution of the skin color can be modeled with a 2D Gaussian distribution $p(u_r,u_g,\sigma_r,\sigma_g)$, where u_r and u_g are the mean values of the r and g components from the sample data, respectively, and σ_r and σ_g are their respective standard deviation. The parameters $(u_r,u_g,\sigma_r,\sigma_g)$ can be obtained by training based on a set of known face regions. Therefore, a pixel in an image is classified into skin color class and non-skin color class by calculating its probability from the following Gaussian function:

$$G(r,g)=\exp[-(r-u_r)^2/2\sigma_r^2,\ -(g-u_g)^2/2\sigma_g^2], \quad (1)$$

where (r, g) are the chromatic colors of the pixel. The skin color determination of each pixel should combine neighboring pixels of it to avoid the detection of thin lines in the eye image. Fig. 1 (a) is an example of the original eye image and Fig. 1 (b) shows the region of non-skin color and the area of skin color is marked by black.



(a) (b)

Fig. 1 The original image [15] and the result of skin color classification

B. Illumination Normalization

After the coarse localization, illumination correction could focus just on irises not on eye images. It is well known that each gray value in the image 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 [16]. For iris recognition system, it is also difficult to produce good detection and 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.

For example, if R is the observed image and h is the histogram feature of standard lighting condition we get, the modification strategy [17] 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.

$$T = G^{-1} \circ H, \quad (2)$$

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

$$R_t(x,y) = T(R(x.y)) = G^{-1} \circ H(R(x,y)), \quad (3)$$

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

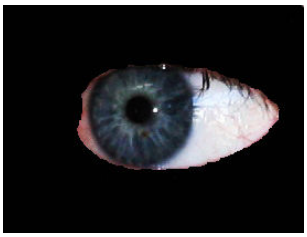


Fig. 2 The result of illumination normalization

III. Iris Detection and Recognition

A. Iris Detection and Boundary Extraction

For the fine detection of the iris, the AdaBoost [18] can automatically select some weak classifiers from the weak classifier space. It constructs a strong classifier through the weighted integration of selected weak classifiers to detect the target. Some authors proposed modified versions of AdaBoost just like Schapire and Singer [19], and J. Friedman, T. Hastie, and R. Tibshirani [20]. They were used extensively on face detection [21], [22]. Iris has very fine textures compared with

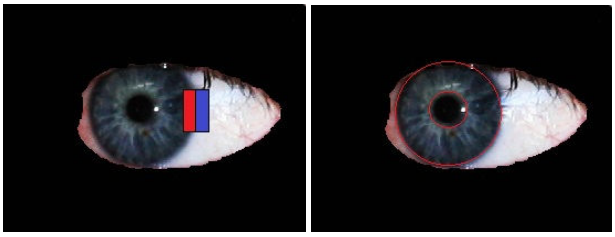
Open Science Index, Computer and Information Engineering Vol:8, No:1, 2014 publications.waset.org/9997132/pdf

the other area of the eye image such that the AdaBoost has the ability to detect the iris and extract the exact boundary between iris and non-iris region.

The proposed iris detection method applied the Adaboost algorithm of Viola and Jones [18]. 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 under unconstrained environment in the proposed system. An integral image generated by only simple operations allows for very fast feature evaluation.

The second step is a simple and efficient classifier that is built by selecting a small number of important features from a huge set 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.

In Fig. 3, the red and blue rectangles show an example of the Haar-like features for extracting the boundary of the iris and two red circles show the result after the fine iris detection.



(a) (b)

Fig. 3 The Haar-like features and the result after the fine 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 [23]. 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 neighbors:

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

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:

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

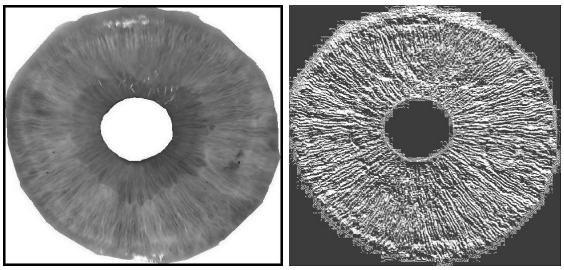
where $g(x,y)$ is the thresholding function:

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

After LBP, we followed the setup of [23] 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.



(a) (b)

Fig. 4 The gray scale iris and the features generated by local binary patterns

The basic idea of the weighting value comes from the distance to the center of the iris since most noise or error detection happened on the outer border. The map of Gaussian weighting scheme is shown in Fig. 5. There are two Gaussian weighting functions used in the weighting scheme and each of them can be calculated by (9). One is for the inner boundary and the other is for the outer boundary.

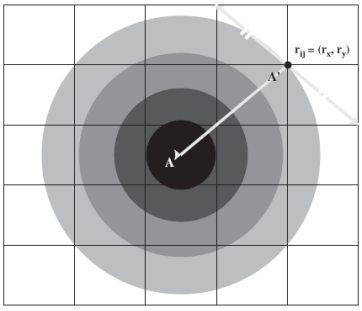


Fig. 5 The map of Gaussian weighting scheme

$$P_{i,j}(r_{xy|ij}) = \sum_{\forall r_{xy|ij}} \frac{1}{2\pi\sigma_x\sigma_y} \times \exp\left\{-\frac{1}{2}\left[\left(\frac{r_x}{\sigma_x}\right)^2 + \left(\frac{r_y}{\sigma_y}\right)^2\right]\right\}, \quad (9)$$

IV. Experimentation Results

For simulating the variant environment, an online testing system was built as the experimental platform, including a notebook with a 3rd generation Intel® Core i5 3230M processors and Windows 7 Professional. The built-in webcam captured the iris image online.

In the experiment, 50 individuals are enrolled in the training database and 20 images are captured for each person under different lighting conditions in Fig. 6. Totally, the online test under different lighting conditions is performed 1000 times. The average accuracy of verifications for the online test is about 92.5%.

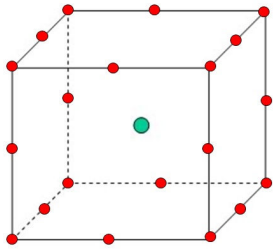


Fig. 6 The cube for simulating the variant lighting conditions

V. Conclusions

This paper presents a weighted approach to unconstrained iris recognition. For solving extremely uneven lighting condition, statistic based illumination normalization is first used in preprocessing to decrease illumination influence directly on coarse iris region. The following detection of the iris image is based on Adaboost algorithm. Based on the distance to the center of the iris, the weighted approach is composed of Gaussian functions. Furthermore, local binary pattern (LBP) histogram is then applied to texture classification with those weights. Experiment showed that the proposed system provided users a more flexible and feasible way to interact with the verification system through iris recognition.

Acknowledgment

This work was supported in part by a grant from National Science Council NSC102-2221-E-364-002.

References

[1] J. G. Daugman, "High confidence visual recognition of persons by a test of statistical independence," *IEEE Trans. Pattern Anal. Machine Int.*, vol. 15, no. 11, 1993, pp. 1148–1161.
[2] J. G. Daugman, "How iris recognition works," *IEEE Trans. Circuits Systems Video Technol.*, vol. 14, no. 1, 2004, pp. 21–29.
[3] P. W. Hallinan, "Recognizing human eyes," *Geometric Methods in Computer Vision*, vol. 1570, pp. 214–226, 1991.
[4] K. W. Bowyer, K. Hollingsworth, P.J. Flynn, Image understanding for iris biometrics: a survey, Computer Vision Image Understanding, vol. 110, no. 2, 2008.
[5] H. Proença, S. Filipe, R. Santos, J. Oliveira, and L. A. Alexandre, "The UBIRIS.v2: A database of visible wavelength iris images captured on-the-move and at-adistance," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 32, 2010, pp. 1529–1535.
[6] J. Daugman, "New methods in iris recognition," *IEEE Trans. Systems, Man, Cybernet.*, Part B vol. 37, 2007, pp. 1167–1175.
[7] Z. Sun and T. Tan, "Ordinal measures for iris recognition," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 31, 2009, pp. 2211–2226.
[8] P. Li and H. Ma, "Iris recognition in non-ideal imaging conditions," *Pattern Recognition Letters*, vol. 33, no. 8, 2012, pp. 1012–1018.
[9] H. Proença, L.A. Alexandre, Iris segmentation methodology for noncooperative recognition, IEEE Proceedings of the Vision, Image and Signal Processing, vol. 153, no. 2, 2006, pp. 199–205.
[10] J. G. Daugman, New methods in iris recognition, IEEE Transactions on System, Man, and Cybernetics–Part B: Cybernetics, vol. 37, no. 5, 2007, pp. 1167–1175.
[11] K. W. Bowyer, K. Hollingsworth, and P. J. Flynn, "Image understanding for iris biometrics: A survey," *Computer Vision and Image Understanding*, vol. 110, 2008, pp. 281–307.
[12] H. Proença, L.A. Alexandre, The NICE.I: noisy iris challenge evaluation – part I, in: Proceedings of the of First International Conference on Biometrics: Theory, Applications, and Systems, 2007, pp. 1–4.
[13] H. Proença, S. Filipe, R. Santos, J. Oliveira, and L. A. Alexandre, "The UBIRIS.v2: A database of visible wavelength iris images captured on-the-move and at-a-distance," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 32, 2010, pp. 1529–1535.
[14] D. M. Gavrila , "The visual analysis of human movement: a survey," *Computer Vision and Image Understanding,* vol. 73, 1999, pp. 82-98,.
[15] Iris image database. http://socia-lab.di.ubi.pt/
[16] Y. Moses, S. Edelman, and S. Ullamn, "Generalization on Novel Images in Upright and Inverted Faces," *Perception*, vol. 25, 1996, pp. 443-461.
[17] P. J. Phillips and Y. Vardi, "Efficient Illumination Normalization of Facial Images," *Pattern Recognition Letters*, vol. 17, 1996, pp. 921-927.
[18] P. Viola, M. J. Jonse, "Robust Real-Time Face Detection," *International Journal of Computer Vision*, vol. 57, no. 2, 2004, pp. 137-154.
[19] Y. Freund and R. E. Schapire, "Experiments with a New Boosting Aalgorithm," in *Proc. 13th International Conference on Machine Learning*, Bari, Italy, 1996, pp. 148-156.
[20] R. E. Schapire and Y. Singer, "Improved Boosting Algorithms Using Confidence-rated Predictions." *Machine Learning*, vol. 37, no. 3, 1999, pp. 297-336.
[21] J. Friedman, T. Hastie, and R. Tibshirani, "Additive Logistic Regression: a Statistical View of Boosting," *The Annals of Statistics*, vol.28, no.2, 2000, pp. 337-407.
[22] L. L. Huang, A. Shimizu, "A multi-expert approach for robust face detection," *Pattern Recognition*, vol. 39, 2006, pp. 1695-1703.
[23] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. on PAMI*, vol. 24, no. 7, 2002, pp. 971–987.

Open Science Index, Computer and Information Engineering Vol:8, No:1, 2014 publications.waset.org/9997132/pdf