Improved Iris Recognition using Parabolic Normalization and Multi-layer Perceptron Neural Network

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Abstract: Iris signature is considered as one of the richest, unique, and stable biometrics. This permits to an iris identification system to identify a person even after many years from his first iris signature extraction. In this paper we investigate a new method of iris normalization where iris features are normalized in a parabolic function. Thus iris information close to the pupil is privileged to that close to the sclera. A multilayer perceptron artificial neural network is then used to test the normalization effect and compare it with classical linear normalization method. The study is tested on CASIA V3 database iris images. Accuracy at the equal error rate operating point and receiver operating characteristics curves show better results with the parabolic normalization method and thus propose its use for better iris recognition system performance.

1 INTRODUCTION

Iris recognition is the process of identifying a person using his iris signature. Among other biometric identification techniques, it is considered as the most recent and reliable method. This is due to the rich features, the life time stability and the uniqueness of the iris (Krichen 2007, Daugman 1993; 2007).

An iris recognition system can be decomposed into 5 steps: image acquisition, iris segmentation, normalization, coding and matching. In this paper, we are interested in the normalization process and more precisely on the effect of a non linear normalization on recognition performances.

Iris images are first segmented in order to extract and isolate the iris. Daugman's (1993; 2007) method has been used. Then eye lids and eyelashes are isolated using linear Hough transform and intensity threshold respectively. Segmented iris images are then normalized, encoded and ready to be classified.

In what follows we give a brief review on Daugman's normalization technique, then we introduce our proposed normalization method followed by explanation on feature extraction process, a brief matching review and after it the matching process. Experimental procedures and results are then reported to finish with conclusion.

2 NORMALIZATION

2.1 Daugman's Normalization Review

Daugman (2003) approximates the iris with a circular ring. He normalizes the iris patterns by his 'Rubber Sheet' called method that projects the iris into a dimensionless rectangular shape. Intensity pixels $I_C(x, y)$ in the Cartesian space of the segmented iris are mapped to the Pseudo-Polar space $I_P(r, \theta)$ by the following equations:

$$I_P\{r, \theta\} = I_C\{x(r, \theta), y(r, \theta)\} \tag{1}$$

$$x(r, \theta) = (1 - r)x_p(\theta) + r x_s(\theta) \tag{2}$$

$$y(r, \theta) = (1 - r)y_p(\theta) + r y_s(\theta) \tag{3}$$

where $\left(x_p(\theta), y_p(\theta)\right)$ and $\left(x_s(\theta), y_s(\theta)\right)$ are the coordinates of the internal and external iris boundaries respectively at angle θ. r varies from 0 to 1 corresponding respectively to the internal and external iris circular boundaries and θ varies from 0 to 2π.

2.2 Parabolic Normalization

According to researchers, rich iris information is

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closer to the pupil than to the sclera encouraging us to test a method that takes into account this fact (Krichen 2007).

While Daugman's classical approach is to define *N* equally spaced samples in each angular direction in order to scan linearly the iris, the proposed method experiments the normalization efficiency of non-linearly spaced points. We redefine the spacing of the *N* samples along the radius for each angular direction of the iris. Iris pixels are normalized and projected to the polar space according to a parabolic function starting from the pupil boundary to the iris external boundary. For every angle (θ), samples among varying radius (r) are picked following always the equation (1) and following the two next equations:

$$x(r,\theta) = (1-r^2)x_p(\theta) + r^2 x_s(\theta) \quad (4)$$

$$y(r,\theta) = (1-r^2)y_p(\theta) + r^2 y_s(\theta) \quad (5)$$

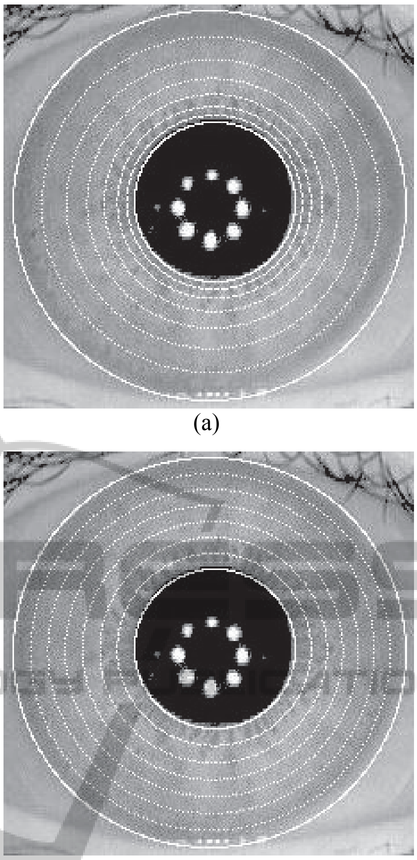
The distance between samples increases with the distance to the pupil as illustrates figure 1.

2.3 Feature Extraction

After normalization characteristic features, the most discriminating information of the iris, are extracted. Many methods exist in the bibliography such as wavelet encoding, zero-crossings of the 1D wavelet (Boles and Boashash, 1998), Haar wavelet (Lim, Lee, Byeon, and Kim, 2001), Laplacian of Gaussian filters (Wildes, 1997) and finally Gabor filters proposed by Daugman (1993) and used in our work. Gabor filters provide a conjoint representation and localization of iris information in space and spatial frequency. It is constructed by modulating a sine or cosine wave with a Gaussian. Signal decomposition is made by implementing a quadrature pair of Gabor filters. Real and imaginary parts are specified with a cosine and a sine modulated respectively by a Gaussian.A 2D Gabor filter over an image domain (r,θ) is given by:

$$G(r,\theta) = e^{-i\omega(\theta-\theta_0)} e^{-(r-r_0)^2/\alpha^2} e^{-i(\theta-\theta_0)^2/\beta^2} \quad (6)$$

where (α,β) specify the effective width and length, and ω is the filter's angular frequency having (r_0,θ_0) the center frequency. The filter's phase output represents the iris features and is used in the matching process (Daugman 1993).



(a)

(b)

Figure 1: Illustration of parabolic normalization (a) compared to Daugman's linear normalization (b).

2.4 Iris Matching

2.4.1 Matching Review

Hamming distance was the first matching method used by Daugman (1993). It s a simple Boolean that compares images, pixel by pixel generating a match percentage. It is not the most accurate, but its fast computation is an essential advantage over other metrics, such as Bayesian and Euclidean distance or nearest feature line (Park, Lee, Smith, Park, 2003 and Yuan, Shi, 2005 and Ma, Wang and Tan, 2002).

Due to these drawbacks in classical classification methods, use of neural networks for iris recognition has been drawing attention (Broussard, Kennell, Ives and Rakvic 2008 and Chen and Chu 2009). A competitive learning vector quantization neural network has been implemented (Lim, Lee, Byeon, and Kim, 2001 and Cho and Kim 2006), which learns faster than error back propagation mechanisms. Probabilistic Neural Network and Particle Swarm Optimization have been combined to achieve better accuracy (Chen and Chu, 2009). Using a rotation spreading neural network, real-time iris recognition regardless of orientation has been achieved by Murakami, Takano and Nakamura, (2003). Good results are reported as well using neural network based on VHDL prototyping by Reaz, Sulaiman, Yasin and Leng (2004).

2.4.2 Neural Network Matching

To test our normalization method, a Multi-Layer-Perceptron network, feed forward network with a back propagation training method rule, is implemented. The network has three layers: an input layer which consists of as many neurons as there are features in the normalized image; a hidden layer whose number of neurons will be optimized by checking the performance estimated with the training set and the validation set; and an output layer consisting of M neurons, representing each of the M person iris signature in the database.

3 EXPERIMENTAL PROCEDURES AND RESULTS

3.1 Iris Segmentation and Normalization

CASIA V3-Interval database were used in this study. We have chosen 820 images that belong to 100 person (6 to 11 images per person). The 8 bit grayscale images are collected under near infrared with a resolution of 320 * 280 pixels. They are considered as good quality iris images with clear iris texture details. Daugman's method is used to segment the images. After that the segmented images are normalized according to Daugman's model and then according to our parabolic normalization.

3.2 Neural Network Configuration

The input data consists of 7680 input neurons corresponding to the number of iris features. Unknown values related to corrupted iris templates were replaced by a constant value of 0.01. A linear mapping of the iris templates is performed to cover the range of the Hyperbolic Tangent Sigmoid function. To choose the number of neurons in the hidden layer, network performance was tested using a varying number from 5 to 400 neurons. Low validation and test errors results show that 260 neurons is the best choice. Finally the output layer consists of 100 neurons representing the 100 persons of the database.

Weights and biases are initialized according to the Nguyen-Widrow algorithm which distributes the values randomly within the active region of each neuron in the layer. To ensure convergence within a reasonable time, experimental results reported that a learning rate of 0.1 corresponds to the fastest convergence conserving the same performance.

Batch training is selected as the training method instead of online training, since the later would favor the minimization of errors for classes having more training patterns. As for the transfer function, it has been found that choosing *tansig* for the hidden layer and *logsig* for the output layer would result with the optimal performance of the network. Cross-validation was used to prevent over-fitting and mean squared normalized error were found to have superior performance than mean absolute and sum squared error.

3.3 Parabolic Normalization Evaluation

A total of 200 iris images (2 images per person) were randomly selected as the train set and the rest as the test set. The performance of the network was used to evaluate our parabolic normalization in comparison with Daugman's method. The network performance results are summarized in table 1. Training the network takes more time and epochs with the parabolic normalization, but compared to Daugman's normalization, parabolic normalization resulted in 62.5% lower train error and 20% lower validation error measured both on 200 images and in 30.62% lower test error measured on 620 images.

Table 1: Results of the two normalization methods.

Normalization method	Parabolic	Daugman
Training time	204.7	170.7
Epochs	504	411
Train error	0.0015	0.004
Validation error	0.02	0.025
Test error	0.0145	0.0209

No outer imposters are introduced in the match process, thus only patterns from the database classes are used. Each output node represents a distance measurement that can be seen as a similarity score between the iris and the corresponding class. The maximally responding output node represents the class membership of the input pattern.

Receiver operating characteristics (ROC) curves and accuracy at the equal error rate (EER) operating point are used to evaluate the normalization effect. Daugman's normalization method resulted in accuracy at the EER of 96.31 % while our proposed normalization method reported a value of 97.24 %. Figure 2 shows the ROC curves resulting for each of the normalization methods.

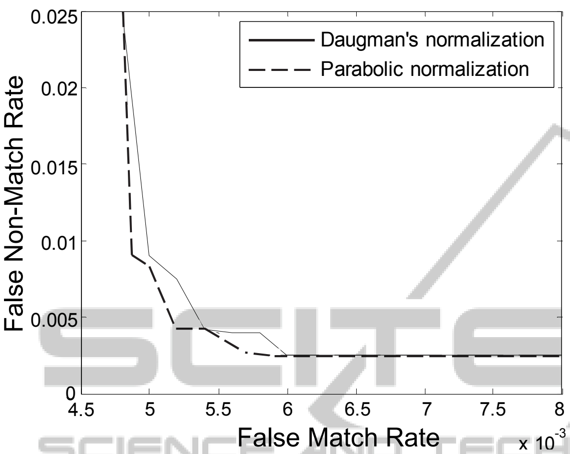


Figure 2: ROC curves resulting from a parabolic normalization compared to Daugman's linear normalization.

The ROC curves give best analyses of accuracy because they present the achieved accuracy over a range of operating points. As can be seen in figure 2, the parabolic normalization improved accuracy at most operating points, especially at low operating points where significant accuracy improvements are shown.

4 CONCLUSIONS

In this paper, we propose a novel iris normalization method that normalizes the iris following a parabolic function. Evaluation of the method is performed at the matching stage using an optimized multilayer perceptron neural network. Results compared to Daugman's normalization show better network performance, more specifically, 62.5%, 20% and 30.62% lower train, validation and test error respectively. In addition better accuracy at the EER operating point and better ROC curves are reported using parabolic normalization. These results show that parabolic normalization is convenient to represent the iris information and contribute in better iris recognition performance.

REFERENCES

Boles, W., Boashash, B., 1998. A human identification technique using images of the iris and wavelet transform. *IEEE Transactions on Signal Processing*, 46(4).

Broussard, R., Kennell, L., Ives, R. and Rakvic, R., 2008. An artificial neural network based matching metric for iris identification. *Proceedings of SPIE*, 6812, 0-11.

CASIA-IrisV3, http://www.cbsr.ia.ac.cn/IrisDatabase.html

Chen, C., and Chu, C., 2009. High performance iris recognition based on 1-D circular feature extraction and PSO–PNN classifier. *Expert Systems with Applications*, 36(7), 10351-10356.

Cho, S., and Kim, J., 2006. Iris recognition using LVQ neural network. *Third international conference on Advances in Neural Networks*, 3(2), 26-33.

Daugman, J., 1993. High Confidence Visual Recognition of Persons by a Test of Statistical Independence. *IEEE Trans. in Pattern Anal. Mach. Intell*, 15(11), 1148-1161.

Daugman, J., 2007. New methods in iris recognition. *IEEE Trans. Syst.,* Man, Cybern. B, Cybern., 37(5), 1167-1175.

Krichen, E., 2007. *Reconnaissance des personnes par l'iris en mode dégradé*, Evry-Val Essonne University, thesis.

Lim, S., Lee, K., Byeon, O., and Kim, T., 2001. Efficient Iris recognition through improvement of feature vector and classifier. *ETRI Journal*, 23(2), 1-2.

Ma, L., Wang, Y. and Tan, T., 2002. Iris Recognition Using Circular Symetric Filters, *16th International Conference on Pattern Recognition Proceedings*, 2, 414- 417.

Murakami, M., Takano, H., Nakamura, K.. 2003. Real-time Iris recognition by a rotation spreading neural network. *Annual SICE conference*, 1, 283-289.

Park, C. H., Lee, J. J., Smith, M. J. T. and Park, K. H., 2003. Iris-Based Personal Authentication Using a Normalized Directional Energy Feature. *Audio and video based biometric person authentication conference*, 224-232.

Reaz, M. B. I., Sulaiman, M. S., Yasin, F. M., Leng, T.A., 2004. Iris recognition using neural network based onVHDL prototyping. *International Conference on Information and Communication Technologies: From Theory to Applications*, 463-464.

Wildes, R., 1997. Iris recognition: an emerging biometric technology. *Proceedings of the IEEE*, 85(9).

Yuan, X. and Shi P., 2005. Advances in Biometric Person Authentication. *Lecture Notes in Computer Science*, 3781, 135-141.

Zhu, Y., Tan, T. and Wang, Y., 2000. Biometric personal identification based on iris patterns*. 15th International Conference on Pattern Recognition*, Barcelona , Spain, 2, 801-804.