

# IRIS RECOGNITION FOR PERSONAL IDENTIFICATION USING LAMSTAR NEURAL NETWORK

Shideh Homayon

Department of Electrical and Computer Engineering  
University of California, Santa Cruz  
City, USA

## **ABSTRACT**

*One of the promising biometric recognition method is Iris recognition. This is because the iris texture provides many features such as freckles, coronas, stripes, furrows, crypts, etc. Those features are unique for different people and distinguishable. Such unique features in the anatomical structure of the iris make it possible the differentiation among individuals. So during last year's huge number of people have been trying to improve its performance. In this article first different common steps for the Iris recognition system is explained. Then a special type of neural network is used for recognition part. Experimental results show high accuracy can be obtained especially when the primary steps are done well.*

## **KEYWORDS**

*iris recognition, biometric identification, pattern recognition, automatic segmentation.*

## **1. INTRODUCTION**

### **1.1 Biometric in general**

Biometrics refers to the identification of human identity via special physiological traits. So scientists have been trying to find solution for designing technologies that can analysis those traits and ultimately distinguish between different people. Some of popular Biometric characteristic are features in fingerprint, speech, DNA, face and different part of it and hand gesture. Among those method face recognition and speaker recognition have been considered more than other during last 2 decades. The idea of automated iris recognition has been proposed firstly by Flom and Safir. They showed that Iris is an accurate and reliable code in biometric identification. First of all iris is an internal part of the body that can be seen easily. Also visible patterns are unique for each individual person. So it is really hard to find two person with identical iris pattern. Also iris pattern even for left and right eyes are different. Moreover those pattern are almost fix and not going to change during life. So the patterns of the iris are almost constant during a person's lifetime. As a result by use of a features that are highly unique the chance of having two individual having the same features is minimal. Considering those uniqueness and proposing algorithm to could extract iris correctly would lead to stable and accurate system for solving human identification problem. Although some new researches revealed there are some methods to

hack this type of systems (such as capturing image from person Iris in press conference), still iris recognition is a reliable human identification technique and reliable security recognition system. For this research we are not going to capture new image by camera, instead a famous data set (CASIA database [1]) is used to evaluate results. This dataset contains thousands of different images and publicly is available upon request.

## 1.2 Background

Alphonse Bertillon and Frank Burch who were ophthalmologists proposed that iris patterns can be a reliable method for identification systems [2, 13] while John Daugman [3] was the first person that invented a system for the identification verification based on iris pattern. Another valuable work proposed by R. Wildes et al. Their method was different both in the algorithm for extracting iris code and the pattern matching technique. Since the Daugman system has been shown high performance and really low failure rate, his systems are patented by the Iriscan Inc. and are also being commercially used in Iridian technologies, British Telecom, UK National Physical Lab etc. So in our research, the Daugman model is used for extracting iris pattern. Besides using common steps used in other works such as image acquisition and pre-processing, iris localization and normalization, our research utilizes a powerful neural network, say LAMSTAR [9] for recognition part. Because of availability of Daugman model [6, 7] and related source code a quick review is provided in each section to describe the theoretical approach and their results. The paper mainly focused on used neural network and its implementation along with initial experimental result and suggestion for improvement of performance.

## 1.3 Image acquisition

To have a reasonable result, this step should be done accurately. Having a high quality image with minimal level of noise reduce the necessary procedure for noise reduction and promote other step's result. Especially when image are taken closely error originated from different steps would be reduced due to removing reflection effect. To focus on our method that is actually a special type of classifier, uses the image provided by CASIA (Institute of Automation, Chinese Academy of Sciences) are used as a data set. These images were taken for the purpose of iris recognition software research and implementation. Due to using Infra-red light for illuminating the eye specular reflections effect has been reduced in this data set. So here some initial steps for decreasing error originated from reflection is not necessary. It is clear that for real-time application reflection removal process is needed.

## 2. IRIS LOCALIZATION

### 2.1 Method

The part of the eye containing information is only the iris region. As is shown iris is located between the sclera and the pupil. So it is necessary to get the iris from eye image. Actually a segmentation algorithm should be used to find the inner and outer boundaries. There are huge number of research for image segmentation such as [5] or that is based on more sophisticated algorithm but the most popular method for segmentation is edge detection. For this purpose Canny edge detector has been shown successful. The Canny detector mainly have three main steps that are finding the gradient, non-maximum suppression and the hysteresis thresholding [8,11]. As

proposed by Wildes, by considering the threshold in a vertical direction the effect of the eyelids would be decreased. Knowing that applying this method remove some pixels on the circle boundary, an extra step that is actually Hough transform would lead to successful localization of the boundary even with absence of those pixels. Also computational cost is lower because the boundary pixels are lesser for calculation. The procedure is summarized to following steps. For a pixel  $gradian\_image(x,y)$ , in the gradient image, and given the orientation  $\theta(x,y)$ , the edge intersects two of its 8 connected neighbours. The point in  $(x,y)$  is a maximum if its not smaller than the values of the two intersection points. By applying next step saying hysteresis thresholding, the weak edges below a low threshold would be eliminated, but not if they are connected to an edge above a high threshold through a chain of pixels all above the low threshold. On the other hand the pixels above a threshold T1 should be separated. Then, these points are marked as edge points only if all its surrounding pixels are greater than another threshold T2. The values for threshold were found tentatively by trial and error, and are 0.2 and 0.19 according to [8].

## 2.2 Normalization

Extracted iris has different size and value. To feed this pattern to a classifier all pattern should be normalized. To normalization an iris regions a method that is called Daugman's rubber sheet model [6,7] has been used. In this method centre of the pupil is used as the reference point and radial vectors pass through the iris region. The procedure is shown in Figure 1. A number of data points are selected along each radial line and this is called the radial resolution. Also the number of radial lines going around the iris is called the angular resolution. Since sometimes the pupil can be non-concentric respect to the iris, a procedure that is called remapping must be utilized to rescale points based on the angle around the circle.

This is given by

$$r' = \sqrt{\alpha\beta} \pm \sqrt{\alpha\beta^2 - \alpha - r_T^2} \tag{1}$$

with

$$\alpha = o_x^2 + o_y^2$$

$$\beta = \cos\left(\pi - \arctan\left(\frac{o_y}{o_x}\right) - \theta\right)$$

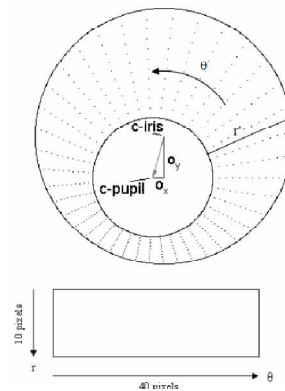


Figure 1



Figure 2. Result of iris localization

Here the displacement of the centre of the pupil relative to the centre of the iris is given by  $o_x, o_y$ , while  $r'$  is the distance between the edge of the iris and edge of the pupil at an angle,  $\theta$  around the region. Also  $r_l$  is the radius of the iris such as Fig (1). The remapping equation first gives the radius of the iris region as a function of the angle  $\theta$ . A constant number of points are chosen along each radial line, then a constant number of radial data points are taken at a particular angle. The normalized pattern was made by transferring the radial and angular position in the normalized pattern to the Cartesian coordinates of data points. From the 'Doughnut' iris region, normalization generate a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. The result for iris localization is shown in Fig (2). In this section all the procedure is the same as [10] model including removing rotational inconsistencies that is done at the matching stage based on Daugman's rubber sheet model.

### 2.3 Results of localization and normalization

The result of normalization step based on mentioned method showed to be liable like some results shown in Figure 3. But, the normalization was not able to reconstruct the same pattern perfectly from images with changing of pupil dilation. This means that deformation of the iris results in small changes of its surface patterns. For example consider situation that the pupil is smaller in one image respect to another. Then normalization process rescales the iris region to reach to constant dimension. Here, the rectangular representation is made by 10,000 data points in each iris. Until now the rotational inconsistencies have not been considered by the normalization. So the two normalized patterns are misaligned in the angular direction. The result of whole process is shown in fig (3). For all images in the folder the template is calculated that is actually a matrix. Size of matrix is  $20 \times 480$ . Then those matrix are saved to be used in future as a training set. This process is shown in figure (4).



Figure 3. resulting matrix after normalization

## 4. CLASSIFIER

In order to provide accurate recognition of individuals, neural network can be used. For this research a special neural networks has been used. So after making our template and some initial steps mentioned before we have a matrix with the dimension of  $20 \times 480$ . So for 16 number of class our classifier should be trained. In the next section implementation using LAMSTAR Neural network has been discussed. We decided to test it because it has been shown that is really powerful in other problems such as character recognition problem.

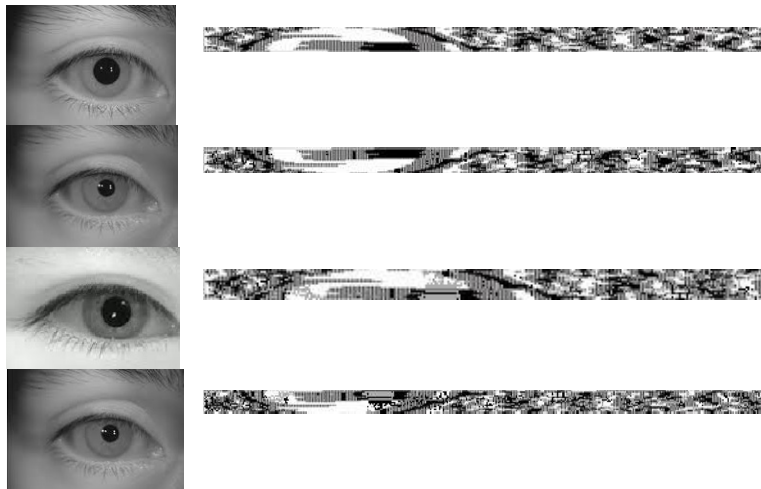


Figure 4. Training set

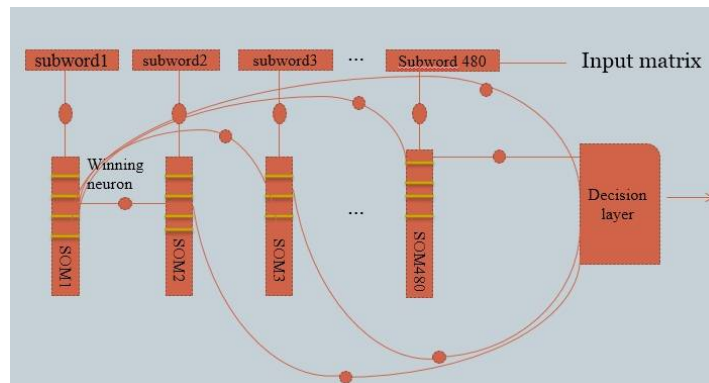


Figure 5. LAMSTAR structure

## 4.1 LAMSTAR neural network

### 4.1.1 Introduction to LAMSTAR

The problem consists in the realization of a LAMSTAR Artificial Neural Network for IRIS recognition. The LAMSTAR neural network, is a complex network, made by a modified version of Kohonen SOM modules. It doesn't need of the training. In fact, the input patterns are divided into many subwords, for example we considered columns of template as our subwords, so we have 480 subwords. These subwords are used for setting the weights of the SOM modules of the LAMSTAR. When a new input word is presented to the system, the LAMSTAR inspects all weights in SOM. If any pattern matches to an input subword, it is declared as winning neuron for that particularly subword. The SOM-module is based on "Winner take All" neurons, so the winning neuron has an output of 1, while all other neurons in that SOM module have zero output. Here, the SOM is built statically.

This means that for every subword, we instantiate every time a new matrix that represents the SOM, and if computing the products between the stored weights and the input subword, we obtain a winner "1", we don't establish a new neuron. Otherwise, if computing that products, no one of the neurons that are present in the SOM module converge to "1", in other words, if we haven't a winner neuron, we instantiate a new neuron in the SOM module.

Every time that we instantiate a neuron, we normalize the new weights following the function such as [12, 15]:

$$x'_i = \frac{x_i}{\sqrt{\sum_j x_j^2}}$$

To converge the output of the winning neuron to "1" we follow the function below:

$$w_{(n+1)} = w_{(n)} + \alpha[X - w_{(n)}]$$

Where  $\alpha = 0.8$  and it is the learning constant,  $w$  is the weight at the input of the neuron, and  $x$  the subword. A particular case could happen: when the second training pattern is input to the system, this is given to the first neuron, and if its output is close to "1", another neuron isn't built. We create neurons only when a distinct subword appears. The output layer is provided by the punishment and reward principle such as [14, 16]. If an output of the particular neuron is what is desired, the weight of the output layer is rewarded by an increment, while punishing it if the output is not what is desired.

We'll explain better this layer in the design section, reporting also the code for the sake of clarity.

#### 4.1.2 Design

The design of the Neural Network is represented in the figure (5). In this network, we have 16 different representations for eyes which are both left and right eyes of 8 person. The input pattern is templates that has been extracted from images using last pre-processing steps. The size of those templates after normalization is  $20 \times 480$ . Here we considered each column as a word so each word is a vector with size of 20. Also for each person 5 different images is used for training. So we selected images from data set from folders that have more than 5 images for each case to could use remainder for the testing, So after making subwords, we normalize every subword with respect itself, as we said in the introduction section. After the normalization of the input subwords, we have to train the system starting from the SOM layer. We call a function every time that we change the subword. As we can read, we initialize the som\_out (which is the current SOM module), and then if we haven't a winning neuron we create it (flag=0), Other-wise we take the current neuron as winning neuron. Once that the weights of the som modules are set ( $w_{\text{som}}$ ), we proceed to the output training. This is complex because we have to look to the sum of all the weights between the winning neurons of the SOM modules and the output layer (they are firstly set to zero). If the sum of all the weights is negative, we understand that result as "0". If is positive, we understand as "1". So the punishment and the reward is based on adding a small increment. Obviously for a negative sum, the punishment consist into adding a small positive increment, while the reward on adding a small negative increment. And vice versa for the positive sum. In this way, the system converges faster to the desired output if there's a reward, and it takes long if there's a punishment. Briefly, the algorithm follows this few steps:

- 1) Get the train patterns
- 2) Realize the subwords for every pattern
- 3) Normalize every subword
- 4) Set the weights of SOM module, creating every time a new neuron if it isn't a winning neuron for the new subword.
- 5) Set the output of the winning neuron to 1.
- 6) Set the weights of the Decision Layer to zero
- 7) Adjust the weights of last layer taking into account the desired output, with punishment and reward principle.

#### 4.1.3) Normalized version of LAMSTAR

Based on the reward/punishment if in desire firing, a neuron is to be fired then the link weights will be rewarded. In case this happens for a couple of time the link weight value can be high enough to cause undesired neuron firing. To avoid this situation we use normalized LAMSTAR neural network in which we divide link weights by number of times the corresponding neuron was rewarded for desire firing. Considering advantages mentioned above we can add more positive points to LAMSTAR if we use the normalized version. Link weight of a neuron will not grow gradually if it wins much time. Convergence time will be reduced since normalization improve desired firing and Increase efficiency.

### 5. RESULT

The LAMSTAR and modified LAMSTAR are applied on CASIA interval database. Both of them are really fast. For instant required time for training was 66.1584s and for testing 2.5939 seconds while the accuracy was 99.39% for regular LAMSTAR and 99.57% for modified LAMSTAR. After tracing the program on each individual image I found pre-processing needs to be modified. Actually the performance of any classifier is directly depended to performance of algorithm used for finding template. For example rotational inconsistency should be taken into account. So steps including segmentation and normalization must be improved to be able to Get iris accurately and make template that is input of our neural network. It seems with having accurate templates the performance would be increased.

Algorithm	Recognition rate
Duagman	%98.58
LAMSTAR	%99.39
Modified LAMSTAR	%99.57
Table1. Comparison between performance of our proposed method and Duagman	

### 6. CONCLUSION AND FUTURE WORK

In this work a new neural network method is presented for iris identification. A template is achieved using Image processing techniques. Classification is mainly done by LAMSTAR neural network. Structure of this network makes it a good candidate for classifying. The software code for image processing and the network has been written in MATLAB R2014a taking into account image processing toolbox and the fact that it is very user friendly in image processing application

[11]. After reprocessing step all template matrix are saved and in the next step they are loaded as input to classifier. Overall result suggests that normalized LAMSTAR increase efficiency and convergence time. The next step for increasing efficiency is considering rotational inconsistency. Also it seems that having a matrix with 480 columns is not reasonable so reducing its size can be helpful especially for reducing memory that is needed for running for database with more image. In comparison with other methods the performance of Normalized LAMSTAR seems to be better and convergence time is pretty much faster than method based on other network such as Back Propagation. Also stability and not being sensitive to initialization are other positive points of using LAMSTAR. Ability to dealing with incomplete and fuzzy input data sets make LAMSTAR neural network an effective candidate for problems such as Iris classification purpose.

## REFERENCES

- [1] CASIA iris database. Institute of Automation, Chinese Academy of Sciences. <http://sinobiometrics.com/casiairis.h>
- [2] F.Adler, Physiology of the Eye: Clinical Application, fourth ed. London: The C.V. Mosby Company, 1965.
- [3] J.Daugman, Biometric Personal Identification System Based on Iris Analysis, United States Patent, no.5291560, 1994.
- [4] J.Daugman, "Statistical Richness of Visual Phase Information: Update on Recognizing Persons by Iris Patterns," Int'l J. Computer Vision, vol. 45, no.1, pp. 25-38, 2001.
- [5] H.MiarNaimi, M. Salarian, "A Fast fractal Image Compression Algorithm Using Predefined Values for Contrast Sacaling", Proceedings of the World Congress on Engineering and Computer Science USA, October-2007.
- [6] J.Daugman, "Demodulation by Complex-Valued Wavelets for Stochastic Pattern Recognition", IntJ.Wavelets, Multiresolution and Information Processing, vol.1, no.1, pp.1-17, 2003.
- [7] J.Daugman, "How Iris Recognition Works", University of Cambridge, 2001.
- [8] Libor Masek. Recognition of Human Iris Patterns for Biometric Identification. School of Computer Science and Soft Engineering, the University of Western Australia, 2003.
- [9] Langerudi, Mehran Fasihozaman; Javanmardi, Mahmoud; Mohammadian, Abolfazl (Kouros); Sriraj, PS; "Choice Set Imputation", Transportation Research Record: Journal of the Transportation Research Board, 2429, 1, 79-89, 2014, Transportation Research Board of the National Academies, doi: 10.3141/2429-09
- [10] M Salarian, H Hassanpour, A new fast no search fractal image compression in DCT domain, Machine Vision, 2007. ICMV 2007. International Conference on, 62-66.
- [11] Graupe, D. and Kordylewski, H. (1997). A large scale memory (LAMSTAR) neural network for medical diagnosis. In Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 'Magnificent Milestones and Emerging Opportunities in Medical Engineering', volume 3, pages 1332-5, Piscataway, NJ. IEEE Service Center.
- [12] Fasihozaman Langerudi, Mehran; Hossein Rashidi, Taha; Mohammadian, Abolfazl; "Investigating the Transferability of Individual Trip Rates: Decision Tree Approach", Transportation Research Board 92nd Annual Meeting, 13-0218, 2013.
- [13] <http://www.mathworks.com/help/nnet/ug/multilayer-neural-networks.html>.
- [14] Langerudi, Mehran Fasihozaman; Abolfazl, Mohammadian; Sriraj, PS; "Health and Transportation: Small Scale Area Association", Journal of Transport & Health, 2014, Elsevier, doi: 10.1016/j.jth.2014.08.005.
- [15] A.Jain, R.Bolle and S. Pankanti, Biometrics: Personal Identification in a Networked Society, Kluwer, 1999.
- [16] M Salarian, E Nadernejad and H. M. Naimi, A new modified fast fractal image compression algorithm, Imaging Science Journal, vol. 61, Feb.2013, pp. 219-231, doi: 10.1179/1743131X11Y.0000000027.