COST
Communication Science & Technologie N° 4. Janvier 2006

ARTIFICIAL NEURAL NETWORK & MULTILEVEL 2-D WAVELET DECOMPOSITION CODE-BASED IRIS RECOGNITION

R. ADJOUDJ
Evolutionary Engineering and Distributed Information Systems Laboratory, EEDIS, Computer Science Department
Département Informatique, University of Sidi Bel-Abbès, Algeria Tel/Fax: (213)-48-57 77 50, Email : AdjReda@yahoo.fr
A. BOUKELIF
Laboratoire des Télécommunications et du Traitement Numérique de Signal, équipe de recherche des techniques vidéo
Département Electronique, Université de Sidi Bel-Abbès, Algérie Tél :(213)-48-57 82 81, Email : aboukelif@yahoo.f

Abstract:
An iris recognition involves analyzing features found in the colored ring of tissue that surrounds the pupil. This biometric has the potential for higher than average template-matching performance. Easy of use and system integration has not traditionally been strong points with iris scanning devices but as new products emerge, improvements should be expected.
This document demonstrates how a iris recognition system can be designed by artificial neural network as a matching/recognising algorithm, which use Multilevel 2-D wavelet decomposition code of iris image. Note that the training process did not consist of a single call to a training function. Instead, the network was trained several times on various input ideal and noisy images coded by Multilevel 2-D Wavelet decomposition, the images which contents iris.
In this case training a network on different sets of noisy images forced the network to learn how to deal with noise, a common problem in the real world.

Key Words:
Biometric, Pattern Recognition, Artificial Neural Network, Wavelet Decomposition and Image processing.

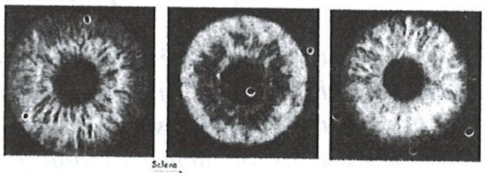
Résumé :
La reconnaissance des personnes par leurs iris implique une analyse des caractéristiques trouvées dans l'anneau coloré du tissu qui entoure la pupille de leurs œil. Ce moyen biométrique a des potentialités dans l'avenir de l'authentifications des personnes.
Ce document démontre comment un système de reconnaissance des iris peut être réalisé par un réseaux de neurones artificiel comme un algorithme de reconnaissance, et qui utilise la décomposition multiniveau en ondelettes 2-D de l'image de l'iris. A noter que le processus d'apprentissage ne consiste pas à un seul appel à la fonction d'apprentissage. Par contre, le réseaux de neurones doit faire l'apprentissage plusieurs fois sur une variété des images idéals et bruitées, codées par la décomposition multiniveau en ondelettes 2-D, dont elles contiennent l'iris.
Dans ce cas, l'apprentissage du réseaux sur différents ensembles d'images bruitées lui force à apprendre comment il se comporte vis-à-vis la variété des images d'iris, un problème fréquent dans le monde réel.

1. Introduction

An iris-based biometric identification scheme involves analysing features that are found in the colored ring of tissue that surrounds the pupil. Complex iris patterns can contain many distinctive features such as ridges, crypts, rings, and freckles [1],[2]. Iris scanning uses a fairly conventional camera and requires no close contact between the subject and the reader. Compared to the close contact between the subject and the reader required by some other biometric recognition systems such as retina scanning, the subject may feel more comfortable using this type of device. The iris is unique from person to person because there are so many different patterns that surround the pupil.The iris is said to be more unique than a fingerprint. It is possible that the iris-scanning device can successfully read the patterns in the iris even when the subject has a pair of glasses on and this idea has been demonstrated to work in an actual system [3]. This recognition ability would be valuable in the flight deck of an aircraft because it is not known whether the person being authenticated is wearing glasses or not [4]. Some research work [24],[27],[29],[30] has also stated that the iris is essentially stable over a person's life. Furthermore, since the iris is an internal organ as well as externally visible, iris-based personal identification systems can be noninvasive to their users [10],[27],[28],[29],[30], which is of great importance for practical applications. All these desirable properties (i.e., uniqueness, stability, and noninvasiveness) make iris recognition a particularly promising solution to security.

1.1 What is the iris:

The iris is the plainly visible, colored ring that surrounds the pupil. It is a muscular structure that controls the amount of light entering the eye, with intricate details that can be measured, such as striations, pits, and furrows. The iris is not to be confused with the retina, which lines the inside of the back of the eye, as shown in fig1(a). No two irises are alike. There is no detailed correlation between the iris patterns of even identical twins, or the right and left eye of an individual. The amount of information that can be measured in a single iris is much greater than fingerprints, and the accuracy is greater than DNA.



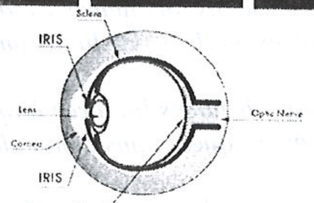


Fig1.(a). Iris localisation.

Fig. 1.(b). Samples of iris images.

1.2. How iris recognition works

The iris-scanning procedure is simple and painless. All the subject needs to do is to stand at least a foot away from the camera and look into the scanning device. The camera then scans the iris into a pattern that is digitised [5]. The scanned digitised pattern is then compared to a previously recorded pattern. These stored patterns are also called templates, the same idea that is used with other biometric techniques such as fingerprint scanning and facial recognition.

In order to capture the rich details of iris patterns, an imaging system should resolve a minimum of 70 pixels in iris radius. In field trials to date, a resolved iris radius of 100 to 140 pixels is more typical [3],[6]. There are many advanced algorithms that are used to aid the scanning device in actually locating the iris by distinguishing it from the pupil.

Iris recognition technology converts the visible characteristics of the iris into a just 512 bytes code, which is a template stored for future verification attempts. Iris-scan technology is primarily deployed in high-security physical access implementations [3].

Iris scanning is more accurate than that of fingerprint scanning [3],[6]. Since the user may have to look at the camera for iris scanning for up to 15 seconds.

Since iris-scanning technologies are harmless to the eye, there should be no concerns about long-term effects. The only thing that one should be concerned about is having consistent lighting in the area in which the iris-scanning device is located. Poor lighting may have an effect on the scanner's results such as the case with facial recognition.

Iris scanning contains both user and environmental influences. Some user influences are [7]:

- Eyelashes.
- Iris color intensity.
- Height of the user .
- User movement.
- User distance from the camera.
- Colored or tinted contact lenses.
- Glasses or sunglasses.
- eyeglasses rather than medium or dark tinted sunglasses.

1.3. Environmental Influences

There are only a few environmental factors for iris scanning techniques:

• Lighting level may have an effect on the iris scanning device outcome. If the lighting level is too dark, an accurate picture of the iris may not be possible and the iris pattern that the device is seeking may not be fairly visible for comparison.

• Obstructions in the eye will play a significant role on how accurate the scan is taken. For example, if there is a speck of dust in the eye or an eyelash inside of the eye then the iris pattern may not be obtained by the device.

2.Related work :

Flom and Safir first proposed the concept of automated iris recognition in 1987 [24]. Since then, some researchers worked on iris representation and matching and have achieved great progress [13]–[23], [27], [28], [30]. Daugman [1] made use of multiscale Gabor filters to demodulate texture phase structure information of the iris. Filtering an iris image with a family of filters resulted in 1024 complex-valued phasors which denote the phase structure of the iris at different scales. Each phasor was then quantized to one of the four quadrants in the complex plane. The resulting 2048-component iriscode was used to describe an iris. The difference between a pair of iriscodes was measured by their Hamming distance. Sanchez-Reillo *et al.* [16] provided a partial implementation of the algorithm by Daugman. Wildes *et al.* [10] represented the iris texture with a Laplacian pyramid constructed with four different resolution levels and used the normalized correlation to determine whether the input image and the model image are from the same class. Boles and Boashash [13] calculated a zero-crossing representation of one-dimensional (1-D) wavelet transform at various resolution levels of a concentric circle on an iris image to characterize the texture of the iris. Iris matching was based on two dissimilarity functions. In [19], Sanchez-Avila *et al.* further developed the iris representation method by Boles *et al.* [13]. They made an attempt to use different similarity measures for matching, such as Euclidean distance and Hamming distance. Lim *et al.* [15] decomposed an iris image into four levels using 2-D Haar wavelet transform and quantized the fourth-level high-frequency information to form an 87-bit code. A modified competitive learning neural network (LVQ) was adopted for classification. Tisse *et al.* [20] analyzed the iris characteristics using the analytic image constructed by the original image and its Hilbert transform. Emergent frequency functions for feature extraction were in essence samples of the phase gradient fields of the analytic image's dominant components [25], [26]. Similar to the matching scheme of Daugman, they sampled binary emergent frequency functions to form a feature vector and used Hamming distance for matching. Park *et al.* [21] used a directional filter bank to decompose an iris image into eight directional subband outputs and extracted the normalized directional energy as features. Iris matching was performed by computing Euclidean distance between the input and the template feature vectors. Kumar *et al.* [22] utilized correlation filters to measure the consistency of iris images from the same eye. The correlation filter of each class was designed using the two-dimensional (2-D) Fourier transforms of training images. If the correlation output (the inverse Fourier transform of the product of the input image's Fourier transform and the correlation filter) exhibited a sharp peak, the input image was determined to be from an authorized subject, otherwise an imposter. Bae *et al.* [23] projected the iris signals onto a bank of basis vectors derived by independent component analysis and quantized the resulting projection coefficients as features.

From the methods described above, we can conclude that there are four main approaches to iris representation : phase-based methods [10], zero-crossing representation [13], [19], texture analysis [8], [14], [15], [17], [18], [21], and intensity variation analysis [23], [27]. However, the question of which approach is most suitable for extracting iris features has never been answered.

3. Proposed design

It is often useful to have a machine perform pattern recognition. In particular, machines which can read iris images are very cost effective. A machine that reads passenger passports can process many more passports than a human being in the same time. This kind of application saves time and money, and eliminates the requirement that a human perform such a repetitive task. This document demonstrates how iris recognition can be done with a backpropagation artificial neural network, but above the visible characteristics of the iris was converted into a 576-byte code by using Multilevel 2-D Wavelet decomposition.

4. Problem statement

An artificial neural network is to be designed and trained to recognize the iris wavelets code of the database that is actually used [8],[9],[11],[12]. An imaging system that converts each iris image in 2-D wavelets code centered in the system's field of vision is available. The result is that each iris image is represented as a vector of 576 reals values. (firstly : Image size ~ 240 x 240).

4.1 Creating an iris code :

The picture of an eye is first processed by software that localises the inner and outer boundaries of the iris, and the eyelid contours, in order to extract just the iris portion, the some examples of iris localization is shown in Fig.1.(b).Eyelashes and reflections that may

cover parts of the iris are detected and discounted.
Sophisticated mathematical software then encodes the iris pattern by a process called Demodulation. This creates a phase code for the texture sequence in the iris, similar to a DNA sequence code. The Demodulation process uses functions called multilevel 2-D wavelets decomposition that make a very compact yet complete description of the iris pattern, regardless of its size and pupil dilation, in just 576 bytes (fig2). The phase sequence is called an Iris wavelets vector or Iris wavelets code, and it captures the unique features of an iris in a robust way that allows easy and very rapid comparisons against large databases of other templates. The Iris wavelets vector is immediately encrypted to eliminate the possibility of identity theft and to maximize security. For example, here is the iris from *our own database* and the wavelets vector of this iris :

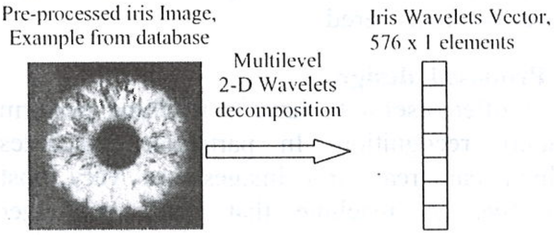


Fig 2.Iris Wavelets Code

Perfect classification of N ideal input wavelets code of images is required, and reasonably accurate classification of images of iris (N is equivalent to a number of distinguish class of iris in each database). The N 576-element input wavelets vector of images are defined as a matrix of input vectors (wavelets vector size ~ 576 x 1). The target vectors are also defined with variable called targets. Each target vector is a N-element vector with a 1 in the position of the iris it represents, and 0's everywhere else. For example, the iris number one is to be represented by a 1 in the first element (as this example is the first iris of the database), and 0's in elements two through N.

5. Iris recognition :

In less than a few seconds, even on a database of millions of records, the Iris wavelets vector generated from an image is compared to previously enrolled ones to see if it matches any of them. The decision threshold is automatically adjusted for the size of the search database to ensure that no false matches occur even when huge numbers of Iris wavelets vector are being compared with the live one. Some of the bits in an Iris wavelets Code signify if some data is corrupted (for example by reflections, or contact lens boundaries), so that it does not influence the process, and only valid data is compared. Decision thresholds take account of the amount of visible iris data, and the matching operation compensates for any tilt of the iris. A key advantage of iris recognition is its ability to perform identification using a one-to-all search of a database, with no limitation on the number of Iris Code records and no requirement for a user first to claim an identity, for example with a card. For our method we use a artificial neural network for matching and perform recognition using a one-to-all search of a database.

5.1 Neural network

The network will receive the 576 real values as a 576-element input wavelets vector of image (wavelets vector size ~ 576 x 1). It will then be required to identify the iris by responding with a N-element output vector (for more detail about N see above). The N elements of the output vector each represent a iris. To operate correctly the network should respond with a 1 in the position of the iris being presented to the network. All other values in the output vector should be 0.

5.2. Architecture of neural network

The neural network needs 576 inputs and N neurons in its output layer to identify the iris.
The network is a two-layer log-sigmoid/log-sigmoid network like use in [8],[9],[12]. The log-sigmoid transfer function was picked because its output range (0 to 1) is perfect for learning to output boolean values (see fig3).
The hidden layer has 100 neurons. This number was picked by a series of experiments. If the

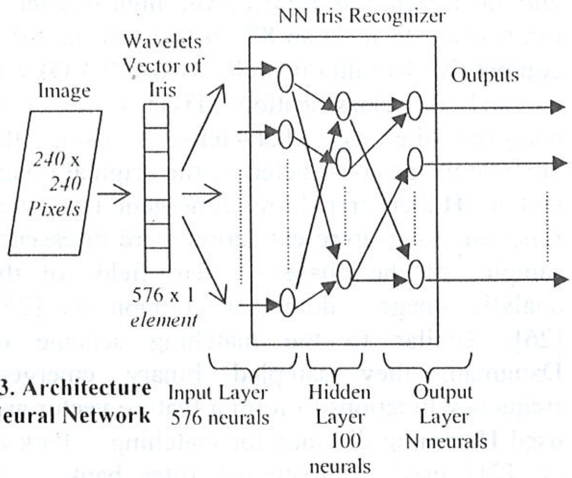


Fig 3. Architecture of Neural Network

network has trouble learning, then neurons can be added to this layer [8],[9],[11],[12].The network is trained to output a 1 in the correct position of the output vector and to fill the rest of the output vector with 0's. However, noisy input images may result in the network not creating perfect 1's and 0's. After the network has been trained the output will be passed through the competitive transfer function. This function makes sure that the output corresponding to the iris most like the noisy input image takes on a value of 1 and all others have a value of 0.The result of this post-processing is the output that is actually used [8],[9],[11],[12].

5.3 Training

To create a neural network that can handle input images (wavelets code images) it is best to train the network on ideal images. To do this the network will first be trained on ideal images (wavelets code images) until it has a low sum-squared error. Then the network will be trained on 10 sets of ideal and noisy images of wavelets code iris. The network is trained on two copies of the noise-free database at the same time as it is trained on noisy images. The two copies of the noise-free database are used to maintain the network's ability to classify ideal input images. Unfortunately, after the training described above the network may have learned to classify some difficult noisy images of iris at the expense of properly classifying a iris (wavelets code). Therefore, the network will again be trained on just ideal images of wavelets code iris. This ensures that the network will respond perfectly when presented with an ideal iris. All training is done using backpropagation with both adaptive learning rate and momentum.

5.3.1. Training with iris wavelets code(network 1 "net1"): The network is initially trained with iris wavelets code for a maximum of 10 000 epochs or until the network sum-squared error falls below 0.1 (see a fig 4).

5.3.2. Training without iris wavelets code (network 2 "net2"): Now, we created a new neural network, that trained without iris wavelets code but directly with only image of iris (as inputs) for a maximum of 10 000 epochs or until the network sum-squared error falls below 0.1, and we compare the results of the two neural networks(see a Table1).

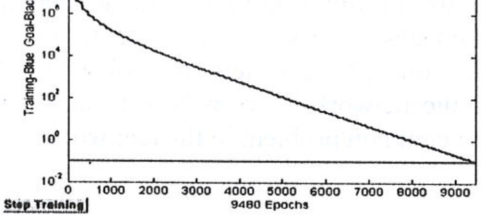


Fig4.Training of net1

6. Experiment and Test

To evaluate the performance of the proposed method, we collected a large number of iris images using a scanner sensor to form *our own Database*, the samples of iris images is shown in fig1. (b). The database includes 294 iris images (N=294) from 49 different subjects. The images are acquired during different sessions and with different kinds of noise, which provides a challenge to our system.

To test the system, an iris with noise can be created and presented to the two networks, and an other database of iris can be downloaded and presented to the our system as data-sets which named *CASIA Iris Database* [27], the samples of iris images from this database is shown in fig.5, To the best of our knowledge, this is the largest iris database available in the public domain. The subjects consist of 203 members of the CAS Institute of Automation (N=203, for more detail about N see above).

Table1 shows the results of recognition rate and performance of a proposed system (see table 1 for more example of iris with different kind of noise i-e. synthetic noise.).

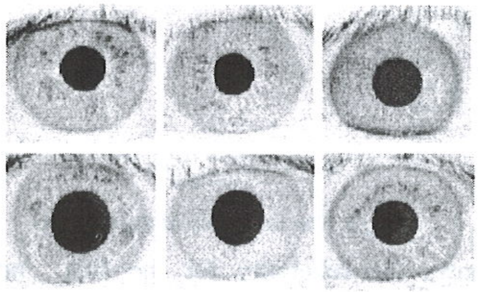


Fig.5.the samples iris images from *CASIA database*

7. System performance

The reliability of the neural network pattern recognition system is measured by testing the network with hundreds of input images of iris with varying quantities of noise. We test the two networks at various noise levels and then graphs the percentage of each network errors versus noise. Noise with mean of 0 and standard deviation from 0 to 100 are added to input images. At each noise level 100 presentations of different noisy versions of each iris are made and the network's output is calculated. The output is then passed through the competitive transfer function so that only one of the N outputs, representing the iris of *our own database*, has a value of 1. The number of erroneous classifications are then added and percentages are obtained (see a fig 6).The dashed line (blue dashed line) on the graph

Architecture Of Neural Network	Inputs Of Neural Network	Training & Test database	Time of Training	Recognition Rate (RR)				
				Database Without Noise	Database With Noise			
					Salt & Pepper noise	Poisson Noise	Speckle noise	Gaussian Noise
Artificial Neural Network1 " Net1"	Wavelets codes of iris	Our Own Database. "N = 294"	40 min 39 sec	98,55 %	95,92 %	98,91 %	87,62 %	83,67 %
		CASIA iris database "N = 203"	35 min 02 sec	87,11%	86,11 %	85,15%	75,66%	75,11%
Artificial Neural Network2 " Net2"	Naturals images of iris	Our Own Database, "N = 294"	2 hours 15 min 45 sec	89,90 %	86,21 %	79,20 %	96,81 %	96,72 %
		CASIA iris database "N = 203"	1 hour 21 min 06 sec	73,60%	72,22%	63,88%	66,66%	66,52%

Table 1. Recognition results on each iris image database (Image size ~ 240 x 240) on a PC with 1.7 GHz CPU. RR: Recognition Rate. N: a number of distinguish class of iris in each database.

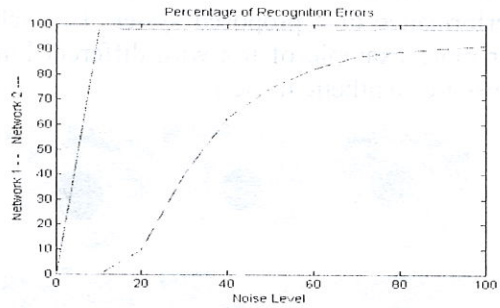


Fig 6. The reliability of the two nets

shows the reliability for the first network "net1"(with iris wavelets codes as inputs) trained with and without noise. The reliability of the second network"net2" when it had only been trained without iris wavelets code is shown with a solid line(green-line). Thus, training the two networks on noisy input images of iris greatly reduced their errors when they had to classify or to recognize noisy images of iris. The two network did not make any errors for iris with noise of mean 0.00 or 1.00. When noise of mean is greater than 1.00 was added to the images second network began to make errors but the first network began to make errors until10.00.

If a higher accuracy is needed the two networks could be trained for a longer time or retrained with more neurons in their hidden layers respectively. Also, the resolution of the input images of iris could be increased to say, a 640 by 480 matrix. Finally, the two networks could be trained on input images with greater amounts of noise if greater reliability were needed for higher levels of noise.

8. Conclusion

Iris recognition is challenging problems and there is still a lot of work that needs to be done in this area. Over the past ten years, iris recognition has received substantial attention from researchers in biometrics, pattern recognition, computer vision, and cognitive psychology communities. This common interest in iris recognition technology among researchers working in diverse fields is motivated both by the remarkable ability to recognize people and by the increased attention being devoted to security applications. Applications of iris recognition can be found in security, multimedia, and entertainment domains. We have demonstrated how a iris recognition system can be designed by artificial neural network using multilevel 2-D wavelets decomposition vector of iris as inputs(for optimising the size of iris image and saving training time of neural network).Note that the training process did not consist of a single call to a training function. Instead, the network was trained several times on various input ideal and noisy images of iris. In this case training a network on different sets of noisy images forced the network to learn how to deal with noise, a common problem in the real world.

9. References

[1]J.Daugman, "Biometric personal identification system based on iris analysis," U.S. Patent 5 291 560, 1994.

[2] J. Daugman, "High confidence visual recognition of persons by a test of statistical independence," *IEEE Trans. Pattern Analy. Machine Intell.*,vol. 15, pp. 1148–1161, Nov. 1993.

[3]D.Zhang, *Automated Biometrics: Technologies and Systems*. Norwell, MA: Kluwer, 2000.

[4] C.M. Carrillo, ''continuous biometric authentication for authorized aircraft personnel '', master thesis, a proposed design, naval postgraduate school monterey, california, June 2003.

[5]M.Esser, "Statistical richness of visual phase information: update on recognizing persons by iris patterns," *Int. J. Comput. Vis.*, vol. 45, no. 1, pp.25–38, 2001.

[6] C. Sanchez-Avila and R. Sanchez-Reillo, "Iris-based biometric recognition using dyadic wavelet transform," *IEEE Aerosp. Electron. Syst Mag.*, vol. 17, pp. 3–6, Oct. 2002.

[7] A. Jain, R. Bolle, and S. Pankanti, Eds., *Biometrics: Personal Identification in a Networked Society*. Norwell, MA: Kluwer, 1999.

[8] R. Adjoudj, A. Boukelif, "Artificial Neural Network-Based Iris Recognition", the International Conference on Computing, Communications and Control Technologies, Paper No. T645XC, CCCT 2004, Austin (Texas), USA, on August 14-17, 2004.

[9]H.Demuth, M.Beale, *Neural Network Toolbox User's Guide",* for use with Matlab, The MathWorks,1998.

[10]R. Wildes, J. Asmuth, G. Green, S. Hsu, R. Kolczynski, J. Matey, and S. McBride, "A machine-vision system for iris recognition," *Mach. Vis. Applic* , vol. 9, pp. 1–8, 1996.

[11] R. Adjoudj, A. Boukelif, " Detection et reconnaissance des visages basée sur les reseaux de neurones artificiels", *Communication Science & Technologie Journal*, Ecole Normal Supérieur de l'Enseignement Technique d'Oran, Algeria , Decembre 2004.

[12] R. Adjoudj, A. Boukelif, "Artificial neural network-based face recognition" , International Symposium on Control , Communications and Signal Processing, Paper No 1107, ISCCSP 2004 , Hammamet, Tunisia, March 2004.

[13] W. Boles and B. Boashash, "A human identification technique using images of the iris and wavelet transform," *IEEE Trans. Signal Processing*, vol. 46, pp. 1185–1188, Apr. 1998.

[14] Y. Zhu, T. Tan, and Y. Wang, "Biometric personal identification based on iris patterns," in *Proc. Int. Conf. Pattern Recognition*, vol. II, pp. 805–808, 2000.

[15] S. Lim, K. Lee, O. Byeon, and T. Kim, "Efficient iris recognition through improvement of feature vector and classifier," *ETRI J.*, vol.23, no. 2, pp.1–70, 2001.

[16] R. Sanchez-Reillo and C. Sanchez-Avila, "Iris recognition with lowtemplate size," in *Proc. Int. Conf. Audio and Video-Based Biometric Person Authentication*, pp. 324–329, 2001.

[17] L. Ma, Y. Wang, and T. Tan, "Iris recognition based on multichannel Gabor filtering," in *Proc. 5th Asian Conf. Computer Vision*, vol. I, pp. 279–283, 2002.

[18]A.Ross , "Iris recognition using circular symmetric filters," in *Proc.16th Int. Conf. Pattern Recognition*, vol. II, pp. 414–417,2002.

[19] C. Sanchez-Avila and R. Sanchez-Reillo, "Iris-based biometric recognition using dyadic wavelet transform," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 17, pp. 3–6, Oct. 2002.

[20] C. Tisse, L. Martin, L. Torres, and M. Robert, "Person identification technique using human iris recognition," in *Proc. Vision Interface*, pp. 294–299, 2002.

[21] C. Park, J. Lee, M. Smith, and K. Park, "Iris-based personal authentication using a normalized directional energy feature," in *Proc. 4th Int.Conf. Audio- and Video-Based Biometric Person Authentication*, pp. 224–232, 2003.

[22] B. Kumar, C. Xie, and J. Thornton, "Iris verification using correlation filters," in *Proc. 4th Int. Conf. Audio- and Video-Based Biometric PersonAuthentication*, pp. 697–705, 2003.

[23] K. Bae, S. Noh, and J. Kim, "Iris feature extraction using independent component analysis," in *Proc. 4th Int. Conf. Audio- and Video-Based Biometric Person Authentication*, pp. 838–844, 2003.

[24] L. Flom and A. Safir, "Iris Recognition system," U.S. Patent 4 641 394,1987.

[25] T. Tangsukson and J. Havlicek, "AM-FM image segmentation," in *Proc.EEE Int. Conf. Image Processing*, pp. 104–107, 2000.

[26] J. Havlicek, D. Harding, and A. Bovik, "The mutli-component AM-FM image representation," *IEEE Trans. Image Processing*, vol. 5, pp.1094–1100, June 1996.

[27] L.Ma, T.Tan, Y.Wang, D.Zhang,"Efficient Iris Recognition by Characterizing Key Local Variations, " IEEE *transactions on image processing*, vol. 13, no. 6,pp 739-749, June 2004.

[28] R. Wildes, J. Asmuth, G. Green, S. Hsu, R. Kolczynski, J. Matey, and S. McBride, "A machine-vision system for iris recognition," *Mach. Vis.Applic.*, vol. 9, pp. 1–8, 1996.

[29] R. Wildes, "Iris recognition: an emerging biometric technology," *Proc.IEEE*, vol. 85, pp. 1348–1363, Sept. 1997.

[30] R.Wildes, J. Asmuth, S. Hsu, R. Kolczynski, J. Matey, and S. Mcbride, "Automated, noninvasive iris recognition system and method," U.S. Patent 5 572 596, 1996.